Enhancing Photovoltaic Cell Classification through Mamdani Fuzzy Logic: A Comparative Study with Machine Learning Approaches Employing Electroluminescence Images

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Abstract. This study introduces a Mamdani Fuzzy Logic model designed to classify solar cells based on their energetic performance. The model incorporates three distinct inputs, namely the proportions of black pixels, gray pixels, and white pixels, extracted from Electroluminescence images of the cells. Additionally, an output is included to signal potential issues with input data. The development of the model involved utilizing cells with known performance, determined through the measurement of Intensity-Voltage Curves. The efficacy of the model was demonstrated through testing with a validation set, yielding an accuracy rate of 99.0% in the Polycrystalline dataset and 98% in the Monocrystalline. In comparison, traditional machine learning methods such as Ensemble Classifiers and Decision Trees achieved inferior accuracy rates. These results show the superior problem-solving capability of the presented Fuzzy Logic model over conventional machine-learning approaches.

Keywords: Fuzzy Logic · Photovoltaic · Electroluminescence · Machine Learning.

1 Introduction

The use of traditional energies has been reduced in the last years in favor of more accessible, renewable, cheaper and cleaner sources [1]. Solar energy is among the

most relevant renewable energies for smart cities due to its facility to be installed in urban areas. However, Photovoltaic (PV) modules can suffer of diverse kinds of problems (thermal problems, mechanical defects, etc) that decrease their performance. The verification of the state of the different modules is vital to optimize their production.

The maintenance of the PV facilities has been traditionally made by human supervision. However, this method is not affordable in big installations or urban areas due to the high amount of modules or the difficulty of accessing the modules. Artificial Intelligence (AI) is the key to solving this issue since it can help to monitor the conditions of the modules and to optimize the production of the farms [2, 3]. AI has shown to be extremely important for almost any kind of problems, being able to model complex kinds of data patterns and perform with great results the tasks [4–6]

Analyzing the state of PV cells is a complex and widely discussed issue. Most research addresses this problem by detecting defects on the surface of the modules. Various techniques, such as Thermography, Electroluminescence (EL), and Photoluminescence (PL), are employed to gather more detailed information about the surface. For more information on these techniques, please refer to the bibliography [7, 8]. However, this approach does not directly consider the effects these defects (or other issues) have on the performance of PV cells.

The performance of PV modules is typically measured using the Intensity-Voltage (I-V) curve, which can be obtained at the module level in PV installations or at the cell level in the laboratory.

Few studies have addressed predicting the output power of PV modules or cells using machine learning methods. Hoffmann's works predict the module power using EL images [9] or PL [10]. These studies achieve a Mean Absolute Error (MAE) of 4.4% and 3.7%, respectively, utilizing a deep learning approach with ResNet. However, these works differ from the current proposal as they are conducted at the module level. Other studies, such as [11, 12], focus on detecting defects on the surface of PV cells using EL images and report very high accuracy values. Additional related works can be found in reviews like [13, 14].

Among the various AI models trained using these images, Convolutional Neural Networks (CNNs) base models [15] are the ones that obtain better results due to their facility to recognize patterns over images. However, CNNs also have some drawbacks since they need high amounts of samples for their training phase to obtain better results than other machine learning algorithms and they are also computer-demanding, usually needing a computer provided a Graphical Processing Unit (GPU).

Other models based on Fuzzy Logic have been applied to the classification of PV cells. The proposal found in [16] applies FL to detect different microcracks using EL images of PV modules. Other works [17] use a hybrid between mathematical morphology and fuzzy logic to make a classification of the detects from PV cells, which was limited to identify the defects on texture-less surfaces. Another work presented in [18] compares the performance of different Deep Learning methods with the performance of FL models at plant level. Fuzzy

models have also been applied for tracking the Max Power Point of the modules [19] or to model PV systems [20]. Even after analyzing some reviews of the topic [21, 22] it can be seen that there have not been any major works that tackle the issue of classifying the EL image of a PV module or cell in terms of its energetic performance.

Additional literature on the subject is available in reviews [21, 22]; however, none specifically address the classification of PV cells based on their EL images taking into account directly their performance.

