



THE 21<sup>ST</sup> INTERNATIONAL  
OPERATIONS & MAINTENANCE  
CONFERENCE IN THE ARAB COUNTRIES

# Integrating Deep Learning and Machine Learning for Defect Detection and Maintenance Prediction in Photovoltaic Systems

Predictive Analytics for Solar Energy Reliability

 #OmaintecConf

An Initiative by

Organized by



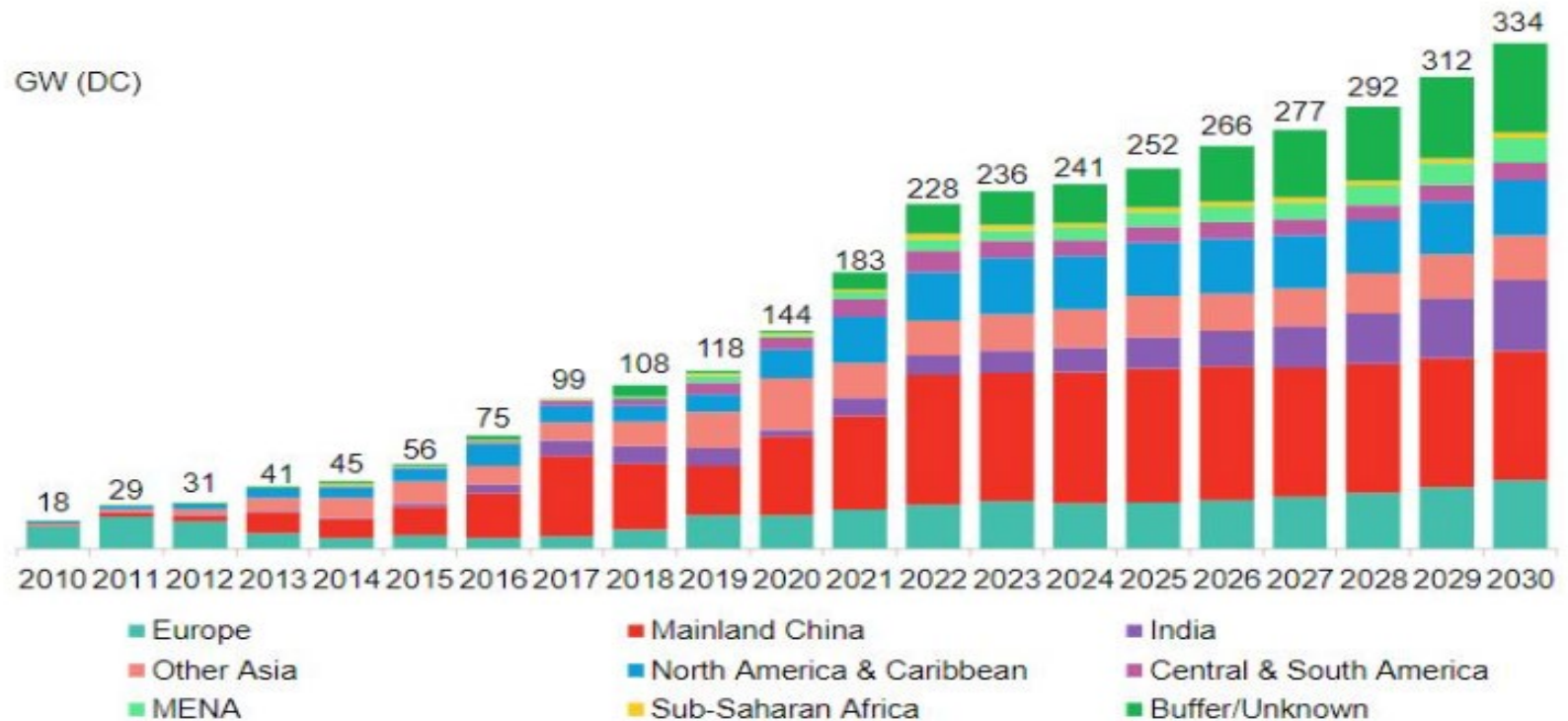
**EXICON.**  
International Group  
مجموعة أكزيكون الدولية



# Embracing Solar: The Future Powered Today

The Bloomberg New Energy Finance (BNEF) reports of analysts expect newly installed PV capacity to be between 252 and 260 GW in 2025.

Commercial and industrial systems will also see their share increase, as these are becoming more and more profitable against the background of **rising electricity prices** and **electricity shortages in the country**.

