

# Computer vision-based method for quantifying iron-related defects in silicon solar cells

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**Abstract.** This study demonstrates the feasibility of employing transfer learning from pre-trained computer vision (CV) models to predict the iron concentration in silicon solar cells, even when the available training datasets are extremely limited. The predictions were based on the kinetic dependencies of the short-circuit current following FeB pair dissociation, which was converted into images using wavelet transformation. The performance of various combinations of CV models and regression algorithms was systematically analyzed. Specifically, several state-of-the-art CV architectures, including EfficientNetB7, MobileNetV2, NASNetLarge, ResNet152V2, Xception, and YOLOv4, were utilized either as classifiers or as feature extractors. Regression models, namely Random Forest, Gradient Boosting, eXtreme Gradient Boosting, Support Vector Regression (SVR), and Deep Neural Networks (DNNs), were trained to predict iron concentration from the extracted features. Training and testing were performed using both simulated and experimental datasets. In both cases, EfficientNetB7 and NASNetLarge provided the most informative features for subsequent regression. Among the regression algorithms, SVR and DNNs were identified as the most effective. These models achieved MSE, MAPE, MedAPE, and  $R^2$  values of up to 0.001, 6%, 4%, and 0.999, respectively, for the simulated data, and 0.008, 10%, 5%, and 0.996 for the experimental data.

*Keywords:* defect, Si solar cell, iron contamination, machine learning, computer vision

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## 1. Introduction

Owing to the urgent need to address environmental challenges and growing global demand for renewable energy, the deployment of photovoltaic (PV) systems has been rapidly increasing worldwide. In particular, solar PV generation exceeds 1,600 TWh in 2023 [1, 2], rising by approximately 30% in 2024 [3], and forecasts indicate that the total installed capacity will surpass 6 TW by 2030 [1]. Meanwhile, crystalline silicon photovoltaics, which have benefited from decades of scientific advancement and continuous cost reductions, continued to dominate the market in 2024, accounting for approximately 98% of the global share [4, 5].

As in other semiconductor devices, defects play a decisive role in determining the operating parameters of the solar cells. Therefore, diagnosing defects, particularly determining their concentrations, is critical for maintaining stable performance of PV systems. In recent years, researchers have increasingly complemented established defect characterization methods with machine learning (ML) approaches that improve the accuracy, speed, and cost efficiency of these analyses. The use of ML methods for analysing macroscopic defects (such as cracks, finger failures, hotspots, and scratches) and point defects, however, differs significantly. Researchers typically detect macroscopic defects in PV systems using two main approaches [6, 7]. The first approach, Electrical Testing Techniques, involves analysing characteristic electrical curves of parameters such as current, voltage, and power. The second approach, Imaging-Based Techniques, involves analysing electroluminescence (EL) [8] or photoluminescence [9] images of solar cells. Numerous review studies demonstrate extensive use of ML in both approaches [10, 11, 12, 13, 14, 15, 16].

Although point defects represent one of the primary limitations of PV devices, researchers have developed considerably fewer ML techniques - specifically for their analysis. Existing ML-based approaches include extracting recombination active center parameters from lifetime measurements [17, 18, 19], detecting radiation-induced defects using Raman spectroscopy [20, 21], estimating the concentration of contaminant impurities from the ideality factor of the current-voltage characteristics [22], and analysing variations in photovoltaic conversion parameters [23]. Nevertheless, a relatively limited number of such methods are offered.

One of the main challenges in applying ML methods effectively is that training the models requires a large amount of labelled data [12]. In practice, researchers often cannot obtain such large volumes of experimental data; therefore, they commonly employ approaches such as simulations, in which hundreds of thousands of dependencies are computed [17, 18, 19,

24, 23]; Physics-Informed Neural Networks (PINNs), which incorporate physical laws into the loss function to generate synthetic data [25, 26]; or Transfer Learning, in which a model trained on one task is adapted to another related task [27, 28]. However, simulations can be highly demanding in terms of time and computational resources; PINNs are primarily suitable for phenomena described by partial differential equations, and pre-trained models are not available for all types of physical problems. At the same time, one of the most extensively studied tasks in machine learning is computer vision (CV), for which many pre-trained models have been publicly released. Moreover, these models are typically trained on extremely large standard datasets. For example, EfficientNetB7 was trained on approximately 1.2 million images from the ImageNet dataset.

This study primarily aimed to apply standard pre-trained CV models to analyze the electrophysical measurement results related to point defects. In particular, we focus on quantifying iron in boron-doped crystalline silicon solar cells by examining short-circuit current ( $I_{sc}$ ) relaxation following intense illumination. Iron is one of the most prevalent, ubiquitous, and efficiency-limiting metallic impurities in such structures [29, 30], which, as noted earlier, forms the foundation of the photovoltaic market. In Si:B, iron tends to form iron-boron pairs under equilibrium conditions, which intense illumination can dissociate [31, 32]. In fact, the aforementioned  $I_{sc}$  variations directly reflect the recovery process of iron-boron pairs [33].

It should be noted that the use of well-established computer vision benchmark architectures such as YOLO, MobileNetV2, EfficientNet, ResNet, Xception, GoogleNet, and other convolutional neural networks (CNNs) is a common approach for identifying macrodefects from EL measurements [8, 34, 6, 35, 36, 37, 38, 39]. However, in this case, the measurement result is an image, makes the approach relatively straightforward. In our case, it was necessary to transform the time dependence into an image representation. Standard approaches to solving such problems involve the use of Fourier or wavelet transforms, and last were applied in this study. In photovoltaics, wavelet transforms are typically used for processing solar cell images to enhance the detection of macrodefects [40, 41], but they can also be employed to convert one-dimensional non-stationary signals into two-dimensional spectrograms and thereby enable the effective extraction of subtle features [42].

By applying computer vision models to wavelet spectrograms represented as images, we generated high-dimensional feature vectors and used them as inputs for traditional regression models. The  $I_{sc}(t)$

dependencies for training the regression models were obtained via simulations and experimental measurements. In both cases, the hybrid Transfer Learning approach produced predictions with sufficiently high accuracy (within a few percent) even when training models on small datasets containing fewer than 30 samples. Importantly, the proposed approach is highly versatile and can be extended to a wide range of tasks related to defect characterization and other applications.

## 2. Methodology

### 2.1. General outline of the method

Figure 1 illustrates the workflow of the ML pipeline used to extract iron contamination from  $I_{sc}(t)$  dependencies. The process consisted of three main blocks: Data Acquisition, CNN Feature Processing, and Predictive Regression. The first stage involves either simulating or experimentally measuring the time dependence of the short-circuit current in a solar cell after the induced decay of the FeB pairs. These procedures are described in detail in Subsections 2.2 and 2.3. For the experimental curves, the data were smoothed using a Savitzky–Golay filter [43]. Subsequently, a continuous wavelet transform [44] was applied to convert the one-dimensional time dependencies into two-dimensional spectrograms represented as images, where each point corresponds to the amplitude of the wavelet coefficient at a specific time and frequency. The Morlet wavelet was employed, and the procedure was implemented using the Python package PyWavelets. Examples of the resulting images are shown in Figure 2b and Figure 2c. Data augmentation was then performed by flipping the images along the x- and y-axes and rotating them by  $90^\circ$ ,  $180^\circ$ , and  $270^\circ$ . This procedure is known to improve the accuracy of ML model predictions, particularly when only small datasets are available [45].

During the CNN Feature Processing stage, all images (both original and augmented) were processed using one of the standard CV models to extract a feature set for each image. The selected models and feature extraction settings are described in Subsection 2.4. No CNN fine-tuning was performed, and the models were used in their pre-trained form, as downloaded. In general, the dimensionality of the feature vectors obtained from the CNN outputs substantially exceeds the number of available samples, implying a high degree of redundancy. Therefore, to enable comparison and mitigate this effect, Principal Component Analysis (PCA) was applied in some cases to reduce the feature dimensionality with negligible loss of total variance.

The obtained feature sets served as inputs to the regression models based on one of the standard

algorithms described in Subsection 2.5, which aimed to predict the iron concentration ( $N_{Fe}$ ) in the solar cell. In the first case, the regression models were trained on a simulated training dataset and tested on both the simulated test dataset and experimental data. In the second case, a portion of the experimental results was used for training, whereas the remaining part was reserved for testing the corresponding models. During training, feature sets derived from the original wavelet spectrograms and their augmented versions were treated as separate samples. During testing, the median of the predicted values obtained from the original and augmented images was used as the final prediction. Model performance was evaluated using the metrics described in Subsection 2.6.

### 2.2. Simulation details

To obtain the  $I_{sc}(t)$  dependencies,  $I$ - $V$  curve simulations were performed for a silicon  $n^+$ - $p$ - $p^+$  structure under monochromatic illumination using SCAPS-1D version 3.3.11. The SCAPS-1D software [46] is a widely used tool for modeling solar cells while accounting for defect states [47, 48, 49, 50, 51, 52].  $I_{sc}$  values were extracted from the simulated  $I$ - $V$  curves using a standard procedure [53].