The primary contribution of this paper is to introduce an innovative approach for analyzing the condition of photovoltaic cells, utilizing the data derived from Electroluminescence (EL) imaging and the energy production metrics obtained from the Current-Voltage (I-V) Curve. In addition to this novel analytical method, the paper presents a model grounded in Fuzzy Logic (FL), which adeptly addresses the problem by evaluating the intensity distribution of the pixels within the EL images. The application of FL in this context offers several advantages, including the generation of rules that are intuitive and easily comprehensible to humans, as well as lower computational requirements compared to alternative methodologies such as Neural Networks. Furthermore, this work builds upon and extends our previous proposal detailed in [23], enhancing its scope and applicability by including Monocrystalline Cells in the sample data. The novelty of this work lies in the interdisciplinary integration of advanced image processing techniques and fuzzy logic models, something that has not been extensively explored in existing literature. This approach not only improves the accuracy of fault diagnosis and operational efficiency of photovoltaic systems but also provides a scalable platform for future research and practical applications in the monitoring and maintenance of solar installations.

The paper presents the following structure: Section 2 presents the fundaments of fuzzy logic, Section 3 details the methodology used in the experiments that have been performed, Section 4 presents the results obtained and the findings, finally Section 5 explains the conclusions of this work.
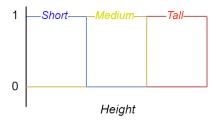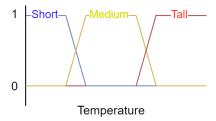
2   Fuzzy Logic Introduction

Fuzzy Logic (FL), introduced by Lotfi Zadeh in 1965 [24], is a mathematical framework designed to address uncertainty and imprecision in human reasoning. Traditional logic operates on binary (true/false) values, which are often insufficient for capturing the complexity of human decision-making processes. Fuzzy Logic aims to handle approximate reasoning and linguistic variables by allowing degrees of truth, rather than adhering strictly to binary values.

Architecture and Working Principles Fuzzy Logic extends traditional logic [25] by permitting values to range from completely true to completely false, thereby overcoming the binary limitations of classical logic. While traditional logic functions in a binary manner, where propositions are either true or false,

Fuzzy Logic introduces degrees of truth between 0 and 1. This flexibility allows Fuzzy Logic to model complex systems where precise inputs and outputs are difficult to define. Figure 1 illustrates the difference between representing temperature in both types of logic.

(a) Representation of Temperature with traditional logic

(b) Representation of Temperature with fuzzy logic

Fig. 1: Comparison of the representation of Temperature using Traditional Logic and Fuzzy Logic

The foundation of Fuzzy Logic lies in Membership Functions, which assign membership grades to elements within a universe of discourse. These functions capture the fuzzy boundaries of linguistic variables, enabling the representation of human-like reasoning in computational systems. Membership functions yield values in the range of $[0, 1]$, where 0 indicates no membership in the category and 1 signifies full membership.

One of the key strengths of Fuzzy Logic is its ability to handle uncertain and ambiguous information naturally and intuitively. This capability makes it particularly valuable in scenarios where traditional approaches fail to capture the nuances of real-world problems. Furthermore, Fuzzy Logic systems are interpretable; their rules and decisions can be understood and validated by domain experts, fostering trust and acceptance in practical applications.

At the heart of Fuzzy Logic are its inference algorithms, which translate vague, qualitative rules into precise, quantitative decisions. These algorithms enable Fuzzy Logic systems to emulate human-like reasoning processes, allowing them to navigate complex, real-world scenarios with ease.

There are several Fuzzy Logic inference algorithms, each with unique strengths and applications. One widely used method is the Mamdani inference method [26], which employs fuzzy sets and linguistic variables to model human expertise and intuition. Mamdani systems combine fuzzy rule bases with fuzzy inference engines to generate crisp, actionable outputs from fuzzy inputs. This algorithm is renowned for its simplicity and interpretability, making it ideal for applications where transparency and user understanding are paramount.

Another prominent inference algorithm is the Takagi-Sugeno (T-S) method [27], which differs from Mamdani in its treatment of the consequent part of fuzzy

rules. Instead of using linguistic variables, Sugeno systems utilize mathematical functions to represent the output of each rule. This approach simplifies the inference process and can lead to more computationally efficient systems, especially in control applications where precise numerical outputs are desired.

In addition to Mamdani and T-S methods, hybrid approaches combine elements of both to leverage their respective advantages. These hybrid algorithms offer flexibility and adaptability, allowing designers to tailor inference systems to specific problem domains and application requirements.