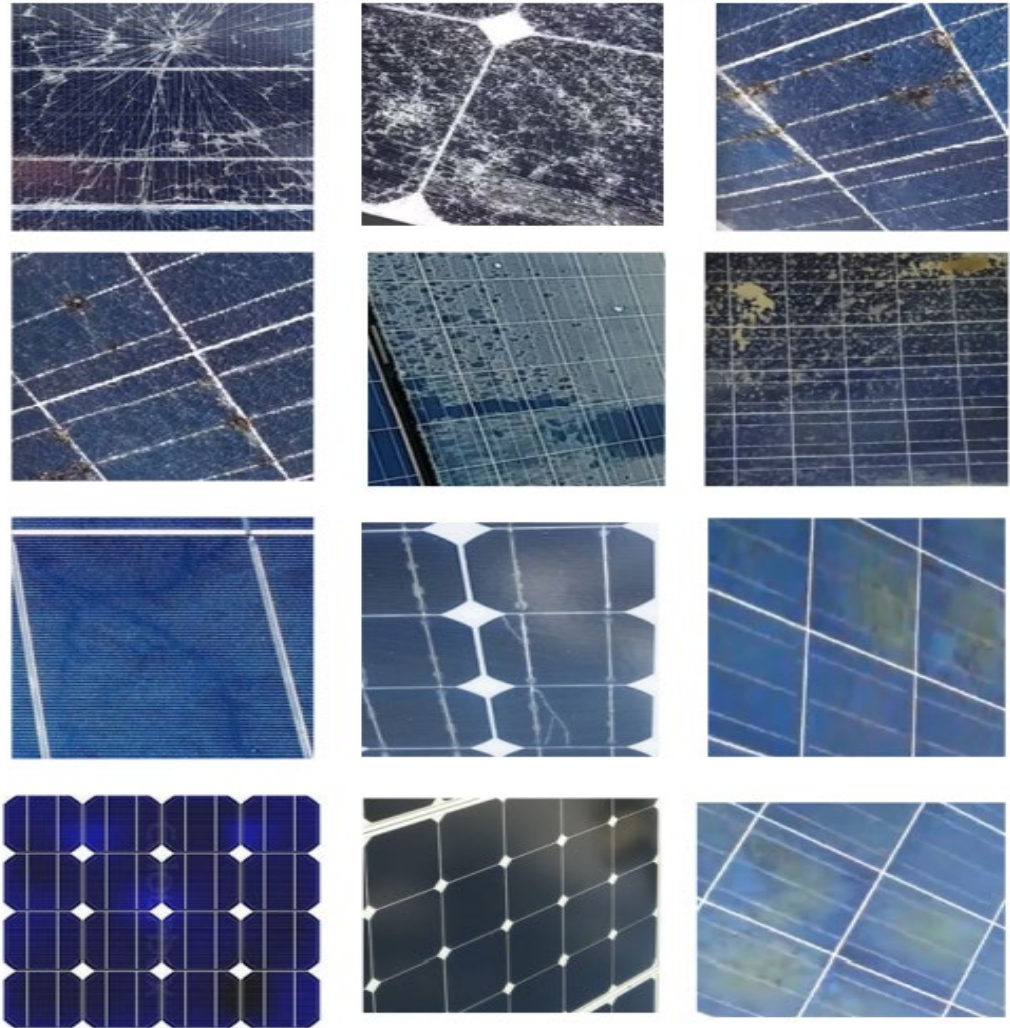


Source: BloombergNEF

# Overview of PV System Challenges

Here are some common types of defects (intrinsic, extrinsic) found in PV panels:

- 1. Micro-Cracks
- 2. PID (Potential Induced Degradation)
- 3. Snail Trails
- 4. Hot Spots
- 5. Soiling
- 6. Delamination and Discoloration
- 7. Corrosion
- 8. Cell Mismatch and Shading
- 8. Inverter and Junction Box Failures



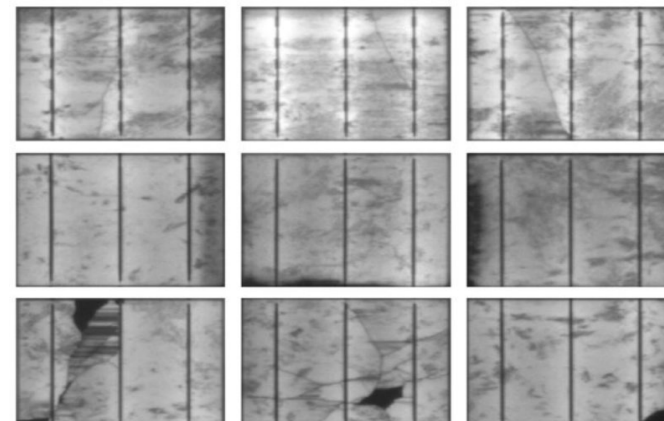
Method	Process
Visual	Discoloration, surface soiling, browning,
Thermal	Thermal extraordinary heating
Electrical	Illuminated I-V curve measurement, Transmittance line diagnosis

Fig. 3. Samples of solar panels with defective and normal surfaces.

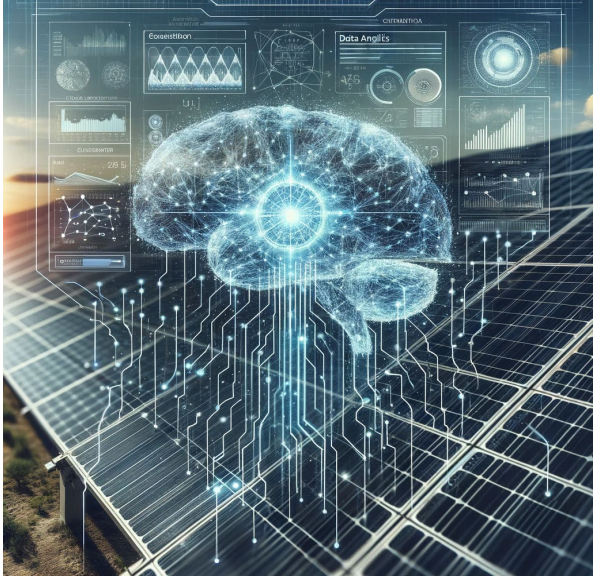


# Problem statement

- Regular monitoring and maintenance of PV panels are essential to detect these defects early and address them promptly.
- Traditionally, maintenance teams conduct **visual inspections** and use instruments like **I-V curve** tracers to detect anomalies.
- limitations: Time-consuming, Subjective, Intermittent, Reactive.
- Solution: the advanced predictive capabilities offered by **data analysis, machine learning and deep learning**. to predict when a failure is likely to occur and taking preventative measures before it happens.
- Advanced techniques like **thermal imaging, electroluminescence**, and the use of **drones** for inspection are increasingly employed to identify and analyze these defects efficiently.