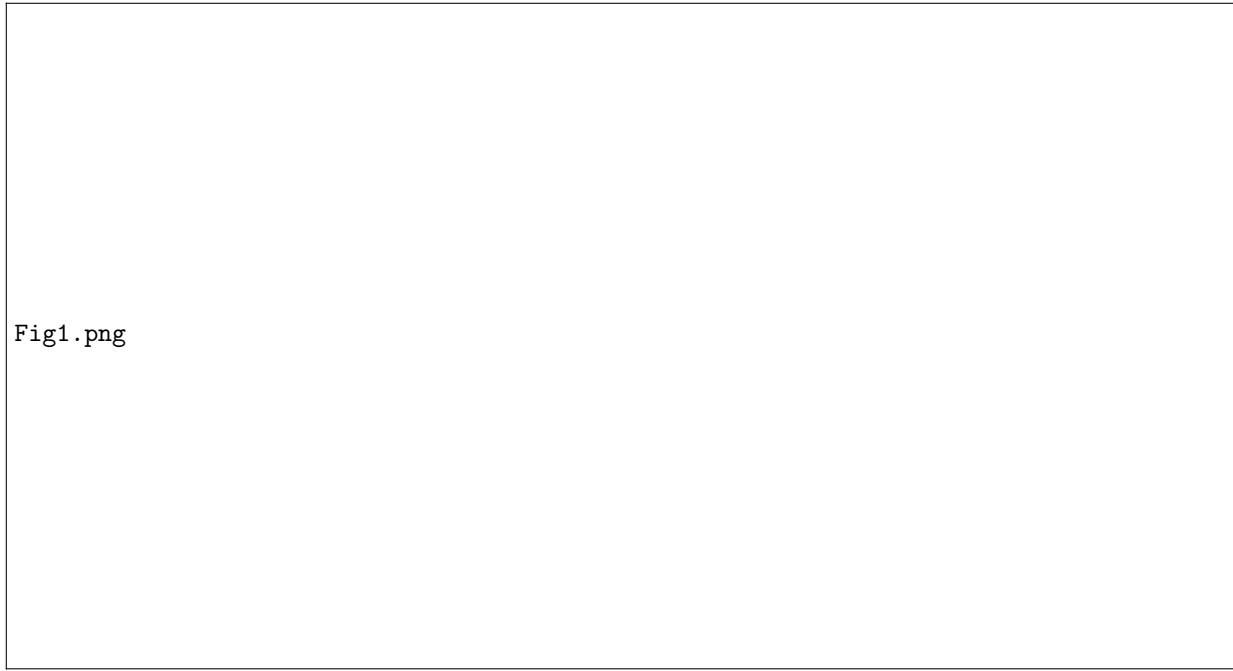
During the simulations, the base thickness of the structure was set to  $380\text{ }\mu\text{m}$ , and boron was used as the doping element with a concentration of  $N_B = 1.36 \times 10^{15}\text{ cm}^{-3}$ . The temperature was maintained at  $340\text{ K}$ , and monochromatic illumination with a wavelength of  $940\text{ nm}$  and an intensity of  $5\text{ W/m}^2$  was applied, corresponding to the experimental conditions (see Subsection 2.3). One of the modeling parameters was the total concentration of iron impurity atoms,  $N_{Fe}$ . It was assumed that Fe atoms were uniformly distributed throughout the base and  $p^+$  layer of the solar cell and could exist either in interstitial positions, with a concentration  $N_{Fe_i}$ , or as FeB pairs, with a concentration  $N_{FeB}$ . The time dependence of  $N_{Fe_i}$  after pair dissociation follows the well-known expression [54, 55]:

$$N_{Fe_i}(t) = (N_{Fe_i,0} - N_{Fe_i,eq}) \times \exp(-t/\tau_{ass}) + N_{Fe_i,eq}, \quad (1)$$

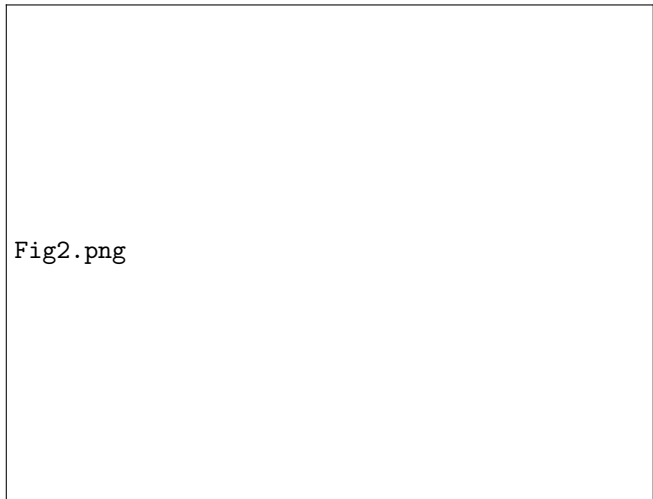
where where  $N_{Fe_i,0}$  is the concentration of interstitial iron atoms formed due to FeB pair dissociation,  $N_{Fe_i,0} = N_{Fe_i}(t=0) = N_{Fe}$ ;  $N_{Fe_i,eq}$  is the portion of interstitial iron atoms that remain unpaired in the equilibrium state  $N_{Fe_i,eq} = N_{Fe_i}(t \rightarrow \infty)$ , according to [54, 55]

$$N_{Fe_i,eq} = \frac{N_{Fe}}{\left[1 + N_B \cdot A_z \cdot \exp\left(\frac{E_b}{kT}\right)\right] \left[1 + \exp\left(\frac{E_F - E_{Fe_i}}{kT}\right)\right]}, \quad (2)$$

$E_b$  is the binding energy of the FeB pairs (taken as  $0.582\text{ eV}$  [55]),  $A_z$  depends on the number of possible orientations of the pair and lattice site density (taken



**Figure 1.** Workflow of the ML pipeline



**Figure 2.** Simulated time dependencies of short-circuit current (a) and corresponding wavelet spectrograms for iron concentrations of  $10^{10} \text{ cm}^{-3}$  (b) and  $10^{14} \text{ cm}^{-3}$  (c). The data in panel a are shown with filled squares for the concentration corresponding to panel b and with open circles for that corresponding to panel c.

as  $10^{-23} \text{ cm}^3$  [54]),  $E_F$  is the Fermi level,  $E_{\text{Fe}_i}$  is the position of the donor  $\text{Fe}_i$  level relative to the valence band maximum (taken as 0.394 eV [32]),  $\tau_{\text{ass}}$  is the characteristic time of the complex association, according to [56, 32, 57]

$$\tau_{\text{ass}} = A \times \frac{T}{N_A} \exp\left(\frac{E_m}{kT}\right), \quad (3)$$

$E_m$  is the energy of  $\text{Fe}_i^+$  migration (taken as 0.66 eV

[32, 56, 57]),  $A$  is the constant (taken as  $5.7 \times 10^5 \frac{\text{s}}{\text{K cm}^3}$  [57]). The iron-boron pair concentration  $N_{\text{FeB}}$  was estimated as follows:

$$N_{\text{FeB}}(t) + N_{\text{Fe}_i}(t) = N_{\text{Fe}}. \quad (4)$$

Overall, the concentrations of iron-related defects depended not only on time but also on their spatial position within the structure, reflecting the non-uniformity of the  $(E_F - E_{\text{Fe}_i})$  difference.

The parameters used in the simulations are summarized in table 1. Additional details on the procedure for modeling the  $I$ - $V$  curves of silicon solar cells containing iron impurities can be found in [24, 58].

To create the training dataset, 25  $N_{\text{Fe}}$  values were selected and evenly distributed on a logarithmic scale from  $10^{10} \text{ cm}^{-3}$  to  $10^{14} \text{ cm}^{-3}$ . Examples of the resulting dependencies are shown in Figure 2, along with the corresponding wavelet spectrograms. The simulated test dataset consisted of 10 dependencies calculated for 10  $N_{\text{Fe}}$  values that were not included in the training dataset.

### 2.3. Experiment details

The proposed method was validated using measurements of  $n^+p$ - $p^+$  silicon solar cells fabricated on 380  $\mu\text{m}$  thick  $p$ -type boron-doped Cz wafers ( $N_B = 1.36 \times 10^{15} \text{ cm}^{-3}$ ). The  $n^+$  (0.7  $\mu\text{m}$ , 20–30  $\Omega/\square$ ) and  $p^+$  (0.6  $\mu\text{m}$ , 10–20  $\Omega/\square$ ) layers were formed by phosphorus and boron diffusion, respectively. The details of the fabrication procedure are provided elsewhere [33].