Applications Fuzzy Logic has been applied across various domains where decision-making involves uncertainty and ambiguity. It is widely used in control systems, such as fuzzy logic controllers for industrial processes and robotics. Additionally, Fuzzy Logic is employed in pattern recognition, image processing, natural language processing, and information retrieval. Consumer electronics, like washing machines and air conditioners, utilize fuzzy control for efficient and adaptive operation.

Advantages and Limitations Fuzzy Logic offers several advantages. It can effectively model and control nonlinear systems, enabling flexible and robust decision-making under uncertainty. Fuzzy Logic systems are interpretable and can handle imprecise and incomplete information more naturally than traditional binary logic. As a result, Fuzzy Logic has been successfully applied in diverse engineering and scientific fields.

However, Fuzzy Logic also has limitations. Designing fuzzy systems requires expert knowledge to define appropriate fuzzy sets and rules, which can be time-consuming and subjective. Fuzzy Logic may struggle with complex decision-making tasks involving high-dimensional data or dynamic environments. Additionally, tuning fuzzy systems for optimal performance can be challenging due to the subjective nature of linguistic variables and rules.

3 Methodology

This section provides the details about the methodology used in order to create the presented fuzzy logic model. It includes the gathering of the data, its pre-processing and labelling and the creation of the model with the selection and optimization of the membership functions and the fuzzy rules. For the analysis conducted in this study, we utilized MATLAB as the primary software environment due to its robustness and comprehensive suite of toolboxes. The Image Processing Toolbox provided essential functions for image analysis, enhancement, and transformation. We used imread to load electroluminescence images, imadjust to enhance image contrast, Additionally, the imhist function was employed to calculate the grayscale histogram of the analyzed images, providing critical data for further analysis.

3.1   Recollection of the Data

The acquisition of the data was performed with two different methodologies: The obtention of an image of the surface of the PV cell and the measuring of the performance of the PV cell.
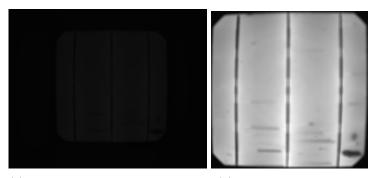
Obtaining an Image of the PV Cell The information that the visible spectrum provides of the conditions of the PV cells is quite limited. Different techniques can be used to obtain details about the surface of PV cells: Thermography, Photoluminescence, and Electroluminescence (EL) [7, 8]. For this work, the EL technique has been chosen since it can detect more defects than other techniques and it is the most used technique in related problems [13], however, it has the inconvenience of being invasive. The images have been taken with a silicon "In-GaAs C12741-0" camera with an lens with the following specifications: a focal length of 8 and an "f" number of 1.4. The images were taken surrounding the cell in a box in order to reduce the luminous noise produced by the sun. Different kinds of masks were used to produce shadows in the surface of the cell.

Measuring the performance of the PV Cell The performance of the PV cells has been obtained by calculating the Max Power Point (MPP) of the cell. The MPP has been calculated after measuring the values of Current and Voltages of the cells by using an I-V Tracer at level cell [28]. More information about obtaining the MPP will be explained in the next sections.

More information about the gathering process can be found in our previous work [29]. The dataset used in this work is an extension of the original dataset used in that work including PV cells of various technologies: Polycrystalline of 4 busbar (666 samples), Monocrystalline (556 samples).

3.2   Preprocessing of the Images

The images were processed by performing various fixes: The removal of the white pixels in the image provoked by the dead pixels found in the lens of the camera, the removal of the white pixels provoked by the luminous noise, improving the visibility of image by fixing the scale of the lighting due to the low width of the histogram, removing the dark surrounding areas of the image. Fig 2 presents a sample before the preprocessing and after it. These processes were performed automatically using Python scripts, more information can be found in our previous work [29].