# Role of Machine Learning (ML) and Deep Learning (DL)

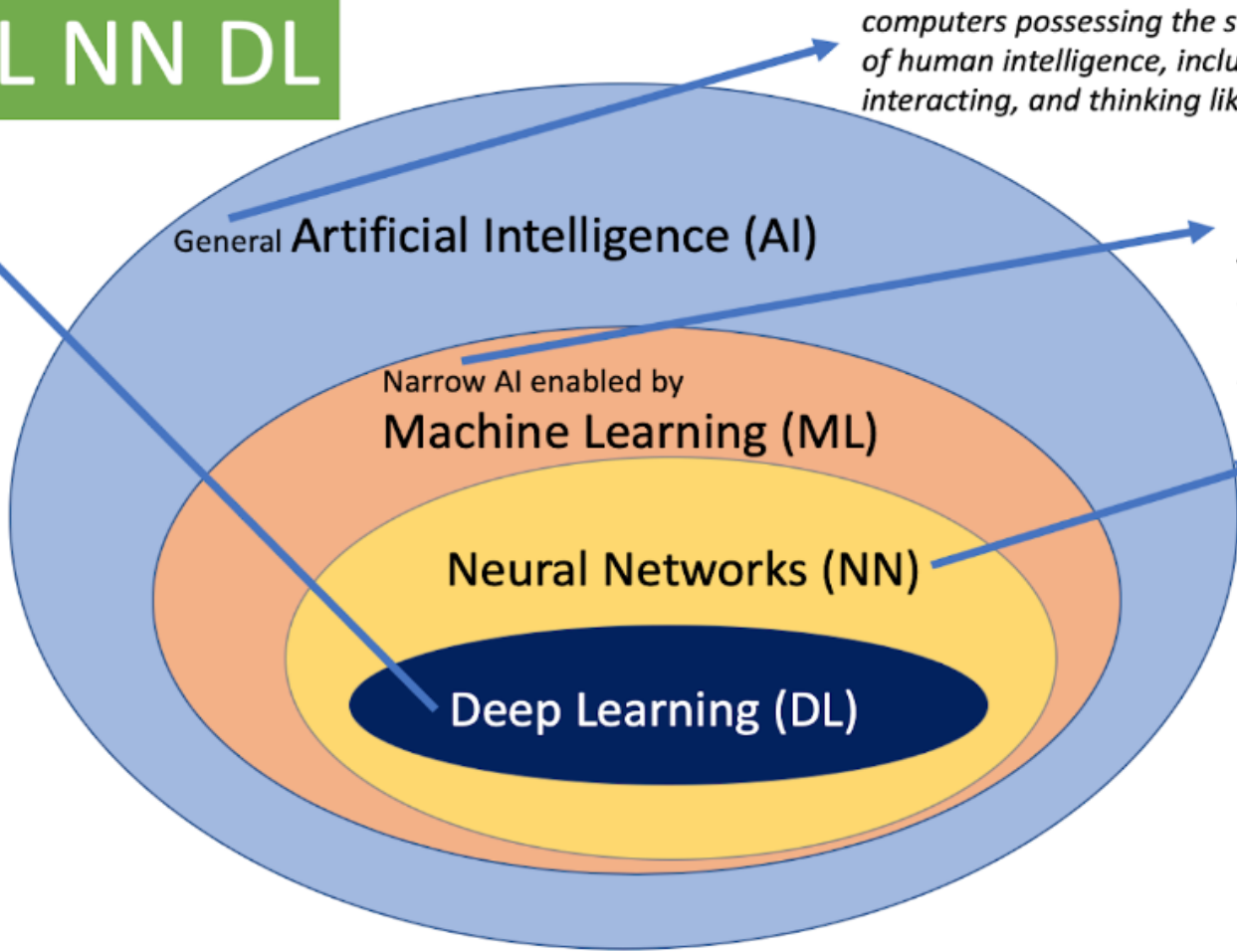


These technologies enable:

- Anomaly Detection
- Pattern Recognition
- Predictive Insights

## AI ML NN DL

*the word "deep" comes from the fact that DL algorithms are trained/run on deep neural networks. These are just neural networks with (usually) three or more "hidden" layers*



*computers possessing the same characteristics of human intelligence, including reasoning, interacting, and thinking like we do*

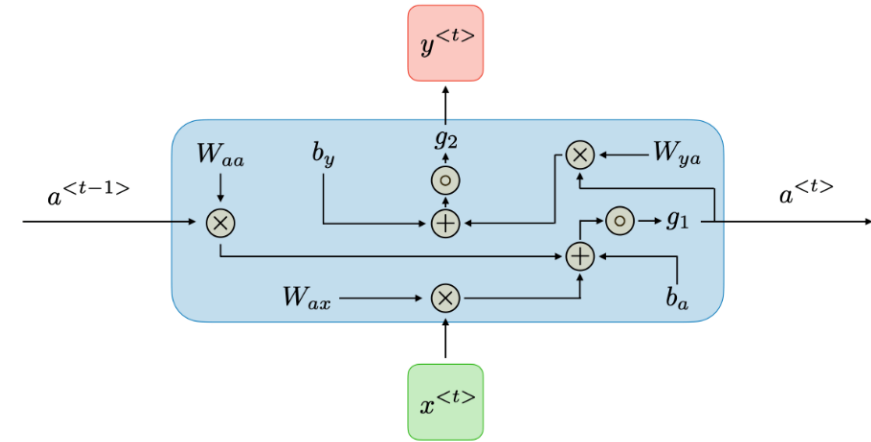
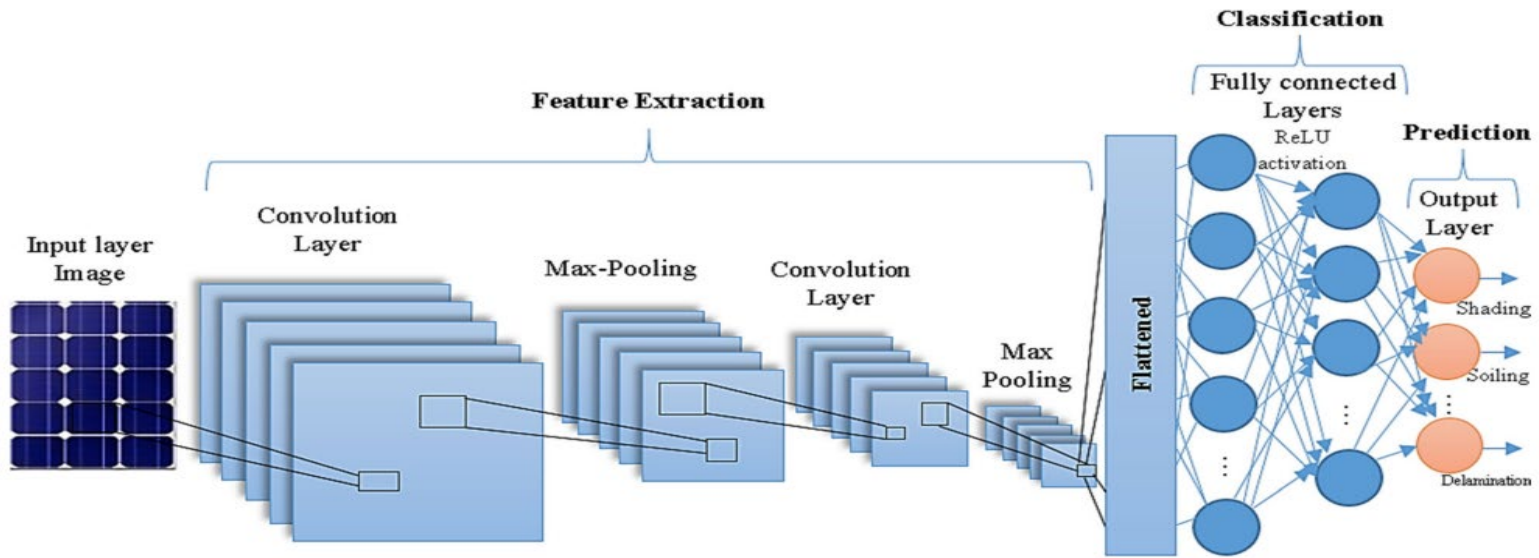
*technologies that can accomplish specific tasks such as playing chess, recommending your next Netflix TV show, and identifying spam emails*