**Table 1.** Input parameters used in the simulation of short-circuit current kinetics

Solar cell parameters	$p^+$ -layer [59]	$p$ -layer real sample	$n^+$ -layer [59]
Thickness ( $\mu\text{m}$ )	7.75	380	0.39
Doping concentration profile	non-uniform	uniform	non-uniform
Doping [maximum] concentration ( $\text{cm}^{-3}$ )	$4.8 \cdot 10^{18}$	$1.36 \cdot 10^{15}$	$3 \cdot 10^{20}$

Silicon properties				
Bandgap (eV)		1.1136	[60]	
Bandgap narrowing* (meV)		0.84	[61]	
Light absorption coefficient ( $\text{cm}^{-1}$ )		227	[62]	
Density of states at conduction band ( $\text{cm}^{-3}$ )		2.885	[63]	
Density of states at valence band ( $\text{cm}^{-3}$ )		2.629	[63]	
Band-to-band recombination coefficient* ( $\text{cm}^3/\text{s}$ )		$1.256 \cdot 10^{-15}$	[64]	
Auger recombination coefficient* ( $\text{cm}^6/\text{s}$ )		electron	hole	
		$1.29 \cdot 10^{-30}$	$3.88 \cdot 10^{-31}$	[65, 66]
Thermal velocities ( $\text{cm/s}$ )		$2.16 \cdot 10^5$	$1.79 \cdot 10^5$	[67]
Carrier mobility* ( $\text{cm}^2/\text{Vs}$ )		1008	349	[68]
Effective mass ( $\text{cm}^2/\text{Vs}$ )		0.36	0.82	[69]

*\* listed values correspond to the  $p$ -layer; for  $p^+$  and  $n^+$ -layers, it was assumed that these values depend on location and are determined by the local concentration of ionized dopants*

Defect characteristic	$\text{Fe}_i$	$\text{Fe}_i\text{B}_s$		
Level type	donor	donor	acceptor	
Level energy (eV)	$E_V + 0.394$	$E_V + 0.10$	$E_C - 0.262$	[70, 71, 72]
Capture cross section electrons ( $\text{cm}^2$ )	$6.2 \cdot 10^{-15}$	$4 \cdot 10^{-13}$	$2.4 \cdot 10^{-15}$	[70, 71, 72]
Capture cross section holes ( $\text{cm}^2$ )	$8.3 \cdot 10^{-17}$	$2 \cdot 10^{-14}$	$4.4 \cdot 10^{-14}$	[70, 71, 72]
Migration energy (eV)	0.66			[32, 56, 57]
Binding energy (eV)		0.582		[55]

Current–voltage curves and  $I_{\text{sc}}$  kinetics were measured using a Keithley 2450 source meter. A 940 nm SN-HPIR940nm-1W LED (intensity 5 W/m<sup>2</sup>) was used as a monochromatic light source, and its output was stabilized by a W1209 thermostat and a feedback-controlled power supply. The cell temperature was regulated by a thermoelectric cooler with an STS-21 sensor and maintained constant using a PID algorithm in the control software. FeB pair dissociation was induced by intense (approximately 7000 W/m<sup>2</sup>) halogen lamp illumination. The illumination intervals were selected according to a previous study [73]. The kinetics of the short-circuit current were measured in the dark at 340 K for 3000 s. According to Eq. (3), this interval is sufficient for the complete restoration of the iron–boron pairs to their equilibrium concentration.

Figure 3a shows an example of the measured  $I_{\text{sc}}(t)$  dependence. The signal contained some noise because, despite using a thermostat, the LED temperature fluctuated by approximately 0.4 K. A Savitzky–Golay filter was applied for smoothing, with the window lengths and filter order selected adaptively according to Krishnan and Seelamantula [43]. Only the current values corresponding to the time points used

in the simulations were retained for the wavelet transformation. The smoothed curve is shown in Figure 3a, while the remaining panels of the figure display the spectrograms obtained from the raw experimental curve and the processed dependence.

The iron concentration  $N_{\text{Fe}}$  was determined using the methodology described in [74, 33], which is based on fitting the kinetics of the short-circuit current following FeB pair dissociation. A total of 28 samples with iron concentrations ranging from  $10^{11} \text{ cm}^{-3}$  to  $2 \times 10^{13} \text{ cm}^{-3}$  were examined. The entire experimental dataset was used as the test set to evaluate the models trained using the simulated data. In cases where the models were trained using experimental data, 20 randomly selected samples were included in the training set, while the remaining eight samples were used for testing.

#### 2.4. Computer vision models

Several computer vision models available in Keras were employed to extract graphical features from the wavelet spectrograms, namely EfficientNetB7, ResNet152V2, MobileNetV2, Xception, and NASNet-Large. Although these models have different archi-

Fig3.png

**Figure 3.** (a) Experimentally measured time dependence of the short-circuit current for a sample with  $N_{\text{Fe}} = 2.8 \cdot 10^{13} \text{ cm}^{-3}$  (a, open squares) and the same dependence after applying the Savitzky–Golay filter (filled circles). Panels (b) and (c) show the wavelet spectrograms corresponding to the curves with filled squares and open circles, respectively.

tures, they all belong to the CNN class, are designed for object classification, and have previously been successfully applied to processing EL images of solar cells [6, 35, 36, 38, 39]. Two feature extraction strategies were evaluated for all models: in the first, the class-specific probability distributions (soft labels) were passed to the subsequent stage of the pipeline, while in the second, the raw feature vectors directly extracted by the computer vision model were utilized.

Furthermore, the CSPDarknet53 model, which served as the CNN backbone for YOLOv4, was employed. Models of this family feature a more sophisticated CNN architecture that is not optimized for single-object classification, but for multi-object detection in images. They are widely used in imaging-based techniques [8, 34, 36]. The employed model produced three feature maps, and for subsequent processing, only the highest-level layer or the two deepest layers were selected.

It is well known that increasing feature dimensionality does not necessarily enhance the total information variance. Principal Component Analysis (PCA), which constructs new, uncorrelated features (principal components) was applied to mitigate the impact of redundant data. PCA is a widely used and effective technique in machine learning, particularly for improving performance in Electrical Testing Techniques [75, 76]. In this study, PCA was applied to the training datasets with an explained variance threshold of 99.9%. In other words, the principal components explaining no less than 99.9% of the total variance in the original features were selected, thus achieving a

substantial reduction in feature dimensionality. This pre-processing procedure was selectively applied to a subset of the computer vision models — specifically, those demonstrating good performance on the test sets without PCA — with the aim of assessing the feasibility and effectiveness of this approach.

Given the remarkably high dimensionality of the features produced by YOLOv4, the feasibility of applying an alternative dimensionality reduction technique was examined. Specifically, global average pooling was applied to each convolutional feature map, replacing the spatial map with its mean value, thereby yielding a single scalar value per channel.

The configurations of the computer vision models used in this study are summarized in table 2. The table also lists the notations that are subsequently used to refer to these configurations.

### 2.5. Regression algorithms

Five ML algorithms were employed to develop regression models for predicting iron concentrations: Random Forest (RF), Gradient Boosting (GB), eXtreme Gradient Boosting (XGB), Support Vector Regression (SVR), and Deep Neural Network (DNN). The models were implemented using Python libraries: Keras for DNN; Scikit-learn for RF, GB, and SVR; and XGBoost for XGB.

Each regression model was trained using features obtained from all configurations listed in table 2 and subsequently used to make predictions. The only exception involved the uncompressed features extracted by YOLOv4, for which the available computational resources (2.9 GHz AMD Ryzen 7 4800H CPU, 8 GB RAM, GeForce GTX 1650 4 GB) permitted the use of SVR only. The target variable of all models was  $\log N_{\text{Fe}}$ . Such logarithmic transformation is a standard approach for achieving higher prediction accuracy when the target quantity spans several orders of magnitude [77, 78]. Both input features and target values were normalized to have zero mean and unit standard deviation within the training set.

For each scenario, regression models were optimized to enhance the predictive performance. Hyperparameter tuning was performed using the Optuna toolkit, employing a TPE sampler and Hyperband pruner to ensure efficient selection. The complete list of tuned hyperparameters and their respective search ranges is provided in Tables S1–S5 (Supplementary Material). Five-fold cross-validation was implemented during model tuning, with 20% of the training data used as a validation set to evaluate models trained on the remaining 80%. The resulting optimal hyperparameter combinations are presented in Tables S6–S10.

**Table 2.** Summary of used pretrained CV models and feature extraction variants

Base model	Model type	Feature processing	Output dimension	Model Label
EfficientNetB7	Classifier	None	1000	ENB7:CL
	Feature extractor	None	2560	ENB7:FE
		PCA	39	ENB7:FE:P
MobileNetV2	Classifier	None	1000	MNV2:CL
	Feature extractor	None	1280	MNV2:FE
		PCA	124	MNV2:FE:P
NASNetLarge	Classifier	None	1000	NAS:CL
		PCA	30	NAS:CL:P
	Feature extractor	None	4032	NAS:FE
ResNet152V2	Classifier	None	1000	R152:CL
	Feature extractor	None	2048	R152:FE
		PCA	137	YL:FE1:P
Xception	Classifier	None	1000	XCP:CL
	Feature extractor	None	2048	XCP:FE
		PCA	142	YL:FE2:P
YOLOv4 (CSPDarknet53)	Feature extractor (raw, top layer)	None	86528	YL:FE1
		PCA	137	YL:FE1:P
	Feature extractor (raw, top & penultimate layers)	None	433640	YL:FE2
		PCA	142	YL:FE2:P
	Feature extractor (pooled, top layer)	None	512	YL:FP1
		PCA	142	YL:FE2:P
	Feature extractor (pooled, top & penultimate layers)	None	1024	YL:FP2

Consequently, 87 distinct combinations of computer vision and regression models were investigated. Each combination was subsequently trained and evaluated using both simulated and experimental data. To identify the results for each case, a composite label was employed, derived from the last column of table 2 and the abbreviated name of the regression algorithm.

## 2.6. Model evaluation

A rigorous assessment of model performance across diverse metrics is essential for constructing a robust regression model. The evaluation metrics for iron quantification were the mean squared error (MSE), mean absolute percentage error (MAPE), median absolute percentage error (MedAPE) and coefficient of determination ( $R^2$ ), as defined in Eqs. (5)-(9).