(a) Image before performing prepro-   (b) Image after being fixed
cessing

Fig. 2: A sample image prior to and following the various steps of preprocessing

3.3   Maximum Power Normalization

Each measured I-V curve is used to determine the MPP which provides infor-
mation about their energetic production. However, it is necessary to use the
following process to obtain that information from the I-V curves:

1. The cells are divided according their technology, since each kind of PV cell
   has a different production of energy.
2. The values of the I-V curves are used to compute the Power-Voltage (P-V)
   Curves of the cells.
3. Computing the MPP of the cells using the maximum found in the P-V curve
4. The irradiance used in the measuring of the curve is used to divide the
   measurements. For each group:
   (a) The mean value and standard deviation of each group are used to perform
       a Z-Score normalization in the computed MPP values.
   (b) The obtained values are go through a Min-Max normalization after com-
       puting the maximum and minimum values of each group
   (c) The outcome of Min-max normalization produces has domain of $[0, 1]$, a
       mean value of 0.5, and a standard deviation of 0.2.
5. Ultimately, the final value serves as a measure of the relative performance
   of a cell, where lower values indicate lower energetic production, and higher
   values correspond to cells with higher energetic production.
6. Finally, 3 intervals are decided to represent the problem as a classification.
   (a) Class 0 ($[1, 0.81)$) corresponds with the cells with a performance close to
       the expected value.
   (b) Class 1 ($[0.81, 0.572]$) corresponds to cells that do not have the highest
       performance but are not underperforming either.
   (c) Class 2 ($(0.572, 0]$) corresponds with the cells that are underperforming
       due to various reasons.

3.4   Feature Extraction

One of the most important limitations of traditional AI methods such as FL is that they are not able to deal directly with images. To solve this issue, it is important to extract the most important characteristics (features) from the images. This section will explain what features were chosen and how they were extracted.

The histograms of the images 3 are similar in their structure, they present three sections: A peak related to the low values of the pixels (Dark colors), another with the middle values (gray colors), and finally a third peak related to white values. The dark values are related to the zones that are not emitting light in the EL images, those zones are the ones that will not produce energy when the PV cells is working. The brighter values are related to the zones that are emitting light as a reaction to the injected electrical current, these zones produce energy when the PV is working. The extremely bright values are related to the zones that are emitting more light than the usual values due to different factors.
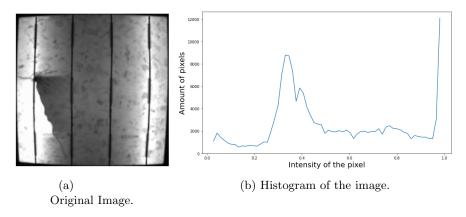

(a)
Original Image.

(b) Histogram of the image.

Fig. 3: Sample of a preprocessed EL image of a PV cell and its corresponding intensity histogram.

After following a comprehensive analysis of all the images in the dataset, a discernible pattern emerges, indicating that certain aspects are consistently present across the majority of images. Notably, the quantity of dark areas demonstrates a direct correlation with the performance of the cells, with a higher prevalence of dark areas suggesting diminished production efficiency.

An analysis of all the images provides the conclusion that an increase on the proportion of dark areas reduces the performance of the cell. Taking this into account, the intensity histogram of the images has been divided into three areas (Blacks, Grays, and Whites), using each of them as an input feature. The process followed to obtain them is the following:

– The datasets are partitioned into two distinct sets: Training (80%) and Validation (20%). The following steps were iteratively executed for each set within each dataset.

– Two different groups are created for each dataset: The training set (80% of the data) that will be used in the training process and the Validation set (20% of the data) that will be only used in the testing of the model. The following steps are iteratively executed for each set.

– The accumulated histogram of all the images if computed with its values normalized from 0 to 1.

– The limits between the three groups are chosen by finding the minimum point between the three main peaks in the histogram (0.35 and 0.7).

– The proportion of pixels for each group is calculated. This process is repeated for each image.

