# Machine Learning-Assisted Fabrication of PCBM-Perovskite Solar Cells with Nanopatterned TiO<sub>2</sub> Layer

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### Abstract

To unlock the full potential of PSCs, machine learning (ML) was implemented in this research to predict the best combination of mesoporous-titanium dioxide (mp-TiO<sub>2</sub>) and weight percentage (wt%) of phenyl-C<sub>61</sub>-butyric acid methyl ester (PCBM), along with the current density  $(J_{sc})$ , open-circuit voltage  $(V_{oc})$ , fill factor (ff) and energy conversion efficiency (ECE). Then, the combination that yielded the highest predicted ECE was selected as a reference to fabricate PCBM-PSCs with nanopatterned TiO<sub>2</sub> layer. Subsequently, the PCBM-PSCs with nanopatterned TiO<sub>2</sub> layers were fabricated and characterized to further understand the dual effects of nanopatterning depth and wt% of PCBM on PSCs. Experimentally, the highest ECE of 17.336% is achieved at 127 nm nanopatterning depth and 0.10 wt% of PCBM, where the  $J_{sc}$ ,  $V_{oc}$  and ff are 22.877 mA/cm<sup>2</sup>, 0.963 V and 0.787, respectively. The measured  $J_{sc}$ ,  $V_{oc}$ , ff and ECE values show consistencies with the ML prediction. Hence, these findings not only revealed the potential of ML to be used as a preliminary investigation to navigate the research of PSCs, but also highlighted that nanopatterning depth has a significant impact on  $J_{sc}$ , and the incorporation of PCBM on perovskite layer influenced the  $V_{oc}$  and ff, which further boosted the performance of PSCs.

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# Machine Learning-Assisted Fabrication of PCBM-Perovskite Solar Cells with Nanopatterned $TiO_2$ Layer

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Keywords: perovskite solar cells, nanopatterning, PCBM, machine learning, prediction

#### Abstract

To unlock the full potential of PSCs, machine learning (ML) was implemented in this research to predict the best combination of mesoporous-titanium dioxide (mp-TiO<sub>2</sub>) and weight percentage (wt%) of phenyl-C<sub>61</sub>-butyric acid methyl ester (PCBM), along with the current density ( $J_{sc}$ ), open-circuit voltage ( $V_{oc}$ ), fill factor (ff) and energy conversion efficiency (ECE). Then, the combination that yielded the highest predicted ECE was selected as a reference to fabricate PCBM-PSCs with nanopatterned TiO<sub>2</sub> layer. Subsequently, the PCBM-PSCs with nanopatterned TiO<sub>2</sub> layers were fabricated and characterized to further understand the dual effects of nanopatterning depth and wt% of PCBM on PSCs. Experimentally, the highest ECE of 17.336% is achieved at 127 nm nanopatterning depth and 0.10 wt% of PCBM, where the  $J_{sc}$ ,  $V_{oc}$  and ff are 22.877 mA/cm<sup>2</sup>, 0.963 V and 0.787, respectively. The measured  $J_{sc}$ ,  $V_{oc}$ , ff and ECE values show consistencies with the ML prediction. Hence, these findings not only revealed the potential of ML to be used as a preliminary investigation to navigate the research of PSCs, but also highlighted that nanopatterning depth has a significant impact on  $J_{sc}$ , and the incorporation of PCBM on perovskite layer influenced the  $V_{oc}$  and ff, which further boosted the performance of PSCs.

#### 1. Introduction

Machine learning (ML), which belongs to an important branch of artificial intelligence, has gained fame in the fields of energy materials and solar cells.<sup>[1]</sup> ML is a science of getting computers to perform tasks without being explicitly programmed, and it can learn from past results and provide fast predictions of unknown results.<sup>[2]</sup> Furthermore, ML also can infer the potential rules and relationships among materials, and between materials and the features of the complex system composed of materials only through the data itself without knowing the physical laws.<sup>[3]</sup> With the proven capabilities of ML, ML can have a significant impact to greatly increase the speed of doing research in perovskite solar cells (PSCs). To optimize PSCs, the conventional method mostly depends on trial-and-error methods, which is not only time consuming, but has limited test options and leads to the cost of opportunity loss by doing something else with the available time. Therefore, by applying ML, researchers may examine a tremendous amount of data on PSCs and make predictions by uncovering patterns and relationships in the data. These predictions can then be used to guide experiments, enabling researchers to optimize the development of PSCs more efficiently than traditional methods.