*neural networks are a specific group of algorithms used for machine learning that model data using graphs of Artificial Neurons. Those neurons are a mathematical model that "mimics approximately how a neuron in the brain works"*

# Examples of AI models

Once data is collected, ML/DL algorithms come into play, offering advanced defect detection capabilities:

- Convolutional Neural Networks (CNNs)
- Recurrent Neural Networks (RNNs)
- Autoencoders
- YOLO



# Transfer learning models

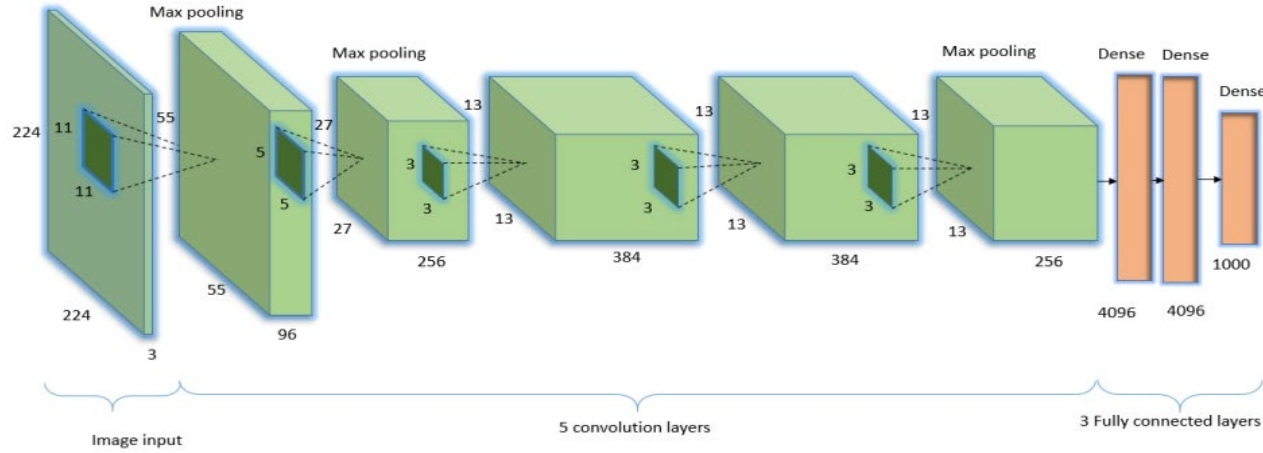


Fig. 2. AlexNet Architecture

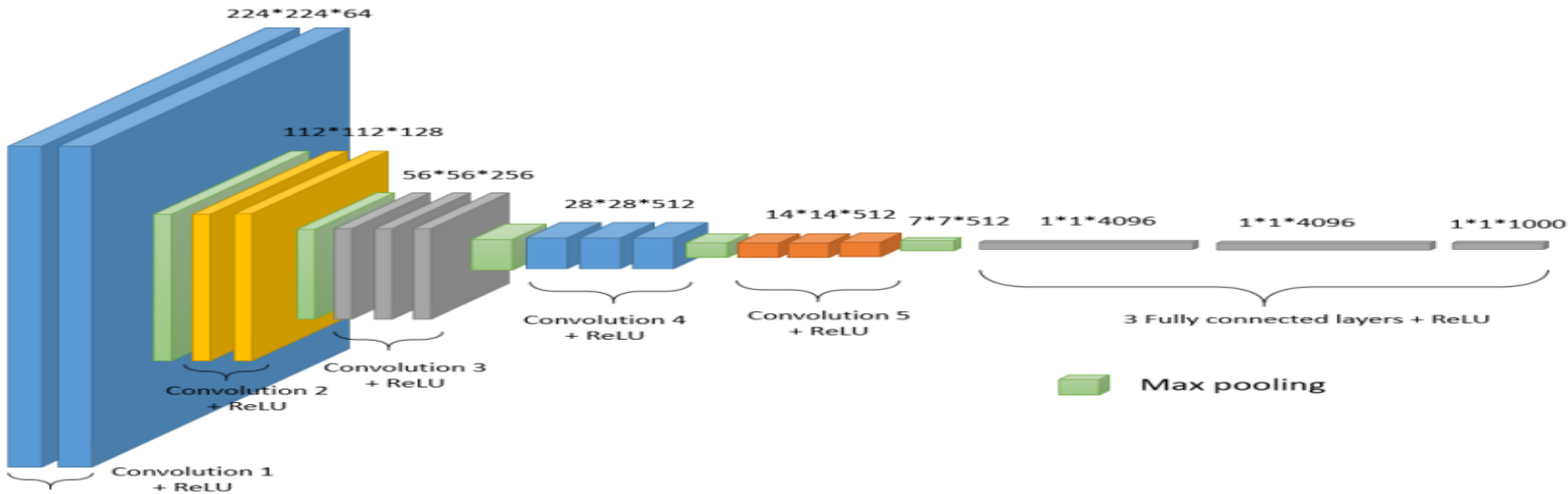
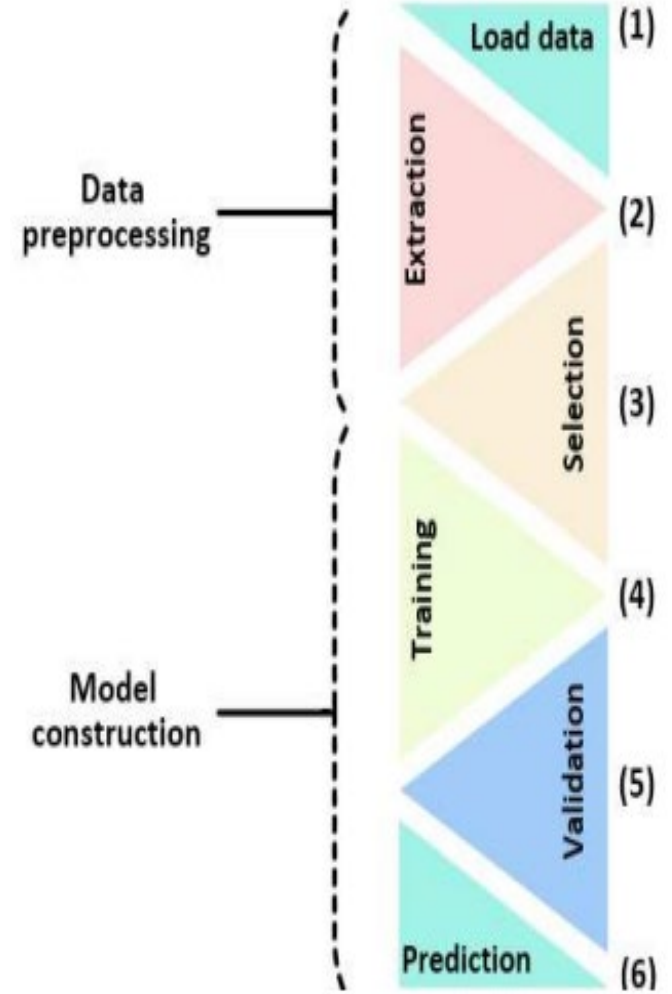