3.5   Model

This paper presents various FL Models based on the Mandami Inference Logic. As explained before, the main objective of this research is to classify PV cells being the criteria in their performance. These kinds of models present good perks for this problem since they are symbolic models which means that they produce rules that can be directly understood by humans . Moreover, FL models do not require high-spec devices. To implement the fuzzy logic system, we used the Fuzzy Logic Toolbox in MATLAB. We created a new fuzzy inference system (FIS) with newfis, added input and output variables using addvar, and defined membership functions with addmf. The rule base was established using addrule, incorporating expert knowledge and empirical data. The fuzzy inference process was executed with evalfis, and the results were defuzzified to obtain crisp values that represent the health and performance of the photovoltaic cells. This combination of MATLAB's toolboxes enabled efficient processing of EL images, robust feature extraction, and precise implementation of a fuzzy logic model, ensuring the accuracy and interpretability of our analysis.
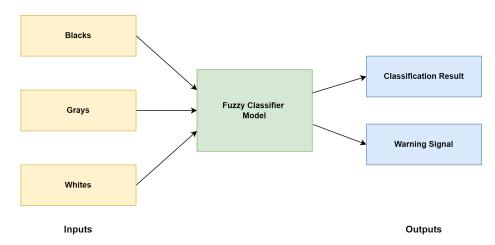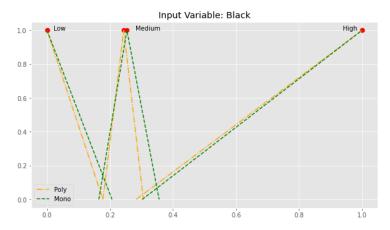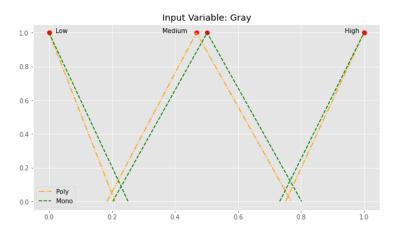
Fig. 4: Structure of the designed Fuzzy Logic model with its three inputs (Black, Grays, Whites) and the 2 outputs (Classification Results and Warning Signal).

The models (see Fig. 4) with the extracted features as inputs and with two outputs: The results of the classification and an output that works as a warning about inputs that are not logical in this context (proportions not adding 100% or really high values in an input such as grays 100%).
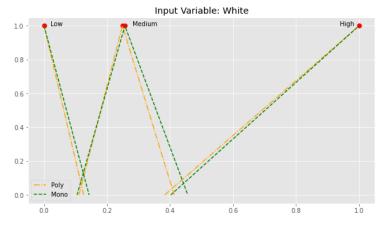
Membership Functions Each one of the inputs (Blacks, Grays, and Whites) is represented with three Membership functions related to the proportion of pixels of that type in the image: Low, Medium, and High. The membership functions varies depending on the case of Monocrystalline cells and Polycrystalline cells (see Fig. 5).

(a) Membership functions of the input variable: Proportion of Black pixels

(b) Membership functions of the input variable: Proportion of Gray pixels

(c) Membership functions of the input variable: Proportion of White pixels

Fig. 5: The membership functions for the three different inputs of the Fuzzy Logic Model. Green Values shows the values for the Monocrystalline dataset and Green Values of the Polycrystalline dataset

The classification output has been represented also as three different membership functions (see Fig. 6): High (Class 0), Medium (Class 1), and Low (Class 2). Each one is related to the amount of power produced by the cell and its performance. The same membership functions are used in both models.
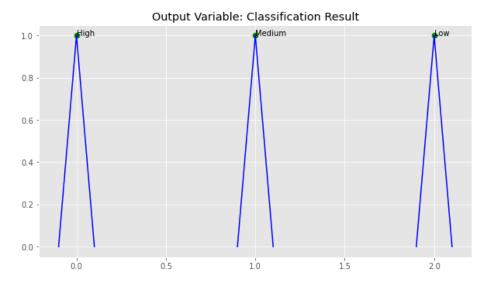

Fig. 6: Membership functions obtained for the classification output of the Fuzzy Model

The Warning output is represented with a pair of membership functions: Negative and Positive (See Fig. 7).
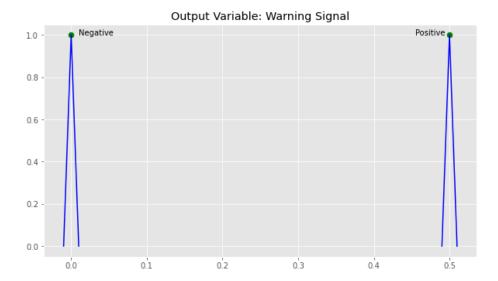
Fig. 7: Membership function obtained for the Warning Output designed to detect invalid combinations of inputs

Rules The conclusive ruleset of the models is detailed in Table 1, the Monocrystalline model and the Polycrystalline model present the same rules.

The rules were formulated based on the expertise of professionals in the field. Their understanding of the impact of defects on cell performance, coupled with information derived from the I-V curve's output power, was leveraged to establish rules for categorizing images into their respective classes. The aim was to optimize the accuracy of the classification results within the training set.

The warning output in no considered for the metrics in the training, since its finality is to indicate incorrect values in the inputs. The process of finding the best parameters has been completely manual. This is clearly different from other algorithms such as Machine Learning methods.