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (\hat{y}_i - y_i)^2, \quad (5)$$

$$\text{MAPE} = \frac{1}{N} \sum_{i=1}^N \text{MAPE}_i, \quad (6)$$

$$\text{MAPE}_i = \frac{|N_{\text{Fe,PRED},i} - N_{\text{Fe,TRUE},i}|}{N_{\text{Fe,TRUE},i}} \times 100\%, \quad (7)$$

$$\text{MedAPE} = \frac{1}{2} \left[ \text{MAPE}_{\lceil \frac{N}{2} \rceil} + \text{MAPE}_{\lfloor \frac{N}{2} + 1 \rfloor} \right], \quad (8)$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (N_{\text{Fe,TRUE},i} - N_{\text{Fe,PRED},i})^2}{\sum_{i=1}^N (N_{\text{Fe,TRUE},i} - \overline{N_{\text{Fe,TRUE}}})^2}, \quad (9)$$

where  $\hat{y}_i$  is the predicted value of the target variable for the  $i$ -th data point,  $y_i$  is the corresponding known value (obtained by logarithmic transformation and normalization of the iron concentration);  $N$  denotes the number of samples in the dataset ( $N = 25$  for the simulated training set, 20 for the experimental training set, 10 for the simulated test set, and 28 and 8 for the experimental datasets used to test models trained on the simulated and experimental sets, respectively);  $\text{MAPE}_i$  is the absolute percentage error for  $i$ -th data point;  $N_{\text{Fe,PRED},i}$  is the predicted iron concentration,  $N_{\text{Fe,TRUE},i}$  is the known value (either the parameter used in the simulation or obtained from experimental iron determination);  $\overline{N_{\text{Fe,TRUE}}}$  is the mean of the true values in the dataset.

MSE is one of the most widely used metrics for evaluating model accuracy, and the training objective was specifically defined to minimize this quantity. However, because the computation of  $y_i$  involves both normalization and logarithmic transformation of  $N_{\text{Fe}}$ , the MSE metric alone does not fully reflect the accuracy of the iron concentration estimation. Therefore, MAPE, which quantifies the mean relative deviation, was also employed. In addition, MedAPE, representing the error value below which 50% of the predictions fall, provides a more robust measure

against the influence of individual outliers, which can have a particularly large effect on mean-based metrics in smaller datasets. Finally, the  $R^2$  was used to quantify the fraction of the variance in the target variable explained by the model, thereby indicating how well the predicted values reproduce the observed data; a value of 1 corresponds to perfect agreement.

### 3. Results and discussion

#### 3.1. Simulated data

Figure 4 illustrates the representative prediction results obtained from the models trained using the simulated training dataset. The complete set of results covering all the 87 investigated configurations is provided in Figure S1 of the Supplementary Material.

Figure 5 presents the MAPE and  $R^2$  scores obtained when the models were applied to the training dataset. Although these metrics are sufficiently representative, the corresponding MedAPE and MSE values are shown in Figure S2 (Supplementary Material). The most notable observation from Figure 4 and Figure 5 is that, despite the very limited size of the training dataset (25 samples), most models demonstrate high training performance; in many cases, the mean relative error is approximately 1% or lower, and it rarely exceeds 10%. At the same time, the  $R^2$  score drops below 0.980 in only 8 out of 87 cases. It is also worth noting that the MedAPE values generally do not exceed the MAPE and are, in fact, smaller in most instances (see Figure S2). These consistently high performance metrics indicate that (i) the wavelet transformation produced highly informative images that effectively encoded information about the Fe concentration, and (ii) the CV models successfully extracted features correlated with the concentration.

Among the regression models, GB and SVR exhibited the best performance, whereas DNN produced the least favorable results. This outcome is entirely consistent with expectations because both Gradient Boosting and Support Vector Regression are well known to perform effectively when the number of samples is limited and the feature space exhibits a low noise level, as is characteristic of synthetic datasets. In contrast, neural networks contain a large number of parameters and therefore do not tend to exhibit perfect generalization under such conditions.

Among the CV models, EfficientNetB7 and NASNetLarge demonstrated the best performance, whereas ResNet152V2 and YOLOv4 exhibited the weakest results. This discrepancy can be attributed to the fact that the former two are relatively modern architectures specifically designed to extract generalizable features, and are therefore well suited to wavelet spectrograms, which are characterized by

a multi-scale structure. In contrast, ResNet152V2 is primarily optimized for object classification, whereas YOLO is less effective for regression tasks involving global image patterns, as it focuses on localized object detection.

It is also evident that using class probabilities as descriptors degrades the prediction quality compared with the cases in which image features are employed directly. This indicates that the internal feature maps of the CNN models provide a more informative representation of visual patterns, enabling the regressor to establish a stronger relationship with concentration. Moreover, the application of PCA, even though it retains 99.9% of the variance, results in reduced predictive accuracy. This observation suggests that the image patterns associated with variations in iron concentration may constitute only a minor portion of the overall data variance.

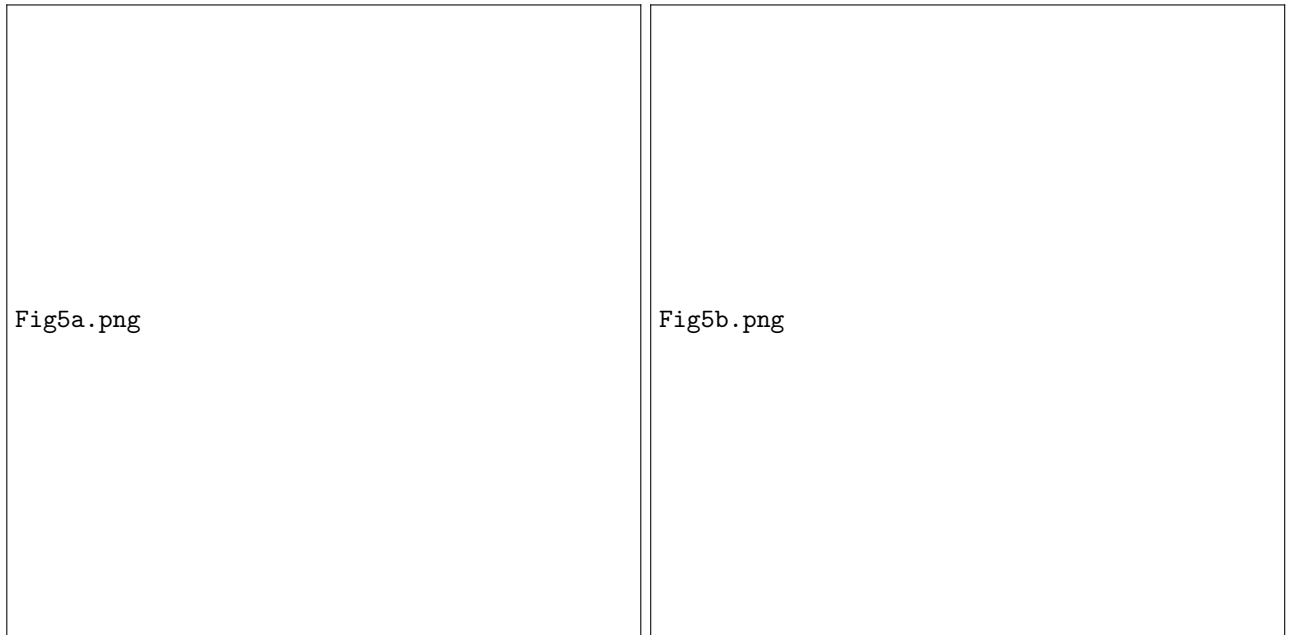
The ability of models to achieve high accuracy on the training set is a prerequisite for effective performance on unseen data; however, this does not guarantee reliable prediction outcomes. Consequently, the evaluation of an independent test set is essential. This step becomes particularly critical when the training set is small because the test results provide primary evidence for model generalizability. Figure 4 and Figure 6 present the prediction results obtained for the test set generated from synthetic data (detailed versions are available in Figures S1 and S3 of the Supplementary Material). As expected, prediction performance declined; however, the reduction in accuracy varied across the regression algorithms. Specifically, this degradation was least pronounced for the DNN, which achieved the best overall performance. The poorest metrics were obtained for RF and GB, whereas SVR and XGB performed slightly worse than DNN but with a relatively small margin. This behavior can be attributed to the ability of the DNN to smoothly approximate the continuous dependencies. In contrast to GB and RF, which rely on the formation of local decision rules, neural networks construct a continuous surface in the feature space. This property enhances interpolation for iron concentration values not represented in the training data. From this perspective, XGB and SVR occupy an intermediate position, explaining their slightly lower performance relative to the DNN.