Fig. 3. VGG16 Architecture





## Our papers

### BA-CNN: Enhancing Photovoltaic Cell Quality Evaluation and Anomaly Detection through Deep Learning

<p>Eman Ashraf dept. of Electronics and Communications Engineering Faculty of Engineering Delta University for Science and Technology Gamasa, Egypt <a href="https://orcid.org/0000-0003-0928-3580">https://orcid.org/0000-0003-0928-3580</a></p>	<p>Shady Yehia EL Mashad Associate Professor, Faculty of Engineering at Shoubra, Benha University</p>	<p>Kabeel A. E.<sup>1,2</sup> <sup>1</sup> Faculty of Engineering, Delta University for Science and Technology, Gamasa, Egypt <sup>2</sup> Mechanical Power Engineering Department, Tanta University, Tanta, Egypt <a href="mailto:kabeel6@f-eng.tanta.edu.eg">kabeel6@f-eng.tanta.edu.eg</a></p>	<p>Warda M. Shaban dept. of Communications and Electronics Engineering Nile Higher Institute for Engineering and Technology, Artificial Intelligence Lab, Mansoura, Egypt <a href="mailto:warda_mohammed@nilehi.edu.eg">warda_mohammed@nilehi.edu.eg</a></p>
-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------	-----------------------------------------------------------------------------------------------------------	---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------	----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------

### Integrating Deep Learning and Machine Learning for Defect Detection and Maintenance Prediction in Photovoltaic Systems

<p>Eman Ashraf dept. of Electronics and Communications Engineering Faculty of Engineering Delta University for Science and Technology Gamasa, Egypt <a href="https://orcid.org/0000-0003-0928-3580">https://orcid.org/0000-0003-0928-3580</a></p>	<p>A.R. Habieeb<sup>1,2</sup> <sup>1</sup> Faculty of Engineering, Delta University for Science and Technology, Gamasa, Egypt, <sup>2</sup> Mechatronics Engineering Program, Faculty of Engineering, Mansura University, Mansura, Egypt <a href="mailto:abedrabiee@gmail.com">abedrabiee@gmail.com</a></p>	<p>Kabeel A. E.<sup>1,2</sup> <sup>1</sup> Faculty of Engineering, Delta University for Science and Technology, Gamasa, Egypt <sup>2</sup> Mechanical Power Engineering Department, Tanta University, Tanta, Egypt <a href="mailto:kabeel6@f-eng.tanta.edu.eg">kabeel6@f-eng.tanta.edu.eg</a></p>	<p>Warda M. Shaban dept. of Communications and Electronics Engineering Nile Higher Institute for Engineering and Technology, Artificial Intelligence Lab, Mansoura, Egypt <a href="mailto:warda_mohammed@nilehi.edu.eg">warda_mohammed@nilehi.edu.eg</a></p>
-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------	-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------	---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------	----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------

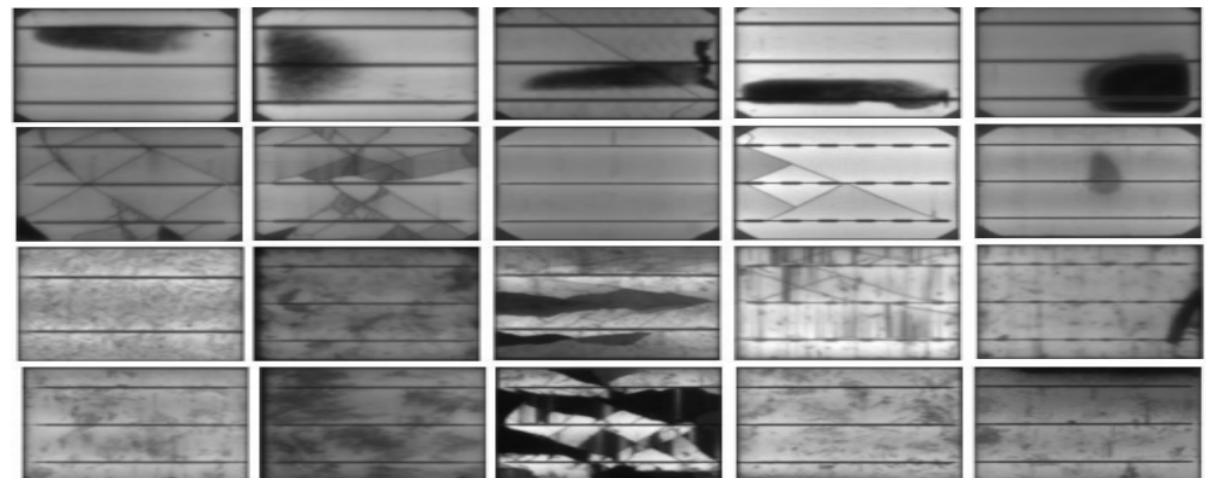
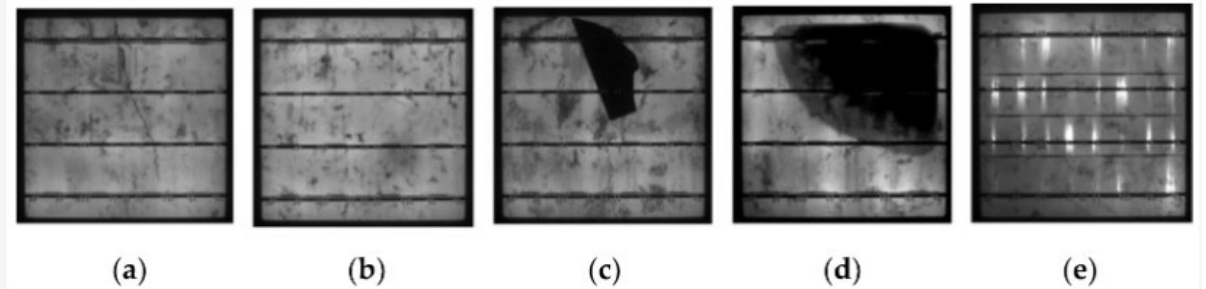