Studies have shown that the performance of PSCs is hindered by low light harvesting. Specifically, the ability of PSCs to absorb light drops significantly between 650-800 nm and diminishes further when the wavelength exceeds 800 nm.<sup>[4-6]</sup> To overcome this issue, one of the strategies that has been implemented is light scattering. The basic idea of light scattering is to confine light propagation and extend the traveling distance of incident light within the photoelectrode film,<sup>[7]</sup> which can be explained using Rayleigh and Mie scattering theories. In general, Rayleigh scattering theory is applicable for small-sized particles, whose diameter is less than about one-tenth the wavelength of the incident light while Mie scattering theory is applicable to large particles, whose diameter is larger than the wavelength of the incident light.<sup>[8]</sup> Apart from that, the introduction of nano/microstructures at the glass/air interface have also been reported to increase the incident photon and the generation of photocurrent.<sup>[9, 10]</sup> Studies also reported that constructing nano/microstructures at the fluorine-doped tin oxide (FTO)/ titanium dioxide (TiO<sub>2</sub>) interface can increase the absorption length for the incident light due to the diffraction effect.<sup>[11-13]</sup> Therefore, to increase the light harvesting property in PSCs, Hwa-Young Yang et al. have also shown the relationship between the transmittance and the electron generation by varying the nanopatterning depth of the mesoporous titanium dioxide (mp-TiO<sub>2</sub>) layer.<sup>[14]</sup>

Next, to improve the electron transport in PSCs, a plethora of materials have been studied and carbon nanomaterials have been widely utilized in PSCs to enhance both the efficiency and stability due to their outstanding chemical, electrical, and mechanical characteristics. It has not only been used as an additive, but has also acted on potential structure alternatives for the charge carrier transportation layer, electrode, and active film.<sup>[15]</sup> Among carbon nanomaterials, fullerene nanometric-sized spherical shapes play an important role for efficient interfacing with perovskites, resulting in a homogeneous distribution of the carbon nanomaterials on the surface of light absorber, thus generating highly selective contacts for electron extraction.<sup>[16]</sup> Phenyl-C<sub>61</sub>-butyric acid methyl ester (PCBM), which is a fullerene derivative of the C<sub>60</sub>, is among the most employed carbon nanomaterials in PSCs due to the alignment of energy levels and high electron mobility.<sup>[17, 18]</sup> Previous research has demonstrated that by controlling the amount of PCBM in the lead(II) iodide (PbI<sub>2</sub>) precursor solution, the fill factor (ff) increased significantly as PCBM are able to fill in the pinholes and vacancies between perovskite grains that produce continuous pathways for electron extraction. Moreover, when PCBM was mixed with perovskite to create a PCBM-perovskite structure, the charge recombination lifetime and carrier diffusion length increases as the electron was transported over longer distances in the film compared to pure perovskite film.<sup>[19]</sup>

Based on the mentioned articles, studies have shown that the most optimized nanopatterning depth will affect the current density  $(J_{sc})$ , and the incorporation of PCBM into perovskite is able to significantly enhance the ff of the PSCs. Therefore, with the potential of ML to be used as a preliminary approach, it is expected that the combination of ML with light management and electron transport strategies will yield a better performance of PSCs. Herein, ML is used to assist the fabrication of PCBM-PSCs with nanopatterned TiO<sub>2</sub> layer by deciphering the relationship between nanopatterning depth of mp-TiO<sub>2</sub>and weight percentage (wt%) of PCBM to predict the best combination of the two variables. Not only that, the photovoltaics parameters, that are  $J_{sc}$ , open-circuit voltage ( $V_{oc}$ ), ff and energy conversion efficiency (ECE) are also predicted by the ML. Subsequently, the PCBM-PSCs with nanopatterned TiO<sub>2</sub> layer are prepared and characterized to further understand the dual effects of nanopatterning depth and wt% of PCBM on PSCs. Hence, these findings not only revealed the potential of ML to be used as a preliminary investigation to navigate the research of PSCs, but also highlighted that nanopatterning depths have significant impact on  $J_{sc}$ , and the incorporation of PCBM on perovskite layer influenced the  $V_{oc}$  and ff, which further boosted the performance of PSCs.

2. Results and Discussion



Figure 1. The overall scheme of using ML to assist the fabrication of PCBM-PSCs with nanopatterned  $\text{TiO}_2$  layer, where the process includes a) a collection of experimental data for PSCs with nanopatterned  $\text{TiO}_2$  layer and PCBM-PSCs, (b) predictions of  $J_{sc}$ ,  $V_{oc}$ , ff and ECE for the PCBM-PSCs with nanopatterned  $\text{TiO}_2$  layer through machine learning, (c) the fabrication of PCBM-PSCs with nanopatterned  $\text{TiO}_2$  layer, (d) device characterization and (e) the conclusion for the results obtained.