The relative performance of the computer vision models on the simulated test dataset remained consistent, with no change in the top- and bottom-performing architectures. Specifically, EfficientNetB7 and NASNetLarge yielded the most favorable results, confirming their effectiveness in extracting wavelet image features relevant to concentration prediction. By contrast, ResNet152V2 and YOLOv4 produced the

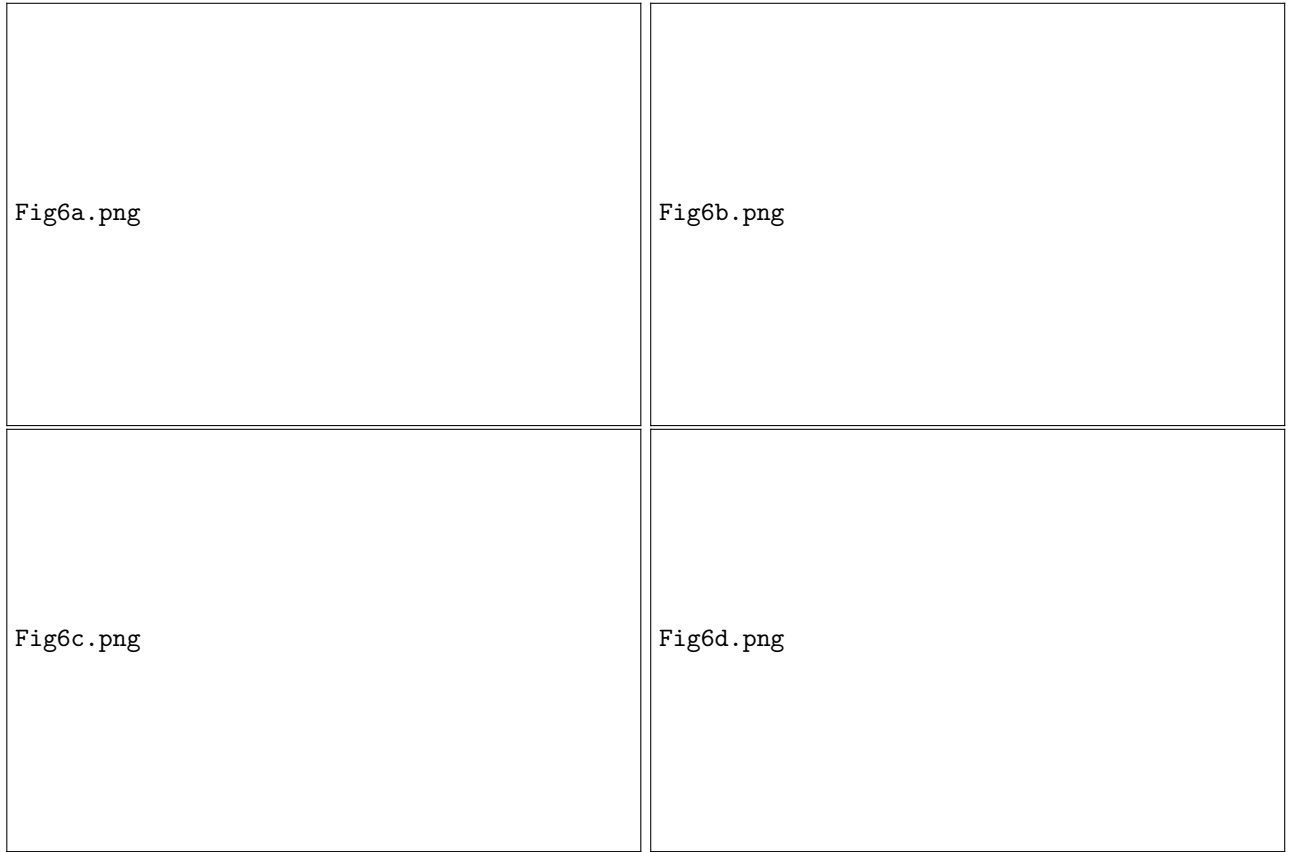




**Figure 4.** Scatter plots compare the reference iron  $N_{\text{Fe,TRUE}}$  with ML-predicted values  $N_{\text{Fe,PRED}}$ , obtained using feature vectors extracted from various CV models combined with different regression algorithms (specific models are indicated in the figures). ML models were trained using a simulated dataset. The open circles correspond to the training phase, whereas the filled circles and open squares correspond to the test phase representing the simulated and experimental datasets, respectively. The black lines are the identified lines serving as the references.



**Figure 5.** Mean absolute percentage error (left panel) and coefficient of determination (right panel) for different combinations of CV models (vertical axis) and regression models (horizontal axis) during the training phase. The models were trained using the simulated dataset.



**Figure 6.** Mean squared error, coefficient of determination, mean absolute percentage error, and median absolute percentage error for different combinations of CV models (vertical axis) and regression models (horizontal axis) during the test phase with the simulated dataset. The models were trained using a simulated training dataset.

least satisfactory outcomes. A notable exception arises in configurations where YOLOv4 features from two layers are combined with either a DNN or SVR. In these cases, performance metrics were considerably improved. This enhancement suggests that the use of a larger number of features enabled the capture of more diverse patterns, which, when coupled with flexible regressors, partially mitigated the limitations observed in the standalone YOLO model.

Interestingly, the PCA application to the test set did not substantially degrade performance; in certain cases, it even produced slight improvements. This indicates that PCA is not universally detrimental, although the resulting gains are generally marginal and unpredictable. Moreover, the differences in metrics between models using class probabilities and those employing raw image features were less pronounced than observed for the training dataset. Nevertheless, uncompressed feature representations consistently maintained a performance advantage.

The top-performing model combinations were identified as follows: ENB7:FE+DNN (MAPE = 5.90%, MedAPE = 4.83%,  $R^2 = 0.996$ ), ENB7:FE:P+DNN (MAPE = 5.96%, MedAPE = 3.68%,  $R^2 = 0.997$ ),

NAS:FE+SVR (MAPE = 5.82%, MedAPE = 5.42%,  $R^2 = 0.987$ ), NAS:FE+XGB (MAPE = 6.19%, MedAPE = 5.12%,  $R^2 = 0.987$ ), and NAS:CL:P+SVR (MAPE = 10.3%, MedAPE = 4.52%,  $R^2 = 0.999$ ). These results correspond to exceptionally high absolute performance metrics, providing clear evidence that the models effectively capture the underlying relationship between the wavelet-based images and the iron concentration.

Having established the effectiveness of the models on the simulated test dataset, we evaluated their performances using experimental measurements. This step is critical for assessing the generalizability of the models to real-world data where additional sources of noise and variability may be present. By comparing the results obtained from the experimental data with those from the simulated dataset, it is possible to identify the potential limitations of the models and to confirm whether the features extracted from wavelet spectrograms remain informative under practical conditions. Figure 7a and Figure 7b show the performance metrics of models trained on synthetic data when applied to experimental measurements. The relationship between predicted

and actual concentrations is illustrated in Figure 4, with additional results provided in Figures S1 and S4. As observed, the mean and median prediction errors fall within the (15–25)% range for only a limited number of configurations, specifically certain combinations of EfficientNetB7 or NASNetLarge with DNN or SVR. Although this outcome is not catastrophic, considering the approximately 10% inherent experimental error in  $N_{\text{Fe}}$  determination, it falls short of ideal expectations. At the same time, the  $R^2$  metric remains acceptably high. Further analysis (Figure 4) indicates that the prediction error depends on the iron concentration level: the relationship between  $N_{\text{Fe,PRED}}$  and  $N_{\text{Fe,TRUE}}$  is linear on a logarithmic scale, but its slope deviates from the line of unity. This observation suggests a systematic prediction bias rather than a complete loss of correlation, implying that the models are capable of capturing relative differences in concentration but do not accurately predict absolute values.

Although the presence of residual noise patterns in the experimental curves, which were insufficiently suppressed by filtering, could contribute to the observed discrepancies, a more plausible explanation lies in the incomplete correspondence between the physical model used for data synthesis and the actual behavior of the solar cells. This mismatch is likely associated with the numerical parameters employed in the fundamental equations of the model (Eqs. (1)–(3)). For instance, the calculation of the characteristic FeB association time (Eq. (3)) adopted values of  $A = 5.7 \times 10^5 \frac{\text{s}}{\text{K cm}^3}$  and  $E_m = 0.66 \text{ eV}$ , which are among the most frequently reported in the literature. However, a considerable scatter exists in these parameters. Specifically,  $E_m$  values ranging from 0.55 eV [79] to 0.69 eV [80] have been reported, including intermediate estimates of 0.64 eV [81], 0.65 eV [82], 0.66 eV [57, 83, 56, 84], 0.67 eV [85], and 0.68 eV [55, 86, 87]. Similarly, the pre-exponential factor  $A$  has been cited as  $4.3 \times 10^5$  [88] or  $5 \times 10^5$  [84, 89]. Moreover, the calculations assumed a spatially invariant  $E_m$  across the device. In practice, the reported diffusion barriers are typically derived for bulk  $p$ -Si, whereas the energy value can vary in regions with different Fermi level positions [90], such as the space-charge region in the present structures. A similar variability exists for the other key parameters. The FeB pair binding energy has been reported to range from 0.45 to 0.67 eV [82, 85, 55, 91], the  $\text{Fe}_i$  donor level position varies between 0.38 and 0.394 eV above the valence band maximum [32, 86, 92, 93], and the pre-exponential factor in denominator of Eq. (2)  $A_z$  has been cited as either  $10^{-23} \text{ cm}^3$  or  $2.7 \times 10^{-22} \text{ cm}^3$  [85]. A deviation of any of these parameter values from their actual physical magnitudes could account for the observed

prediction errors. Furthermore, earlier studies have demonstrated that both the non-uniform distribution of iron across the base thickness and the variation in the base thickness itself can significantly affect iron concentration estimation [82]. Neither of these effects was incorporated into the present modeling framework.