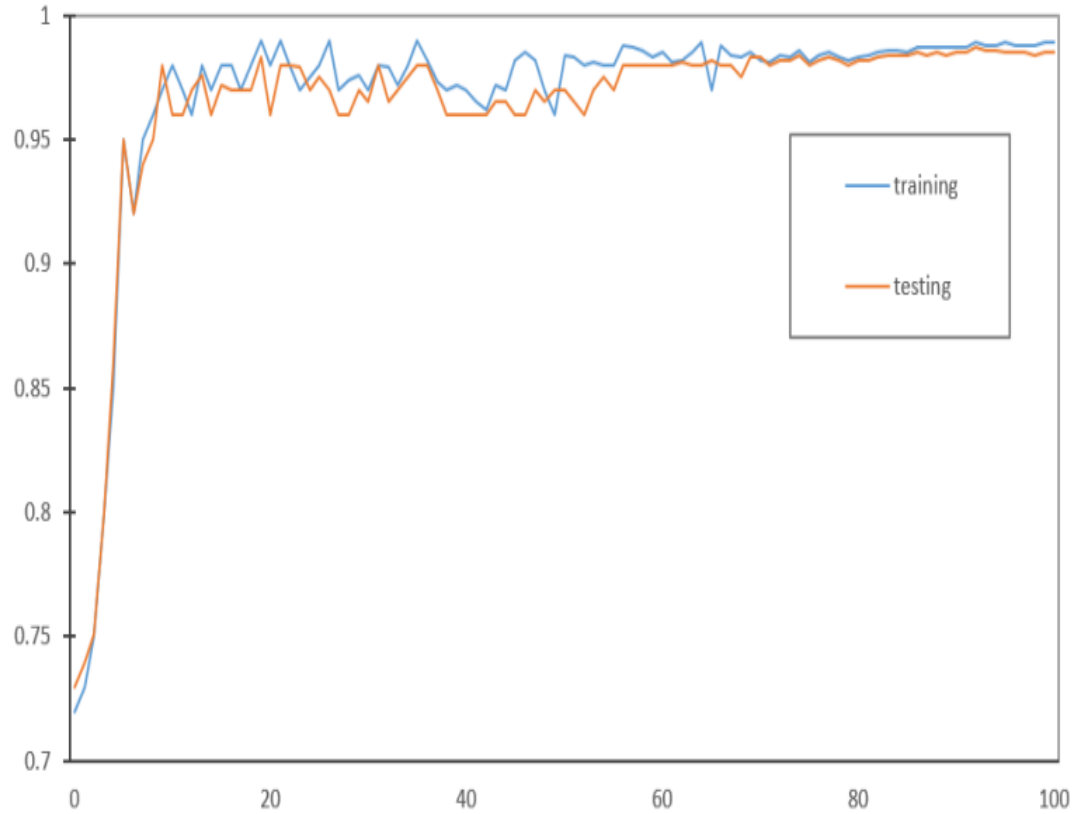


These algorithms are trained on vast datasets, Example of public dataset that consists of high-resolution electroluminescence (EL) images derived from both monocrystalline and polycrystalline PV modules