**Figure 1** shows the overall scheme of using ML to assist the fabrication of PCBM-PSCs with nanopatterned TiO<sub>2</sub> layer. The present process involves the collection of experimental data with the  $J_{sc}$ ,  $V_{oc}$ , ff and ECE values for PSCs with nanopatterned TiO<sub>2</sub> layer and PCBM-PSCs as listed in **Table S1** and **Table S2** in the supporting information. The nanopatterning depth of PSCs with nanopatterned TiO<sub>2</sub> layer were varied to 70, 75, 80, 87, 92, 97, 102, 107, 112, 117, 122, 127, 132, 137, 142, 147, 152, 157 and 167 nm while the wt% of PCBM for PCBM-PSCs were varied to 0.01, 0.03, 0.05, 0.07, 0.10, 0.12 and 0.15 wt%. Subsequently, the dataset was used to predict the best combination of nanopatterned TiO<sub>2</sub> layers. To achieve that goal, a Random Forest (RF) regression model, which is an ensemble method that uses multiple decision of nanopatterning depth and wt% of PCBM that yielded the highest ECE was selected as a reference to fabricate the PCBM-PSCs with nanopatterned TiO<sub>2</sub> layer. After the fabrication process, the device was characterized to further understand the dual effects of nanopatterning depth and wt% of PCBM on PSCs. Lastly, the conclusions were deduced based on the results obtained throughout the process.



**Figure 2** . The performance of Random Forest regression models to predict the a)  $J_{sc}$ , b)  $V_{oc}$ , c) ff and d) ECE.

As demonstrated in **Figure 2**, the RF regression models were utilized to predict the performance metrics of photovoltaic parameters, including the  $J_{sc}$ ,  $V_{oc}$ , ff and ECE. The performance of the RF model was evaluated by using the coefficient of determination (R<sup>2</sup>) and mean squared error (MSE). The R<sup>2</sup> values provide information on how much of the variance is due to the independent variables<sup>[21]</sup> while MSE is used to evaluate the quality of fit in terms of distance of the regressor to the actual training points.<sup>[22]</sup> The bound for R<sup>2</sup> value is (-[?], 1], where -[?] indicates the worst output value and 1 indicates the best value. In other words, an output value of R<sup>2</sup> close to 1 suggested a good prediction of the regression model. For MSE, the value is bounded between [0, +[?]) and 0 MSE value is obtained if the linear regression model fits the data perfectly. <sup>[23]</sup>

In these predictions, the  $\mathbb{R}^2$  values obtained for  $J_{sc}$ ,  $V_{oc}$ , ff and ECE were 0.693, 0.523, 0.839 and 0.694, respectively, and showed that the RF model can explain 69.3%, 52.3%, 83.9% and 69.4% of the variation in the  $J_{sc}$ ,  $V_{oc}$ , ff and ECE with the input features (nanopatterning depth of mp-TiO<sub>2</sub> layer and wt% of PCBM). High  $\mathbb{R}^2$  values for  $J_{sc}$ , ff and ECE indicate that the RF model effectively captures the relationship between the input features with  $J_{sc}$ , ff and ECE, showing the ability of the model to predict accurately. Although the  $\mathbb{R}^2$  value for the  $V_{oc}$  prediction is the lowest among the four parameters, it does not necessarily indicate that the RF model is less accurate for predicting the  $V_{oc}$ , but rather highlights the complex interplay between different factors that influence the performance of the photovoltaic parameters. Despite this, the MSEs for all four parameters were relatively low, suggesting the model can still provide reliable predictions.



Figure 3 . Predictions of (a)  $J_{sc}$  , (b)  $V_{oc}$  , (c)  $f\!\!f$  and (d) ECE of PCBM-PSCs with nanopatterned TiO\_2 layers by using ML.

Next, the RF model was further employed to predict the best combination of nanopatterning depth and wt% of PCBM for  $J_{sc}$ ,  $V_{oc}$ , ff and ECE of PCBM-PSCs with nanopatterned TiO<sub>2</sub> as shown in **Figure 3**. The model was trained using the  $J_{sc}$ ,  $V_{oc}$ , ff, ECE, nanopatterning depths and wt% of PCBM data of PSCs with nanopatterned TiO<sub>2</sub> layer and PCBM-PSCs, that were obtained from previous experiments. The results demonstrated that the highest predicted ECE of 16.73% was achieved with a combination of 127 nm nanopatterning depth and 0.1 wt% of PCBM. The top ten predicted results are also tabulated in **Table 1**. Based on these findings, the best combination of nanopatterning depth and wt% of PCBM were used as a reference to fabricate PCBM-PSCs with nanopatterned TiO<sub>2</sub> layer.

<b>Table 1</b> . Top 10	prediction for the P	CBM-PSCs with nand	opatterned TiO <sub>2</sub> la	yer by	using ML
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Nanopatterning depth [nm]	wt% of PCBM $[wt\%]$	$J_{sc} \; [{\rm mA/cm^2}]$	$V_{oc}$ [V]	$f\!f$	ECE [%]
127	0.10	23.16	0.95	0.75	16.73
127	0.12	23.16	0.95	0.75	16.58
132	0.10	22.73	0.94	0.74	16.27
137	0.10	22.53	0.94	0.75	16.27
142	0.10	22.53	0.94	0.75	16.26
147	0.10	22.60	0.94	0.75	16.25
152	0.10	22.19	0.94	0.75	16.23
157	0.10	22.21	0.94	0.74	16.23
127	0.07	22.83	0.95	0.75	16.22
132	0.12	22.73	0.94	0.74	16.12









**Figure 4.** The solar cell structure of a) pristine PSCs, b) PSCs with nanopatterned  $TiO_2$  layer, c) PCBM-PSCs and d) PCBM-PSCs with nanopatterned  $TiO_2$  layer.