As explained before, neither of the two models has incorporated the validation set into their training processes, thereby diminishing potential biases during testing.

Rule	Black	Gray	White	Classification Output	Warning Signal
1	L	L	L	L (0)	+
2	L	L	M	H (2)	-
3	L	L	H	H (2)	-
4	L	M	L	H (2)	-
5	L	M	M	H (2)	-
6	L	M	H	H (2)	-
7	L	H	L	M (1)	-
8	L	H	M	H (2)	-
9	L	H	H	H (2)	+
10	M	L	L	L (0)	+
11	M	L	M	M (1)	-
12	M	L	H	M (1)	-
13	M	M	L	M (1)	-
14	M	M	M	M (1)	-
15	M	M	H	M (1)	+
16	M	H	L	L (0)	-
17	M	H	M	L (0)	+
18	M	H	H	L (0)	+
19	H	L	L	L (0)	-
20	H	L	M	L (0)	-
21	H	L	H	L (0)	-
22	H	M	L	L (0)	-
23	H	M	M	L (0)	-
24	H	M	H	L (0)	-
25	H	H	L	L (0)	+
26	H	H	M	L (0)	-
27	H	H	H	L (0)	+

Table 1: Fuzzy Ruleset of both models. Black, Gray, and White are the inputs. Classification output and Warning Signal the outputs. H: High; M: Medium; L: Low; +: Positive; -: Negative

Fig. 8 provides the 3D surface diagram about the relationship of the classification output with two inputs: Black and Gray. This diagram shows the information that is built in the model, relating the input values with the output. Low values of blacks imply an output of class 0. Class 1 appears with blacks between 20% and 30%. Finally, Class 2 is related to the remaining cases.
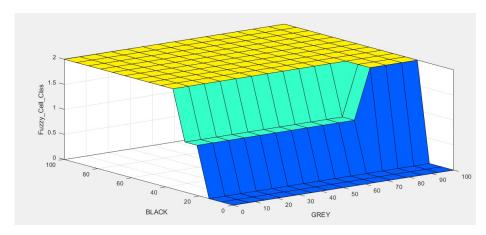
Fig. 8: 3D surface diagram illustrating the impact of inputs Black and Gray on the output.
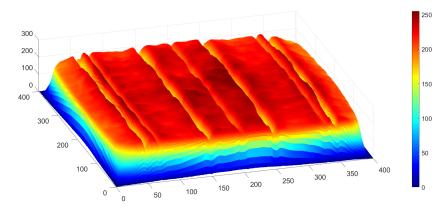
4   Results

This section delineates the capabilities of the models by showcasing their accuracy on the validation sets. Furthermore, it offers a comparative analysis with alternative methods, all of which have been created utilizing the Classification Learner tool in Matlab.
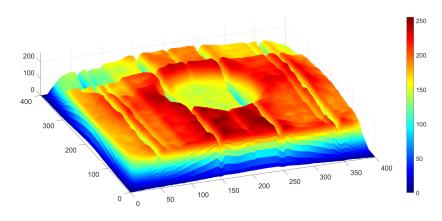
The datasets were divided into two distinct sets: a Training set, constituting 80% of the data, and a Validation set, encompassing the remaining 20%. Figures 9 and 10 illustrate the distribution of the validation set for both datasets (Monocrystalline and Polycrystalline).

In Figure 10a, it is evident that the mean of all images in Class 0 corresponds to cells in good condition. This observation is further reinforced in Figure 9a, where all images of this class are stacked. This rationale can similarly be applied to images of Class 1, as shown in Figures 10b and 9b, which exhibit minor defects or shadows that have a negligible impact on performance.
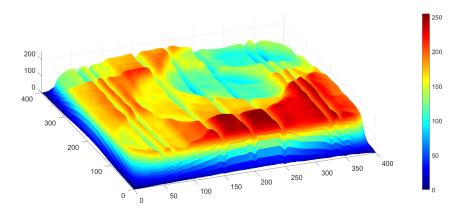
Lastly, Figures 10c and 9c emphasize that images in Class 2 display defects or shadows that diminish the functional areas of the cells. This detailed classification and visualization provide a clear understanding of the condition and quality of the cells across different classes, facilitating a more accurate analysis of the datasets.