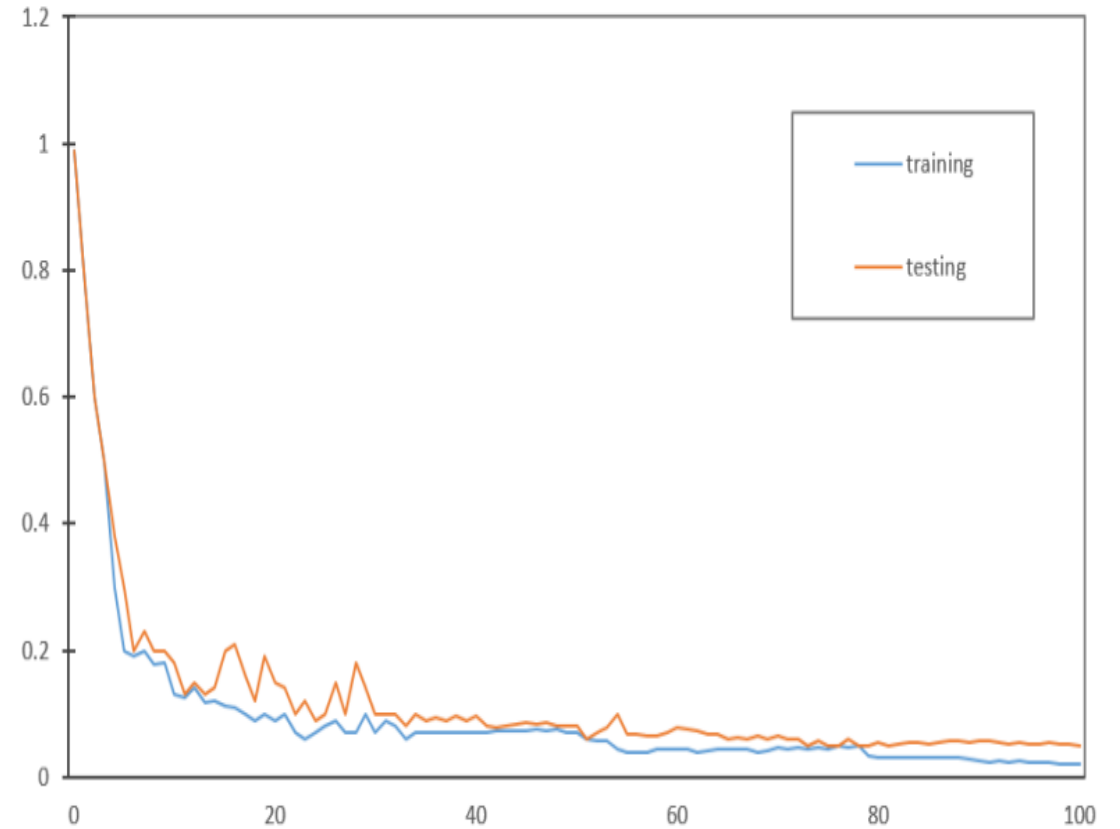
- **ELPV:** a total of 2,624 grayscale images, each with a resolution of 300×300 pixels and an 8-bit depth.
- **PVEL-AD:** contains 36,543 images with various internal defects and heterogeneous background. 10 different categories such as crack (line and star), finger interruption, black core, misalignment, thick line, scratch, fragment, corner, and material defect.

**Figure 1.** Different forms of defects in photovoltaic cells: (a) crack; (b) thick line; (c) fragment; (d) black core; (e) horizontal dislocation.





(a) accuracy

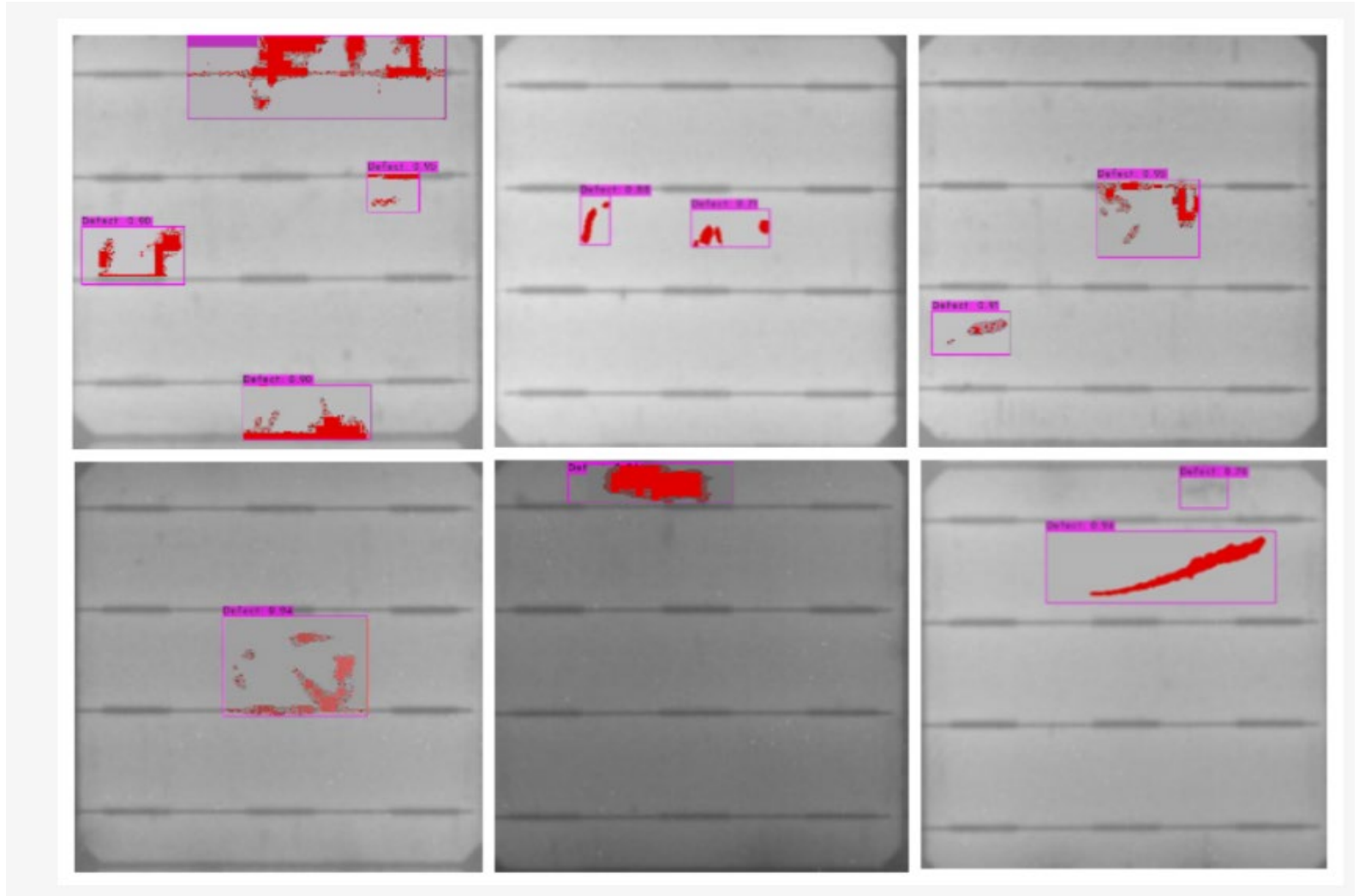


(b) losses

Fig. 9, The training and testing: (a) accuracy (b) losses.