To have a better understanding regarding the dual effects of nanopatterning depth and wt% of PCBM on PSCs and the differences between each PSC, four types of PSCs were fabricated, as shown in **Figure 4**. The fabricated PSCs were pristine PSCs, PSCs with nanopatterned TiO<sub>2</sub> layer, PCBM-PSCs, and PCBM-PSCs with nanopatterned TiO<sub>2</sub> layer. The best combination of nanopatterning depth (127 nm) and wt% of PCBM (0.10 wt%) that yielded the highest predicted ECE was selected as a reference to fabricate the PSCs.



**Figure 5.** FE-SEM images of a) Si master, b) tilted view of PFPE mold, c) top view of nanopatterned  $TiO_2$  layer, d) side view of nanopatterned  $TiO_2$  layer, e) perovskite layer, and f) PCBM-perovskite layer, g) cross-sectional images of PCBM-PSCs with nanopatterned  $TiO_2$  layer, and h) FIB image of PCBM-PSCs with nanopatterned  $TiO_2$  layer.

Figure 5 a shows the field emission scanning electron microscopy (FE-SEM) image of the nanopatterned Si master with 250 nm pore sizes and 250 nm interpore distances. For duplication of nanopatterning on the Si master, the PFPE resin was coated on the surface of Si master and polymerized by UV irradiation for hardening, as shown in Figure 5b. A polyethylene terephthalate (PET) film was used as a flexible substrate of PFPE resin. Figure 5c visualized the form of the nanopatterned  $TiO_2$  with a 280 nm pore size, which look like the moth-eye nanostructure. The depth of the nanopatterned  $TiO_2$  layer is 127 nm, as shown in Figure 5d, which is the most optimized nanopatterning depth.<sup>[14]</sup>Figure 5e and 5f show the grain boundaries of perovskite and PCBM-perovskite layers. Without PCBM, the perovskite layer has lots of grain boundaries with smaller grain sizes. However, with the incorporation of 0.10 wt% of PCBM, larger grain sizes were formed as PCBM filled the pinholes between the small grain sizes. As a result, the grain of perovskite with PCBM has larger sizes and higher density, that indicates better surface morphology of PCBM-perovskite laver.<sup>[19]</sup> The cross-sectional image of PCBM-perovskite layer on the PCBM-PSCs with nanopatterned  $TiO_2$ layer can be observed from Figure 5g. From the FE-SEM images, the PCBM cannot be confirmed because the resolution of FE-SEM was out of range. Thus, Fourier transform infrared (FTIR) analysis was used to verify the PCBM, which will be discussed in a later paragraph. The thicknesses of nanopatterned  $TiO_2$ layer, perovskite, Spiro-OMeTAD, and Au are 131 nm, 400 nm, 250 nm, and 290 nm, respectively, as shown in Figure 5h.



Figure 6. XRD images of a) TiO<sub>2</sub>, b) nanopatterned TiO<sub>2</sub> layer, c) perovskite, and d) PCBM-perovskite layer.

X-ray diffraction (XRD) patterns in **Figure 6** confirmed the crystallinity of nanopatterned TiO<sub>2</sub> layer and PCBM-perovskite layer. The nanopatterned TiO<sub>2</sub> shows anatase phase at  $2\vartheta$  values of 25.2@, 37@, 38@, 38.5@, 48@, 54@, 55@, and 63@, corresponding to the (101), (103), (004), (112), (200), (105), (211), and (118) peaks.<sup>[14, 24]</sup> For the PCBM-perovskite layer, the XRD patterns show that the presence of PCBM did not change the cell dimensions of the perovskite. Both pure perovskite and PCBM-perovskite layers exhibited diffraction peaks at  $2\vartheta$  values of 14.15@, 20.05@, 23.5@, 24.6@, 28.47@, 31.94@, 35.3@, 40.66@,

and 43.12<sup>@</sup>, corresponding to the (110), (112), (211), (202), (220), (310), (312), (224), and (314) crystal planes of tetragonal perovskite, respectively.<sup>[25]</sup> The results verified that the crystalline PCBM-perovskite was well formed on the nanopatterned TiO<sub>2</sub> layer, thus it could achieve better ECE.



Figure 7. FTIR of a) FTO, b) perovskite/FTO, c) PCBM/FTO, and d) PCBM-perovskite/FTO.

To elaborate on the information of the PCBM-perovskite layer, FTIR spectroscopy was carried out and the results are as shown as in **Figure 7**. Figure 7 shows the comparison between the FT-IR spectra of a) FTO, b) perovskite/FTO, c) PCBM/FTO, and d) PCBM-perovskite/FTO. The peaks at 3200 and 3100 cm<sup>-1</sup> are due to the N-H stretching vibration for primary amines, and the 1600 and 1475 cm<sup>-1</sup> double bands belong to the C=C group. The C-N stretching absorption that occurs in the region from 1250-1000 cm<sup>-1</sup> indicates the aliphatic amines<sup>[26]</sup> while the single band at 900 cm<sup>-1</sup> is corresponding to the metal iodide stretching vibration,<sup>[27]</sup> as shown in Figure 7b.