(a) Diagram obtained from images of class 0

(b) Diagram obtained from images of class 1

(c) Diagram obtained from images of class 2

Fig. 9: 3D diagram derived from the consolidation of images belonging to the same class within the validation set.

(a) Mean Image of class 0   (b) Mean Image of class 1   (c) Mean Image of class 2
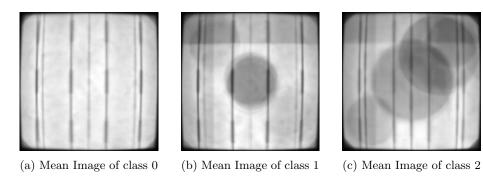
Fig. 10: Image obtained by calculating the mean of all the images within each class from the validation set.

The model obtained an accuracy of 99% in the Validation set of the Polycrystalline dataset. Figure 11 shows the classification results, including the confusion matrix and the obtained accuracy in each case. It can be observed that the results are high in every class; however, Class 1 presents a slightly lower value. Another observation is that there are only classification errors between adjacent classes since there is no instance of confusing an image of Class 0 with an image of Class 2 or vice versa. This indicates that while the model performs exceptionally well overall, the minor misclassifications are limited to more closely related categories, suggesting robustness in distinguishing distinctly different classes.

Fig. 11: Confusion Matrix and Accuracy of the classification of the FL model for Polycrystalline cells on the Validation Set.

The results in the validation set of the Monocrystalline model (Figure 12) are slightly lower than in the previous case, but it still presents an accuracy of 98%. As in the previous case, there are no mistakes between Classes 0 and 2.

True Class	Confusion Matrix			Accuracy
0	32	1	0	98.50%
1	1	30	3	96.90%
2	0	3	62	99.10%
	0	1	2	
	Predicted Class			

Fig. 12: Confusion Matrix and Accuracy of the classification of the FL model for Monocrystalline cells on the Validation Set.

Various algorithms were selected for comparative analysis with the method presented in this work, all of which are available in the Classification Learner application of Matlab. The chosen methodologies encompassed Decision Trees, Discriminant Analysis, Logistic Regression Classifiers, Naive Bayes Classifiers, Support Vector Machines, Nearest Neighbor Classifiers, and Ensemble Classifiers. Notably, Decision Trees and Ensemble Classifiers exhibited the highest results across both Polycrystalline and Monocrystalline datasets.

Refer to Table 2 for a comprehensive presentation of the results of the selected algorithms. While they demonstrated commendable classification capabilities, it can be seen that their performance is still behind the proposed method, as evidenced by the observed accuracy metric. The table highlights the accuracy, precision, recall, and F1-score for each algorithm, providing a detailed comparison.

The superior performance of the proposed method is particularly notable in its ability to handle the subtle variations and complexities within the datasets. This underscores the significance of employing fuzzy logic in addressing the intricacies of the problem at hand. Fuzzy logic enhances the model's robustness and adaptability, allowing it to make more accurate distinctions between closely related classes. As a result, the proposed method achieves higher overall accuracy and more reliable classification outcomes compared to traditional algorithms.

Table 2: Accuracy of the different models

	Fuzzy Model	Ensemble Classifiers	Decision Trees
Polycrystalline	*99.11%*	98.32%	96.45%
Monocrystalline	*98.12%*	96.27%	97.17%

5   Conclusions and future work

Detecting the status of solar cells is a critical challenge due to the valuable insights it offers for optimizing the production PV systems. The innovative application of fuzzy logic models to address this issue is noteworthy, as only a limited number of studies have explored this approach.

The models have been tested with a 99% of accuracy on Polycrystalline images as opposed to the 98% that obtains other ML models. In the case of Monocrystalline images, the fuzzy model obtains a 98% as opposed to the 97% of the other methods.

The presented model suffers from several limitations since the creation of the rules and the optimization of the membership functions are totally manual processes that need the aid of experts of the domain to obtain optimal performance. The solution of this drawback is one of the main focus of our next points of research. Another important limitation of the model is the amount and variety of the data since the used data only consists of two different kinds of PV cells with mostly soiling-simulated defects. This could be solved by the obtention of new PV cells that present different kinds of defects or PV cells of different technologies that have not been considered. The actual model is only capable of working at cell level. For module-level, it would require a previous segmentation of the EL images of the PV modules into singular images of each one of the cells that are part of each module. Time-real applications also could be considered.

6   Acknowledgements

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