A common strategy for improving prediction accuracy involves post-hoc calibration, in which a corrective function is applied to model outputs using parameters derived from a limited subset of experimental data. In the present case, the analysis indicated that quadratic correction of the target variable provided the most suitable adjustment, expressed as follows:

$$\log N_{\text{Fe,PRED}} = 9.51 - 1.71 \cdot \log N_{\text{Fe,PRED}}^* + 0.079 \cdot (\log N_{\text{Fe,PRED}}^*)^2, \quad (10)$$

where  $N_{\text{Fe,PRED}}^*$  denotes the direct model prediction. The performance metrics after post hoc calibration are presented in Figure 7c and Figure 7d. As shown by the data, applying this correction substantially reduced the prediction errors. Specifically, the mean relative error across the 28-sample experimental dataset now lies within the (13–17)% for the best-performing models (approximately 20 out of 87 configurations) and remains below 25% for most of the others. The median error is even lower, reaching (7–10)% in the most favorable cases. In line with the results obtained for the simulated test dataset, the most accurate configurations are EfficientNetB7, NASNetLarge, DNN, SVR, and XGB. Interestingly, MobileNetV2 was also among the top performing combinations, yielding the lowest MedAPE value (7.64%) for the MNV2:CL configuration. This outcome may suggest that the features extracted by MobileNetV2, although less informative for the training and simulated test datasets, capture specific image patterns more relevant to the experimental measurements and applied correction could have further enhanced the effectiveness of these features.

It is worth noting that applying the correction increased the gap between the mean and median absolute percentage errors. This observation suggests that, although the correction improved the overall agreement between the predicted and true values, a few samples still exhibited relatively large residual errors.

This correction also led to a decrease in the  $R^2$  value. This outcome is expected because post-processing can weaken the linear correspondence between the initial predictions and experimental values, even when the overall prediction errors are simultaneously reduced. Therefore, the reduction in  $R^2$  should be regarded as a side effect of enhancing the accuracy of the model, rather than as evidence of its degradation.

Although quadratic correction proved effective, it does not represent a universal solution for transferring



**Figure 7.** Mean absolute percentage error (a,c) and coefficient of determination (b, d) for different combinations of CV models (vertical axis) and regression models (horizontal axis) during the test phase with the experimental dataset without (a, b) and with (c, d) post hoc calibration according to Eq. (10). The models were trained using a simulated dataset.

models from synthetic to experimental data. A more robust approach involves integrating the experimental data into the training process, as implemented in this study below.

### 3.2. Experimental data

Figure 8 shows the correlation between the iron concentrations predicted by the models trained on the experimental data and the reference values derived according to [74, 33]. Representative outcomes for selected CV–regression model combinations are shown for both training and testing, with the extended data provided in Figure S6 of the Supplementary Material.

It should be noted that, compared to training on synthetic data, this case employed an even smaller sample set (20 samples versus 25). However,

these samples covered a narrower range of iron concentrations ( $10^{11}$ – $2 \times 10^{13} \text{ cm}^{-3}$  versus  $10^{10}$ – $10^{14} \text{ cm}^{-3}$ ). Figure 9 presents a subset of the performance metrics obtained during the training phase (a more comprehensive overview is provided in Figure S7). Overall, the results were similar to those shown in Figure 5. In many cases, extremely low errors (below 0.5%) and high coefficients of determination (approaching unity) were observed. This behavior is particularly characteristic of GB, RF, and SVR. As in the previous case, the DNN exhibited weaker performance relative to the other algorithms, although its results slightly improved compared to those for the simulated training dataset. This improvement may stem from the greater homogeneity of the experimental data. The leading performance of EfficientNetB7 and NASNetLarge among the CV models was again



**Figure 8.** Scatter plots compare the reference iron concentrations  $N_{\text{Fe,TRUE}}$  with ML-predicted values  $N_{\text{Fe,PRED}}$ , obtained using feature vectors extracted from various CV models combined with different regression algorithms (specific models are indicated in the figures). ML models were trained using a dataset derived from experimental measurements. The open and filled squares correspond to the training and testing phases, respectively. The black lines are the identified lines serving as the references.

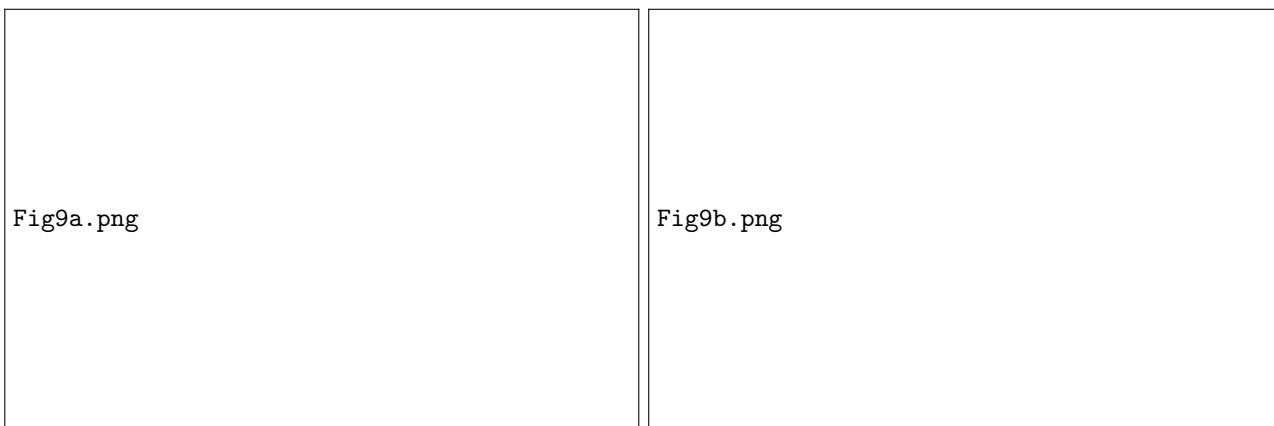
confirmed, indicating that these architectures produce the most relevant features for this task. However, the performance gap relative to other CV models has become less pronounced.

Interestingly, the application of PCA often enhances the performance of the DNN. For example, the MAPE values for ENB7:FE and ENB7:FE:P were 7.3% and 0.97%, respectively. This observation suggests that PCA effectively mitigated the adverse effects of high feature dimensionality when the sample size was limited. In contrast, no similar improvements were observed for other regression algorithms. Moreover, for the experimental training dataset, the difference between MAPE and MedAPE becomes smaller. This reduction implies a more symmetric error distribution and a decreased occurrence of extreme deviations.

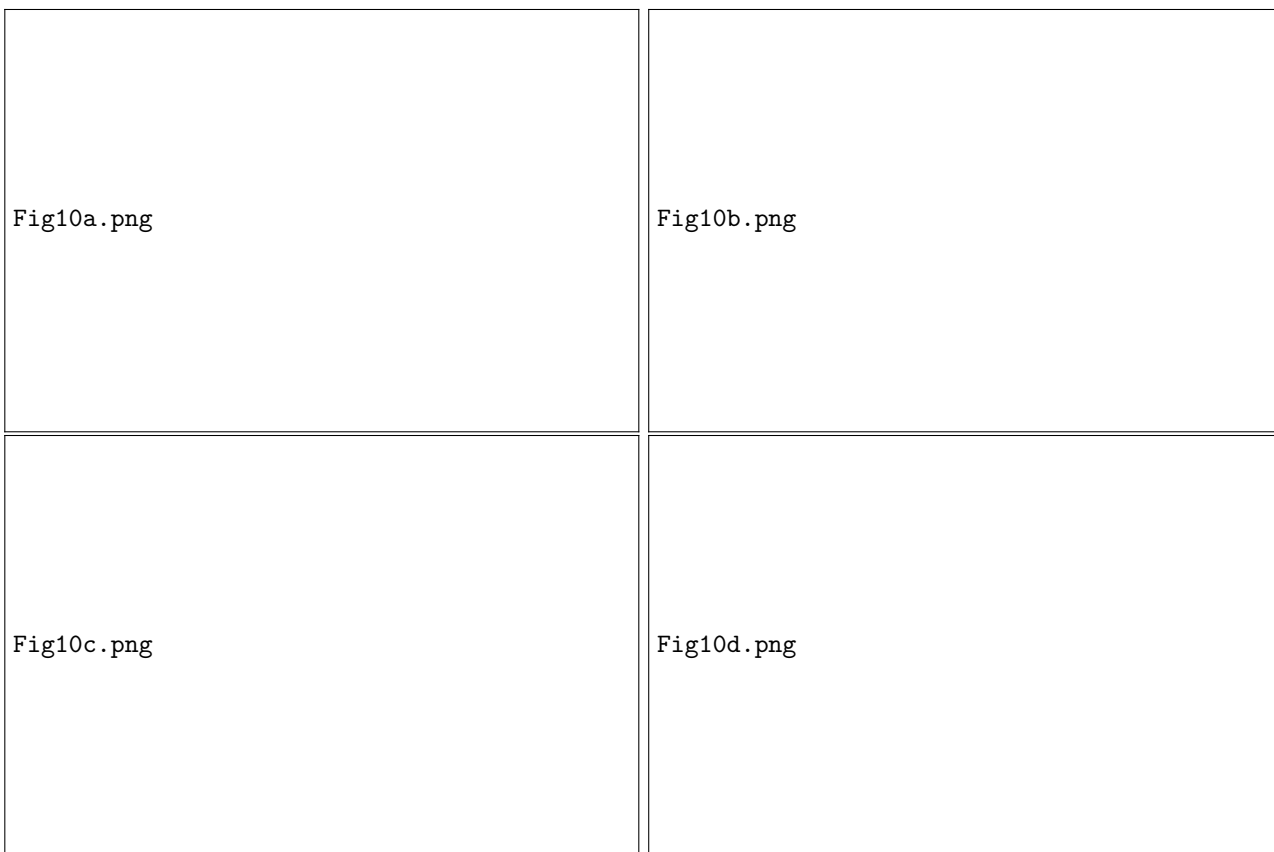
Figure 10 and Figure S8 show heatmaps of the prediction metrics for the test experimental dataset using models trained on a separate subset of experimental data. Compared with the models trained on simulated data, the predictive performance of the experimental test dataset improved substantially. In particular, for several of the best-performing CV-regressor combinations, the MAPE and MedAPE values fall within (7–15)%, which is markedly better than the 20–30% observed previously. Moreover, the  $R^2$  values predominantly exceed 0.97, indicating a strong agreement with the actual dependencies. The accuracy achieved through direct training on