Apart from that, the incorporation of PCBM in the PCBM-perovskite layer was confirmed by comparing Figure 7c and 7d. The absorption bands for PCBM can be observed near 3000 cm<sup>-1</sup>, which indicates the sp<sup>3</sup> C-H absorption of alkanes group while the absorption bands for C=O and C-O that appear within the range of 1750-1735 and 1300-1000 cm<sup>-1</sup> indicate that the compound is an ester. The peak at 1465 cm<sup>-1</sup> is due to the CH<sub>2</sub> bending absorption, which is the characteristic of methylene group<sup>[26]</sup> and the peak at 524 cm<sup>-1</sup> belongs to C<sub>60</sub>.<sup>[28]</sup> It can be seen that the main characteristic peaks of perovskite and PCBM can be identified in Figure 7d, which indicate the good formation of the PCBM-perovskite layer.



**Figure 8.** a) J-V curves, b) EQE, c) integrated  $J_{sc}$ , d) transmittance of PSCs. The black, green, blue, and red lines represent the pristine PSC, PSC with nanopatterned TiO<sub>2</sub> layer, PCBM-PSC and PCBM-PSC with nanopatterned TiO<sub>2</sub> layer.

Table 2. Photovoltaic properties of the PSCs devices.

	Perovskite solar cell	$J_{sc} \; [\mathrm{mA/cm^2}]$	$V_{oc}$ [V]	ſſ	ECE [%]
(a)	Pristine	20.203	0.920	0.704	13.085
(b)	PSCs with	22.302	0.942	0.730	15.336
	nanopatterned $TiO_2$ layer				
(c)	PCBM-PSCs	21.865	0.961	0.783	16.453
(d)	PCBM-PSCs with nanopatterned TiO <sub>2</sub> layer	22.877	0.963	0.787	17.338

The pristine PSC, PSC with nanopatterned TiO<sub>2</sub> layer, PCBM-PSC and PCBM-PSC with nanopatterned TiO<sub>2</sub> layer were fabricated and characterized by J-V curves, external quantum efficiency (EQE), integrated  $J_{sc}$  and transmittance measurement. The  $J_{sc}$ ,  $V_{oc}$ , ff, and ECE of J-V curves were summarized in **Table 2**. From the results obtained, the PSCs with nanopatterned TiO<sub>2</sub> layer and PCBM-PSCs with nanopatterned TiO<sub>2</sub> layer had better  $J_{sc}$  compared to the pristine PSCs and PCBM-PSCs, as shown in **Figure 8** a, due to the improved electron generation through light harvesting on nanopatterned TiO<sub>2</sub> layer.

As visualized in Figure 8b, the intensity of the pristine PSC is higher than other PSCs at the wavelengths below 350 nm. However, at wavelengths ranging from 350 nm to 800 nm, the intensity of the PCBM-PSC with nanopatterned  $TiO_2$  layer is the highest, indicating that more electrons were generated in the range of

350 nm to 800 nm.<sup>[14]</sup> Higher electron generation leads to a higher electron density, which increases the  $J_{sc}$ ,  $V_{oc}$  and ff. Thus, the ECE of PSC will also increase. The integrated  $J_{sc}$  in Figure 8c can be calculated from Equation (1), in which F represents the Faraday constant,  $E_{\varepsilon\lambda}$  is the solar spectral irradiance, and  $N_A$  is the Avogadro constant. The integrated  $J_{sc}$  matched with the measured  $J_{sc}$  of all four types of PSCs.

$$J_{sc, int} = \frac{F \times \int (E_e \times EQE) d}{N_A} (1)$$

The transmittance of pristine PSCs and PCBM-PSCs with nanopatterned TiO<sub>2</sub> layer were measured by using UV-Vis spectrometer, as shown as in Figure 8d. Around 300 nm to 370 nm wavelengths, the transmittance of pristine PSC was higher than PCBM-PSC with nanopatterned TiO<sub>2</sub> layer. On the contrary, for wavelengths higher than 370 nm, the transmittance of PCBM-PSC with nanopatterned TiO<sub>2</sub> layer was higher than the pristine PSC. The transmittance enhancement was due to the rougher surface of PCBM-PSC with nanopatterned TiO<sub>2</sub> layer compared to the pristine PSC, which might induces the changes in the refractive index.<sup>[14]</sup> Furthermore, if the angle of reflected-diffracted light is larger than the critical angle, it causes the total internal reflection because of the decrement in the refractive index values from the TiO<sub>2</sub> to the air.<sup>[29]</sup> Thus, the lower the refractive index, the higher the transmittance.<sup>[30]</sup>