# Detecting PV Defects with ML/DL



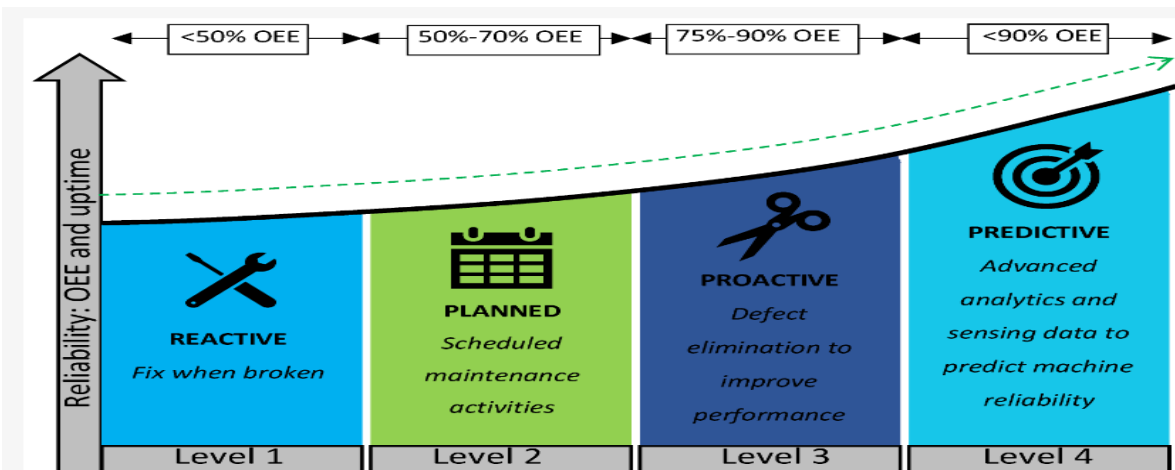
- To shift from reactive to proactive maintenance, The proposed Maintenance Prediction Model capitalizes on the previously localized defect regions from the defect detection process.
- The localized defect features are then utilized as inputs for a specialized maintenance prediction model.
- These attributes encapsulate critical information about the type, size, and severity of defects.
- Subsequently, the maintenance prediction model is trained to harness the relationship between extracted defect features and maintenance requirements.

### Algorithm 3: maintenance prediction model

```

1: function MaintenancePredictionModel(defect_features, maintenance_data):
2:   # Train the maintenance prediction model
   model = train_maintenance_model(defect_features, maintenance_data)
3:   return model
4: function TrainMaintenanceModel(defect_features, maintenance_data):
5:   # Prepare training data
   X_train = defect_features
   y_train = maintenance_data
6:   # Initialize and train the maintenance prediction model (SVM)
   model = initialize_model()
7:   model.train(X_train, y_train)
8:   return model
9:   # Main process
   defect_features = extract_defect_features(localized_defect_regions)
10:  maintenance_data = load_maintenance_data()
11:  maintenance_model = MaintenancePredictionModel(defect_features, maintenance_data)

```





## Field Successes: ML/DL in Action



5. خطوط الطيران الأمريكية: تستخدم خطوط الطيران الأمريكية (American Airlines) تقنيات الذكاء الاصطناعي لتحسين عمليات الصيانة، حيث يتم استخدام الذكاء الاصطناعي للكشف عن الأعطال المحتملة في المحركات ومكونات الطائرة والتنبؤ بالصيانة اللازمة، وذلك لتقليل مدة التوقف الفني وتحسين كفاءة الطائرات.



أدنوك تكمل بنجاح المرحلة الأولى من مشروعها للصيانة التنبؤية المعتمدة على الذكاء الاصطناعي

من المتوقع أن يسهم المشروع بخفض التكاليف بنسبة 20% بعد انتهاء مراحله الأربع في عام 2022

المشروع يأتي في إطار سعي أدنوك لاعتماد أحدث التقنيات المتطورة عبر مختلف مجالات ومراحل أعمالها لتعزيز كفاءة الأصول والارتقاء بالإناء



## Oracle Maintenance

ORACLE

Oracle Fusion Cloud Maintenance is a connected, smart maintenance management solution. Powered by advanced technologies, it enables predictive maintenance and helps you increase reliability and uptime while reducing overall costs.



## Field Successes: ML/DL in Action

RapidValue (Aspire Systems) > Case Studies > Remote Monitoring & Predictive Maintenance App for a Solar Energy System



### Remote Monitoring & Predictive Maintenance App for a Solar Energy System

هيئة كهرباء ومياه دبي  
Dubai Electricity & Water Authority



#### نظام التحكم والفحص الذكي لـ BCS و AOI

يتميز نظام التحكم والاختبار الذكي الخاص بنا لـ BCS و AOI لإنتاج الألواح الشمسية بكفاءة عالية والدقة والتشغيل الآلي الكامل. خصوصاً، يتم استخدام نظام BCS من أجل التثبيت الدقيق للوحة وتجميع اللوحة بجودة عالية. يستخدم نظام AOI لاكتشاف عيوب اللوح، بما في ذلك الشقوق، الأضرار، والخ. يدمج نظام التحكم الذكي التقنيات المتطورة مثل الذكاء الاصطناعي (AI)، الخوارزمية المرئية، التحكم التلقائي لتعزيز أتمتة الإنتاج وكفاءته. يمكنه أيضاً تحديد الأخطاء المحتملة وتصحيحها لتقليل التكلفة والمخاطر.



DNV and GreenPowerMonitor, a DNV company, have developed a predictive maintenance system for solar inverters that uses machine learning models to represent an inverter's normal operation and to identify anomalous behaviour within new streaming data.



# Field Successes: ML/DL in Action

## Patent volumes related to intelligent predictive maintenance

Company	Total patents (2010 - 2022)	Prer larg
General Electric		
Schlumberger		
Halliburton		
Saudi Arabian Oil		
Ecolab		
Linde		
The Weir Group		
Baker Hughes		
Air Products and Chemicals		
Emerson Electric		



Here we present highlights from companies benefitting from PdM, including example successes, why they matter, and the chosen tools and methods.

- U.S. industrial products manufacturer
- Tennessee snack food manufacturer
- Louisiana alumina refinery
- San Diego energy utility
- Singapore rail operator
- Australian iron ore mine





THE 21<sup>ST</sup> INTERNATIONAL  
OPERATIONS & MAINTENANCE  
CONFERENCE IN THE ARAB COUNTRIES

THANK  
YOU!

 #OmaintecConf

An Initiative by

Organized by



**EXICON.**  
International Group  
مجموعة أكزيكون الدولية