experimental data is comparable to that obtained with post-hoc correction; however, the higher correlation coefficients suggest a more faithful representation of both the scale and the variations of the underlying dependency. SVR, DNN, and XGBoost remain the top-performing regressors, whereas EfficientNetB7, NASNetLarge, and — surprisingly — ResNet152V2 (when using image features) are the strongest CV models. YOLOv4 and MobileNetV2 consistently exhibit the weakest performance. Interestingly, for experimental data, using class probabilities as descriptors (:CL) yields results comparable to, and in some cases slightly better than, direct image features (:FE), particularly when strong CV architectures are combined with flexible regressors. This likely reflects the more compact and aggregated nature of class features, which makes them less sensitive to experimental noise. Conversely, for weaker CV models, the :FE configurations retain their advantage, consistent with previous findings. Finally, applying PCA to :FE models improved prediction accuracy, whereas it did not benefit models based on class features. This suggests that reducing the dimensionality of highly noisy features contributes to improving prediction accuracy on experimental data.

In summary, three approaches for predicting iron concentrations from experimental data were evaluated: (i) models trained on simulated data, (ii) models trained on simulated data with post hoc correction,



**Figure 9.** Mean squared error (left panel) and median absolute percentage error (right panel) for different combinations of CV models (vertical axis) and regression models (horizontal axis) during the training phase. The models were trained using an experimental dataset.



**Figure 10.** Mean squared error, coefficient of determination, mean absolute percentage error, and median absolute percentage error for different combinations of CV models (vertical axis) and regression models (horizontal axis) during the test phase. The models were trained using an experimental dataset.

and (iii) models trained directly on experimental data. Training on simulated data alone yielded moderate agreement with experimental measurements; however, systematic biases were observed owing to differences between the synthetic and real systems. Post-hoc correction effectively reduced these biases, lowering the mean and median errors, yet the correlation with the actual variation remained limited. Direct training on experimental data provided the most balanced outcome, achieving both low prediction errors and high correlation coefficients, thereby demonstrating the importance of incorporating real measurements during model development. Thus, training directly on experimental data improves prediction accuracy and eliminates the systematic biases observed in models transferred from synthetic data. At the same time, achieving optimal performance requires both the careful selection of the CV model–regressor combination and the inclusion of real experimental data.

#### 4. Conclusion

This study demonstrates that Transfer Learning from pretrained Computer Vision (CV) models enables accurate regression modeling, even with extremely small training datasets typical of experimental materials research. The proposed workflow involves measuring a characteristic kinetic dependency, transforming it into an image via wavelet analysis, extracting features using a pretrained CV model, and training a regression model on these features to predict material properties. The feasibility of this approach is illustrated by predicting the iron impurity concentration in silicon solar cell from short-circuit current kinetics following FeB pair dissociation using a training dataset of only 20–25 samples.

The performances of models trained on both synthetic and experimental datasets were evaluated. In both cases, EfficientNetB7 and NASNetLarge provided the most informative features, whereas Deep Neural Networks and Support Vector Regression yielded the highest prediction accuracy. The best-performing models achieved MSE, MAPE, MedAPE, and  $R^2$  values of 0.001, 6%, 4%, and 0.999, respectively, for synthetic data, and 0.008, 10%, 5%, and 0.996, for experimental data.

When training models on synthetic data, image feature vectors serve as the most suitable descriptors for the regression model. In contrast, when experimental data are used, prediction accuracy can be improved and the influence of noise reduced by utilizing class probability distributions or applying Principal Component Analysis.

The combination of Transfer Learning from CNNs

with an appropriate choice of descriptor type and regression algorithm represents a promising strategy for materials research in general and for defect characterization in particular, especially when the acquisition of large datasets is difficult or impractical.

#### Supplementary data

Supplementary data to this article can be found online at <https://sur1.li/czsgvx>

#### Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

#### Conflict of interest

The authors declare that there are no conflicts of interest related to this work.

#### Ethics statement

This study does not involve human participants, animals, or procedures requiring ethical approval.

#### References

#### References

- [1] International Energy Agency 2024 Renewables 2024 Tech. rep. IEA Paris licence: CC BY 4.0 URL <https://www.iea.org/reports/renewables-2024>
- [2] Osama A, Tina G M, Gagliano A, Jimenez-Castillo G and Munoz-Rodríguez F J 2025 *Sol. Energ. Mat. Sol.* **287** 113625
- [3] Institute P 2025 Solar generation grew by 30% in 2024, says IEA <https://prometheus.org/2025/02/23/solar-generation-grew-by-30-in-2024-says-iea/> accessed: 2025-10-10
- [4] Fischer M, Woodhouse M, Brammer T and Puzant B 2025 International technology roadmap for photovoltaic (itrpv) Tech. rep. VDMA e. V. Frankfurt am Main, Germany
- [5] Thome F T, Garashli E, Kwopil W, Schindler F and Schubert M C 2025 *Sol. Energ. Mat. Sol.* **293** 113854
- [6] Jia Y, Chen G and Zhao L 2024 *Sci. Rep.* **14** 15170
- [7] Hijjawi U, Lakshminarayana S, Xu T, Piero Malfense Fierro G and Rahman M 2023 *Sol. Energy* **266** 112186 ISSN 0038-092X

- [8] Liu Y, Wu Y, Yuan Y and Zhao L 2024 *Opt. Express* **32** 17295–17317
- [9] Doll B, Hepp J, Hoffmann M, Schüler R, Buerhop-Lutz C, Peters I M, Hauch J A, Maier A and Brabec C J 2021 *IEEE J. Photovolt.* **11** 1419–1429
- [10] Datta S, Baul A, Sarker G C, Sadhu P K and Hodges D R 2023 *IEEE Access* **11** 77750–77778
- [11] Jaiswal R, Martínez-Ramón M and Busani T 2023 *IEEE J. Photovolt.* **13** 2–15
- [12] Buratti Y, Javier G M, Abdullah-Vetter Z, Dwivedi P and Hameiri Z 2024 *Renewable Sustainable Energy Rev.* **202** 114617 ISSN 1364-0321
- [13] Mahdavi pour Z 2024 *Sol. Energ. Mat. Sol.* **278** 113210
- [14] Hopwood M W, Gunda T, Seigneur H and Walters J 2020 *IEEE Access* **8** 161480–161487
- [15] Li B, Delpha C, Diallo D and Migan-Dubois A 2021 *Renewable Sustainable Energy Rev.* **138** 110512 ISSN 1364-0321
- [16] Liu Y, Ding K, Zhang J, Li Y, Yang Z, Zheng W and Chen X 2021 *Energy Convers. Manage.* **245** 114603
- [17] Wang S, Wright B, Zhu Y, Buratti Y and Hameiri Z 2024 *Sol. Energ. Mat. Sol.* **277** 113123
- [18] Buratti Y, Dick J, Le Gia Q and Hameiri Z 2022 *ACS Appl. Mater. Interfaces* **14** 48647–48657
- [19] Buratti Y, Le Gia Q T, Dick J, Zhu Y and Hameiri Z 2020 *npj Computational Materials* **6** 142
- [20] Park S, Lee J, Khan S, Wahab A and Kim M 2022 *Sensors* **22** 596
- [21] Chia J Y, Thamrongsiripak N, Thongphanit S and Nuntawong N 2024 *J. Appl. Phys.* **135** 025701
- [22] Oliikh O, Lozitsky O and Zavhorodnii O 2022 *Prog. Photovoltaics Res. Appl.* **30** 648–660
- [23] Oliikh O and Zavhorodnii O 2025 *Sol. Energy* **300** 113754
- [24] Oliikh O and Zavhorodnii O 2025 *Materials Science and Engineering: B* **317** 118192
- [25] Wang S, Sankaran S and Perdikaris P 2024 *Comput. Methods Appl. Mech. Eng.* **421** 116813
- [26] Li W K and Zhang Y T 2025 *J. Appl. Phys.* **137** 203304
- [27] Kaya M and Hajimirza S 2019 *Sci. Rep.* **9** 5034
- [28] Kim Q, Lee S, Ma A, Kim J, Noh H K, Chang K B, Cheon W, Yi S, Jeong J, Kim B, Kim Y S and Kim D S 2023 *Solid-State Electron.* **201** 108568
- [29] Buonassisi T, Istratov A A, Pickett M D, Heuer M, Kalejs J P, Hahn G, Marcus M A, Lai B, Cai Z and Heald S M 2006 *Prog. Photovolt.: Res. Appl.* **14** 513–531 ISSN 1062-7995
- [30] Schubert M, Padilla M, Michl B, Mundt L, Giesecke J, Hohl-Ebinger J, Benick J, Warta W, Tajima M and Ogura A 2015 *Sol. Energy Mater. Sol. Cells* **138** 96–101
- [31] Kimerling L and Benton J 1983 *Physica B+C* **116** 297–300
- [32] Möller C, Bartel T, Gibaja F and Lauer K 2014 *J. Appl. Phys.* **116** 024503
- [33] Oliikh O, Kostylyov V, Vlasiuk V, Korkishko R, Oliikh Y and Chupryna R 2021 *J. Appl. Phys.* **130** 235703
- [34] Li Z, Zhang S, Qu C, Zhang Z and Sun F 2024 *PLOS ONE* **19** 1–16
- [35] Otamendi U, Martinez I, Quartulli M, Olaizola I G, Viles E and Cambarau W 2021 *Sol. Energy* **220** 914–926
- [36] Chen X, Karin T and Jain A 2022 *Sol. Energy* **242** 20–29
- [37] Munawer Al-Otum H 2024 *Sol. Energy* **278** 112803
- [38] Abdelsattar M, Abdelmoety A, Ismeil M A and Emad-Eldeen A 2025 *IEEE Access* **13** 4136–4157
- [39] Tella H, Hussein A, Rehman S, Liu B, Balghonaim A and Mohandes M 2025 *Case Studies in Thermal Engineering* **66** 105749
- [40] Li W C and Tsai D M 2012 *Pattern Recogn.* **45** 742–756
- [41] dela Rosa M E C, Mateo-Romero H F, Alonso-Gómez V, Ngungu V N, Nava R, Aragonés J I M, Plaza A R, Gonzalez-Rebollo M A, Isaza J R F and Cardeñoso-Payo V 2024 *Renewable Energies* **2** 27533735241304090
- [42] Khanna M, Srinath N K and Mendiratta J K 2020 *Application of Neural Networks and Lifting Wavelet Transform for Long Term Solar Radiation Power Prediction* (Singapore: Springer Singapore) pp 95–105 ISBN 978-981-15-3125-5
- [43] Krishnan S R and Seelamantula C S 2013 *IEEE Trans. Signal Process.* **61** 380–391
- [44] Torrence C and Compo G P 1998 *Bull. Am. Meteorol. Soc.* **79** 61–78
- [45] Ahmad A, Jin Y, Zhu C, Javed I, Maqsood A and Akram M W 2020 *IET Renew. Power Gener.* **14** 2693–2702
- [46] Burgelman M, Nollet P and Degraeve S 2000 *Thin Solid Films* **361–362** 527–532 ISSN 0040-6090
- [47] Masum Mia M, Faruk Hossain M, Rahman M, Badi N, Irfan A and Ferdous Rahman M 2025 *Materials Science and Engineering: B* **311** 117817
- [48] Joshi T K, Sharma G, Sharma Y R and Verma A S 2024 *Phys. B Condens. Matter* **682** 415793