On top of that, the incorporation of PCBM into perovskite also contributed to  $V_{oc}$  enhancement. This is because  $V_{oc}$  is determined by the difference between the conduction band (CB) of electron transport material (ETM) and the valence band (VB) of perovskite, as shown in **Figure 9**. Without PCBM, pristine PSCs and PSCs with nanopatterned TiO<sub>2</sub>layer have only one ETM, that is TiO<sub>2</sub>. However, with the incorporation of PCBM into perovskite, the PCBM-PSCs, and PCBM-PSCs with nanopatterned TiO<sub>2</sub> layer have two ETMs, that are TiO<sub>2</sub> and PCBM. Therefore, the CB of ETM will not depend only on the TiO<sub>2</sub>, but the average value between TiO<sub>2</sub> and PCBM. In simpler words, it can be said that the CB of ETM were elevated by PCBM, which improved  $V_{oc}$ . As the difference between the CB of ETM and the VB of perovskite in PCBM-PSCs and PCBM-PSCs with nanopatterned TiO<sub>2</sub> layer are higher than the pristine PSCs and PSCs with nanopatterned TiO<sub>2</sub> layer, therefore the  $V_{oc}$  of PCBM-PSCs and PCBM-PSCs with nanopatterned TiO<sub>2</sub> layer are higher.



Figure 9. Energy band diagram of a) pristine PSCs, b) PSCs with nanopatterned  $TiO_2$  layer, c) PCBM-PSCs, and d) PCBM-PSCs with nanopatterned  $TiO_2$  layer.



Figure 10. a) impedance of PSCs. The black, green, blue, and red lines represent the pristine PSC, PSC with nanopatterned  $TiO_2$  layer, PCBM-PSC, and PCBM-PSC with nanopatterned  $TiO_2$  layer. b) hysteresis graphs of PCBM-PSC with nanopatterned  $TiO_2$  layer for forward and reverse scanning directions.

Next, to further understand the charge transport process in the pristine PSC, PSC with nanopatterned  $TiO_2$  layer, PCBM-PSC, and PCBM-PSC with nanopatterned  $TiO_2$  layer, electrochemical impedance spectroscopy (EIS) characterization was carried out and the results are shown in **Figure 10** a and tabulated in **Table 3** 

. The series resistance ( $R_s$ ) can be estimated from the high-frequency intercept on the real axis while the recombination resistance ( $R_{rec}$ ) can be assigned to the recombination at the perovskite/TiO<sub>2</sub>interface.<sup>[31]</sup> By analyzing the Nyquist plots, it can be observed that the pristine PSC exhibits the largest semicircle, followed by the PSC with nanopatterned TiO<sub>2</sub> layer, PCBM-PSC, and PCBM-PSC with nanopatterned TiO<sub>2</sub> layer. The largest semicircle indicates low electron-hole density move across the perovskite interface<sup>[32]</sup>, indicating that more charge would take part in the interfacial recombination process.<sup>[33]</sup> Therefore, as the PCBM-PSC with nanopatterned TiO<sub>2</sub> layer has the smallest semicircle, the results further validate that the nanopatterning and PCBM were able to suppress the recombination and increase the electron transport property, owing to the increment in the electron density and the improved surface morphology of PCBM-perovskite layer.

Aside from that, for reverse scanning from positive to negative voltage, the efficiency was 17.336%. When the direction was changed to forward scanning, the efficiency reduced to 16.256%, which is only a 6.23% decrement, indicating that the PCBM-PSC with nanopatterned  $\text{TiO}_2$  layer has only a small and negligible hysteresis as represented in Figure 10b and **Table 4**. These results further showed that PCBM plays a significant role in the suppression of hysteresis. Previous studies have proposed that the origin of hysteresis in PSCs is due to the ion migration and vacancies on perovskite layer. Therefore, through the diffusion of PCBM into the grain boundaries in perovskite, the hysteresis can be suppressed through the formation of physical hindrance for the ion migration or occupying some vacancy space in the perovskite. <sup>[34]</sup>

	Perovskite solar cell	$R_s \left[\Omega\right]$	$R_1 \ [\Omega]$	$R_{\mathscr{Q}} \left[ \Omega \right]$
(a)	pristine	14.73	43.16	50.76
(b)	with 127 nm nanopatterned $TiO_2$ layer	14.64	33.61	41.25
(c)	with 0.10 wt% PCBM on perovskite layer	14.71	29.83	37.34
(d)	with 127 nm nanopatterned $TiO_2$ layer and 0.10  wt% PCBM on perovskite layer	13.68	21.02	25.14

 Table 3. EIS parameters for the PSCs.

Table 4 . Hysteresis of PCBM-PSCs with nanopatterned  $TiO_2$  layer.

	PCBM-PSCs with nanopatterned $TiO_2$ layer	$J_{sc} \; [{ m mA/cm^2}]$	$V_{oc}$ [V]	ff	$\eta~[\%]$
(a)	reverse direction scanning	22.877	0.963	0.787	17.338
(b)	forward direction scanning	22.492	0.951	0.760	16.256

#### 3. Conclusion

In conclusion, ML has been successfully implemented in this research to integrate different factors and predict the best combination of nanopatterning depth and wt% of PCBM. The best combination predicted were at 127 nm nanopatterning depth and 0.10 wt% of PCBM with  $J_{sc}$ ,  $V_{oc}$ , ff and ECE values of 23.162 mA/cm<sup>2</sup>, 0.953 V, 0.753 and 16.727%. As the predicted performance of PCBM-PSCs with nanopatterned TiO<sub>2</sub> layer were higher than the PSCs with nanopatterned  $TiO_2$  layer and PCBM-PSCs, the results proved that ML were capable to learn the relationship between two different factors and predict the performance of new PSCs. Therefore, with the assistance of ML, PCBM-PSCs with nanopatterned TiO<sub>2</sub> layer were fabricated and characterized. The consistencies of experimental results with the predicted values further validate the reliability of the ML model. Through this approach, it has been observed that nanopatterning depth significantly increased the  $J_{sc}$ , attributed to the improved light harvesting through nanopatterning. The nanopatterned  $TiO_2$  layer was able to enhance electron generation, which leads to a higher electron density and thus increases the  $J_{sc}$ . Furthermore, the incorporation of PCBM into the perovskite layer enhanced the electron transport property of PSCs, yielding to the increment in  $V_{oc}$  and ff. This is because PCBM were able to fill in the pinholes and grain boundaries between the perovskites, resulting in a formation of larger perovskite-PCBM grain sizes. Experimentally, the highest ECE obtained was 17.336%, which represented a 32.5% improvement compared to the pristine PSC. These results pave the way to understand the dual effects of nanopatterning depth and wt% of PCBM in the performance of PCBM-PSCs with nanopatterned TiO<sub>2</sub> layer and represent a significant step towards the development of PSCs more efficiently by examining and uncovering patterns of the available data through ML.

4. Experimental Section/Methods

#### 4.1. Machine Learning

# 4.1.1. Prediction of the most optimal nanopatterning depth and wt% of PCBM in PCBM-PSCs with nanopatterned TiO<sub>2</sub> layer

The objective to predict  $J_{sc}$ ,  $V_{oc}$ , ff and ECE of PCBM-PSCs with nanopatterned TiO<sub>2</sub> layer was formulated as a regression problem and 108 datasets were used to train the ML model and another 12 datasets were used for validation. The data consists of  $J_{sc}$ ,  $V_{oc}$ , ff and ECE for the PSCs with nanopatterned TiO<sub>2</sub> layer and PCBM-PSCs that were collected through previous experiments. In this study, a Random Forest regression model was used to train the datasets. Then, the multioutput regressor, which fits one regressor per target, was opted to predict the  $J_{sc}$ ,  $V_{oc}$ , ff and ECE, and Optuna was used for hyperparameter tuning and obtaining the most optimal hyperparameter for the model, as shown in the **Table 5** below.

 Table 5 . Optimal parameters for the ML model

Hyperparameter	Optimal value
n_estimators	86
$\max_{-}depth$	4
$\max_{\text{features}}$	sqrt
random_state	98
$min\_samples\_split$	0.0087

#### 4.2. Device Fabrication

#### 4.2.1. Preparation of perfluoropolyether (PFPE) mold

The PFPE resin (Fluorolink MD700, Solvay Solexis, Milan, Italy) was mixed with 3% w/w photoinitiator (Darocur 1173, Sigma Aldrich, St. Louis, MO, USA) to create the UV-curable resin. Then, the patterned silicon substrate (e.g., Si master) was coated with the UV-curable resin and covered with polyethylene terephthalate (PET) film as a backplane. The PET film was then rolled over to the UV-curable resin to

distribute it evenly and the mixture was cross-linked by exposure to UV light at 365 nm for 5 minutes. After the curing process, the PFPE mold was detached from the Si master.

#### 4.2.2. Preparation of perovskite precursor solution

Methylammonium iodide (MAI) was prepared by mixing 25 mL of methylamine (33 wt% in ethanol, Sigma Aldrich, St. Louis, MO, USA) and 10 ml of hydroiodic acid (55–58%, Kanto Chemical, Tokyo, Japan) in a round-bottom flask, which was kept in an ice bath for 2 hours. The resulting product was then obtained using a rotary evaporator at 60°C for 1 hour. After evaporating, the precipitates were recrystallized several times using ethanol (99.9%, Daejung Chemicals, Siheung-si, Korea) and diethyl ether (99%, Daejung Chemicals, Siheung-si, Korea), followed by an overnight drying at 60°C in a vacuum oven. Finally, 45 wt% of MAI and lead (II) iodide with a 3:1 molar ratio were stirred in N,N-dimethylformamide (DMF, 99.8%, Sigma Aldrich, St. Louis, MO, USA) at 90 °C for 1 hour.