- [49] Ravidas B K, Das A, Agnihotri S K, Pandey R, Madan J, Hossain M K, Roy M K and Samajdar D 2024 *Sol. Energ. Mat. Sol.* **267** 112688 ISSN 0927-0248
- [50] Liu H, Xiang L, Liu Q, Gao P, Zhang Y, Li S and Gao F 2024 *IEEE J. Photovolt.* **14** 59–64
- [51] You L, Zhang X, Ma Q, Zhu W and Wu J 2023 *Phys. Status Solidi A* **220** 2300071
- [52] Abdulmalik M and Danladi E 2023 *Semiconductor Physics, Quantum Electronics & Optoelectronics* **26** 321–331
- [53] Paviet-Salomon B, Levrat J, Fakhfour V, Pelet Y, Rebeaud N, Despeisse M and Ballif C 2017 *Prog. Photovoltaics Res. Appl.* **25** 623–635
- [54] Murphy J D, Bothe K, Olmo M, Voronkov V V and Falster R J 2011 *J. Appl. Phys.* **110** 053713
- [55] Wijaranakula W 1993 *J. Electrochem. Soc.* **140** 275–281
- [56] Khelifati N, Laine H S, Vähänissi V, Savin H, Bouamama F Z and Bouhafs D 2019 *Phys Status Solidi A* **216** 1900253
- [57] Tan J, Macdonald D, Rougieux F and Cuevas A 2011 *Semicond Sci. Technol.* **26** 055019
- [58] Olikh O 2019 *Superlattices Microstruct.* **136** 106309
- [59] Fell A, McIntosh K R, Altermatt P P, Janssen G J M, Stangl R, Ho-Baillie A, Steinkemper H, Greulich J, Müller M, Min B, Fong K C, Hermle M, Romijn I G and Abbott M D 2015 *IEEE J. Photovolt.* **5** 1250–1263
- [60] Pässler R 2002 *Phys. Rev. B* **66**(8) 085201
- [61] Yan D and Cuevas A 2014 *J. Appl. Phys.* **116** 194505
- [62] Green M A 2022 *Prog. Photovoltaics Res. Appl.* **30** 164–179
- [63] Couderc R, Amara M and Lemiti M 2014 *J. Appl. Phys.* **115** 093705
- [64] Niewelt T, Steinhauser B, Richter A, Veith-Wolf B, Fell A, Hammann B, Grant N, Black L, Tan J, Youssef A, Murphy J, Schmidt J, Schubert M and Glunz S 2022 *Sol. Energ. Mat. Sol.* **235** 111467
- [65] Black L E and Macdonald D H 2022 *Sol. Energ. Mat. Sol.* **234** 111428
- [66] Altermatt P P, Schmidt J, Heiser G and Aberle A G 1997 *J. Appl. Phys.* **82** 4938–4944
- [67] Green M A 1990 *J. Appl. Phys.* **67** 2944–2954
- [68] Klaassen D 1992 *Solid-State Electron.* **35** 953–959
- [69] O'Mara W, Herring R and Hant L 1990 *Handbook of semiconductor silicon technology* (New Jersey, USA: Noyes Publications)
- [70] Rougieux F E, Sun C and Macdonald D 2018 *Sol. Energy Mater. Sol. Cells* **187** 263 – 272 ISSN 0927-0248
- [71] Istratov A A, Hieslmair H and Weber E 1999 *Appl. Phys. A: Mater. Sci. Process.* **69** 13–44
- [72] Paudyal B B, McIntosh K R and Macdonald D H 2009 Temperature dependent electron and hole capture cross sections of iron-contaminated boron-doped silicon 2009 34th IEEE Photovoltaic Specialists Conference (PVSC) pp 001588–001593
- [73] Olikh O, Datsenko O and Kondratenko S 2024 *Phys. Status Solidi A* **221** 2400351
- [74] Olikh O, Kostilyov V, Vlasiuk V, Korkishko R and Chupryna R 2022 *J. Mater. Sci.: Mater. Electron.* **33** 13133–13142
- [75] Fadhel S, Delpha C, Diallo D, Bahri I, Migan A, Trabelsi M and Mimouni M 2019 *Sol. Energy* **179** 1–10
- [76] Gao W and Wai R J 2020 *IEEE Access* **8** 159493–159510
- [77] Srivastava Y and Jain A 2023 *J. Appl. Phys.* **134** 225101
- [78] Minagawa H, Tezuka T and Tsuchida H 2024 *Nucl. Instrum. Methods Phys. Res. Sect. B Beam Interact. Mater. At.* **553** 165383
- [79] Lauer K, Möller C, Debbih D, Auge M and Schulze D 2016 Determination of activation energy of the iron acceptor pair association and dissociation reaction *Gettering and Defect Engineering in Semiconductor Technology XVI (Solid State Phenomena vol 242)* (Trans Tech Publications Ltd) pp 230–235
- [80] Zhu X, Yang D, Yu X, He J, Wu Y, Vanhellemont J and Que D 2013 *AIP Adv.* **3** 082124
- [81] Zhu X, Yu X, Li X, Wang P and Yang D 2011 *Scr. Mater.* **64** 217–220
- [82] Kimerling L and Benton J 1983 *Physica B+C* **116** 297–300
- [83] Le T T, Zhou Z, Chen A, Yang Z, Rougieux F, Macdonald D and Liu A 2024 *J. Appl. Phys.* **135** 133107
- [84] Macdonald D, Roth T, Deenapanray P N K, Bothe K, Pohl P and Schmidt J 2005 *J. Appl. Phys.* **98** 083509
- [85] Zhu X, Yu X, Chen P, Liu Y, Vanhellemont J and Yang D 2015 *Int. J. Photoenergy* **2015** 154574
- [86] Macdonald D H, Geerligs L J and Azzizi A 2004 *J. Appl. Phys.* **95** 1021–1028
- [87] Zoth G and Bergholz W 1990 *J. Appl. Phys.* **67** 6764–6771 ISSN 0021-8979 (Preprint <https://pubs.aip.org/aip/jap/article-pdf/>

- 67/11/6764/18634381/6764\\_1\\_online.pdf)  
URL <https://doi.org/10.1063/1.345063>
- [88] Geerligs L J and Macdonald D 2004 *Appl. Phys. Lett.* **85** 5227–5229
- [89] Macdonald D, Cuevas A and Geerligs L J 2008 *Appl. Phys. Lett.* **92** 202119
- [90] Murphy J D, McGuire R E, Bothe K, Voronkov V V and Falster R J 2014 *J. Appl. Phys.* **116** 053514 ISSN 0021-8979
- [91] Hayamizu Y, Hamaguchi T, Ushio S, Abe T and Shimura F 1991 *J. Appl. Phys.* **69** 3077–3081
- [92] Schmidt J 2005 *Progress in Photovoltaics: Research and Applications* **13** 325–331
- [93] Nærland T, Bernardini S, Stoddard N, Good E, Augusto A and Bertoni M 2017 *Energy Procedia* **124** 138–145