# 4.2.3. Preparation of PCBM-perovskite precursor solution

The perovskite solution was created by mixing MAI and lead (II) iodide in a 3:1 molar ratio, 45 wt% with DMF. The perovskite-PCBM layer was prepared by dissolving PCBM (99.5%, Nano-C) into chlorobenzene, then mixing the solution with the perovskite precursor solution.

#### 4.2.4. Preparation of hole transport materials (HTM) solution

To prepare the hole transport materials, 73.5 mg of spiro-OMeTAD (99.62%, Feiming Chemical Limited, Shenzhen, China), 17  $\mu$ l of bis(trifluoromethane)sulfonamide lithium salt (Li-TFSI, 99.95%, Sigma Aldrich, St. Louis, MO, USA) solution (574.2 mg of Li-TFSI in 1 ml of acetonitrile), and 36.2  $\mu$ l of 4-tert-butylpyridine (98%, Sigma Aldrich, St. Louis, MO, USA) were stirred at room temperature for 2 hours in 1 ml of chlorobenzene (99.8%, Sigma Aldrich, St. Louis, MO, USA).

# 4.2.5. Fabrication of PCBM-PSCs with nanopatterned $TiO_2$ layer

The fluorine-doped tin oxide (FTO) glass was cleaned using water, ethanol, and acetone. Then, the compact TiO<sub>2</sub> layer was created by spin-coating a precursor solution made of 1 ml of titanium diisopropoxide bis(acetylacetonate) (75 wt% in isopropanol, Sigma Aldrich, St. Louis, MO, USA) in 6 ml of butanol (99%, Daejung Chemicals, Siheung-si, Korea) onto the FTO at 4000 rpm for 20 s, followed by annealing at 250°C for 10 min. This process was repeated twice. To form the mp-TiO<sub>2</sub> layer, 1 g of TiO<sub>2</sub> paste (Ti-Nanoxide T/SP, Solaronix, Aubonne, Switzerland) was diluted in 12 ml of anhydrous ethanol (99.9%, Daejung Chemicals, Siheung-si, Korea), and spin-coated on a compact TiO<sub>2</sub>/FTO. After slightly evaporating the solvent by prebaking on a hotplate at 70°C for 1 min, the PFPE mold was placed on the mp-TiO<sub>2</sub>/compact TiO<sub>2</sub>/FTO substrate and heat-pressed for 5 min at 70°C with a pressure of 2 bar. After removing the mold, the resulting nanopatterned mp-TiO<sub>2</sub>/compact TiO<sub>2</sub>/FTO substrate was then annealed at 500 °C for 1 hour. The PCBM-perovskite layer was created by spin coating the PCBM-perovskite precursor solution at 700 rpm onto the nanopatterned mp-TiO<sub>2</sub> layer through the hot-casting technique at 90 °C, followed by annealing at 130 °C for 1 hour. The HTM layer was spin coated at 4000 rpm for 60 s and dried overnight in a glovebox. All the procedure were conducted inside a dried air-filled glovebox. Finally, the Au electrode was deposited through thermal evaporation.

# 4.3. Analysis

A field emission scanning electron microscope (FE-SEM, SU-70, Hitachi) was used to examine the morphology and thickness of the device configurations while an X-ray diffractometer (Rigaku Corp., D/max-2500, Tokyo, Japan) was used to confirm the crystallinity of TiO<sub>2</sub> and perovskite layers. To measure the transmittance, a UV-Vis spectrophotometer (Jasco International Co., Ltd., V-730, Tokyo, Japan) was used and the infrared spectra were recorded on the Fourier-transform infrared (FTIR) spectrometer (Nicolet 6700, Thermo Scientific) in the range of  $600 - 4000 \text{ cm}^{-1}$ . Then, a solar simulator (Newport Corp., Model 94022A, Irvine CA, USA) with a source meter (Keithley Instruments Inc., Keithley 2400, Cleveland, OH, USA) under AM 1.5 illumination (100 mW/cm<sup>2</sup>) was used to characterize the photovoltaic properties of PSCs. The characterization was carried out at the Future Energy Convergence Core Center (FECC). All devices were measured by masking 0.1256 cm<sup>2</sup> of the active area with a mask under argon condition. The solar cell quantum efficiency measurement system (PV Measurements Inc., QEX7, Point Roberts, WA, USA) was also used to measure the incident photon to electron conversion efficiencies. Electrochemical impedance spectroscopy was performed using a potentiostat (Solartron 1287) and frequency response analyzer (Solartron 1260) in the range of 10<sup>-2</sup> and 10<sup>6</sup>Hz. The measurements were analyzed using the ZView software (Solartron Analytical) with the aid of appropriate equivalent circuit, where the applied bias voltage and the amplitude of alternating current was set at the open circuit voltage ( $V_{oc}$ ). The impedance measurements were carried out at open-circuit potential under AM 1.5 illumination.

# **Conflicts of Interest**

The authors declare no conflict of interest.

#### **Supporting Information**

Supporting Information is available from the Wiley Online Library or from the author.

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