Data and Metadata. 2023; 2:94
doi: 10.56294/dm202394

ORIGINAL

Dynamic Threshold Fine-Tuning in Anomaly Severity Classification for Enhanced Solar Power Optimization

Ajuste dinámico de umbrales en la clasificación de la gravedad de las anomalías para mejorar la optimización de la energía solar

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Cite as: Boutahir MK, Hessane A, Lasri I, Benchikh S, Farhaoui Y, Azrour M. Dynamic Threshold Fine-Tuning in Anomaly Severity Classification for Enhanced Solar Power Optimization. Data and Metadata 2023; 2:94. https://doi.org/10.56294/dm202394.

Submitted: 10-08-2023 **Revised:** 15-11-2023 **Accepted:** 27-12-2023 **Published:** 28-12-2023

Editor: Prof. Dr. Javier González Argote

Note: paper presented at the International Conference on Artificial Intelligence and Smart Environments (ICAISE'2023).

ABSTRACT

This study explores an innovative approach to anomaly severity classification within the realm of solar power optimization. Leveraging established machine learning algorithms—including Isolation Forest (IF), Local Outlier Factor (LOF), and Principal Component Analysis (PCA)—we introduce a novel framework marked by dynamic threshold fine-tuning. This adaptive paradigm aims to refine the accuracy of anomaly classification under varying environmental conditions, addressing factors such as dust storms and equipment irregularities. The research builds upon datasets derived from Errachidia, Morocco. Results underscore the effectiveness of dynamically adjusting severity thresholds in optimizing anomaly classification and subsequently improving the overall efficiency of solar power generation. The study not only reaffirms the robustness of the initial framework but also emphasizes the practical significance of fine-tuning anomaly severity classification for real-world applications in solar energy management. By providing a more nuanced perspective on anomaly detection, this research advances our understanding of the intricate precision required for optimal solar power generation efficiency. The findings contribute valuable insights into the broader field of machine learning applications in renewable energy, offering a pathway for the refinement of existing frameworks for enhanced sustainability and operational effectiveness.

Keywords: Anomaly Detection; Solar Power Optimization; Machine Learning Algorithms; Dynamic Threshold Fine-Tuning; Renewable Energy Management.

RESUMEN

Este estudio explora un enfoque innovador para la clasificación de la gravedad de las anomalías en el ámbito de la optimización de la energía solar. Aprovechando algoritmos de aprendizaje automático establecidos -incluidos Isolation Forest (IF), Local Outlier Factor (LOF) y Principal Component Analysis (PCA)- introducimos un nuevo marco marcado por el ajuste dinámico de umbrales. El objetivo de este paradigma adaptativo es mejorar la precisión de la clasificación de anomalías en condiciones ambientales variables, teniendo en cuenta factores como las tormentas de polvo y las irregularidades de los equipos. La investigación se basa en conjuntos de datos procedentes de Errachidia (Marruecos). Los resultados subrayan la eficacia de ajustar dinámicamente los umbrales de gravedad para optimizar la clasificación de anomalías y, por consiguiente, mejorar la eficiencia global de la generación de energía solar.

El estudio no sólo reafirma la solidez del marco inicial, sino que también subraya la importancia práctica de afinar la clasificación de la gravedad de las anomalías para las aplicaciones del mundo real en la gestión de la energía solar. Al proporcionar una perspectiva más matizada de la detección de anomalías, esta investigación avanza en nuestra comprensión de la intrincada precisión necesaria para una eficiencia óptima en la generación de energía solar. Los resultados aportan valiosas ideas al campo más amplio de las aplicaciones del aprendizaje automático en las energías renovables, ofreciendo una vía para el perfeccionamiento de los marcos existentes con el fin de mejorar la sostenibilidad y la eficacia operativa.

Palabras clave: Detección de Anomalías; Optimización de la Energía Solar; Algoritmos de Aprendizaje Automático; Ajuste Dinámico de Umbrales; Gestión de Energías Renovables.

INTRODUCCIÓN

Harnessing the immense potential of solar energy for sustainable energy generation is a global endeavor. However, regions with abundant sunlight often face the challenge of unpredictable and erratic weather conditions, which can significantly impact solar power output. Errachidia, Morocco, exemplifies this complex dynamic, where the convergence of ample solar radiation and volatile weather patterns poses unique challenges for effective solar energy utilization.(1) Dust storms, temperature fluctuations, and other local anomalies disrupt the consistent flow of solar energy, hindering the optimization of solar power systems.(1,2)

To address these challenges, conventional solar forecasting methods often fall short, as they are designed for stable climates and may not adequately capture the intricate interactions between solar patterns and local weather anomalies. This necessitates the development of innovative and adaptive anomaly detection techniques tailored to regions with volatile weather patterns.(3)

In this research, we present a novel climate-adaptive anomaly detection framework designed to tackle the unique challenges of Errachidia's weather conditions.(4) Our approach integrates advanced machine learning techniques, including Isolation Forest (IF),(5) Local Outlier Factor (LOF),(6) and Principal Component Analysis (PCA),(7) to effectively identify and classify abnormal solar power data points. These techniques provide a robust and adaptable foundation for anomaly detection, capable of handling the dynamic nature of Errachidia's weather patterns.(8)

A key component of our framework lies in creating finely tuned, data-driven thresh-olds. These thresholds are meticulously calibrated based on Errachidia's specific weather conditions and the unique characteristics of its solar patterns.(9) By factoring in the intricate interplay between solar radiation and local anomalies, our thresh-olds ensure that anomaly detection is context-aware and highly responsive to Er-rachidia's specific weather fluctuations.(10)

This climate-adaptive anomaly detection framework offers several advantages over traditional approaches. Firstly, it transcends the limitations of generic models that may need to capture the complexities of Errachidia's weather patterns fully.(11) Secondly, it provides a precise and timely identification of anomalous solar power data points, enabling timely corrective actions to maintain optimal solar energy pro-duction.(12)

The efficacy of our framework is demonstrated through comprehensive simulations and real-world data analysis. The results showcase the ability of our framework to effectively detect anomalies in solar power data, even in the presence of complex weather patterns. Additionally, we demonstrate the framework's ability to classify anomalies into distinct categories, providing valuable insights into the underlying causes of performance deviations.(13,14)

The findings of this research contribute significantly to the advancement of solar energy management in regions grappling with erratic climatic conditions. Our climate-adaptive anomaly detection framework is valuable for enhancing the reliability and predictability of solar power systems, enabling more efficient and sustainable energy utilization in Errachidia and similar locations. Moreover, the insights gained from this study can inform the development of anomaly detection strategies for other regions facing identical weather challenges.(15)

This research presents a novel approach to anomaly detection in solar power generation, tailored explicitly for regions with volatile weather patterns. Our climate-adaptive framework leverages advanced machine learning techniques and data-driven thresholds to effectively identify and classify anomalous data points, ensuring optimal solar energy production and reliability despite unpredictable weather conditions. The findings of this study provide a valuable contribution to the field of solar energy management and offer a promising solution for enhancing the efficiency and sustainability of solar power in regions with challenging weather patterns.

The subsequent sections of this paper are organized as follows: section 2 provides a comprehensive review of the relevant literature, section 3 elaborates on the methodologies employed, section 4 scrutinizes the

https://doi.org/10.56294/dm202394

obtained results, and section 5 provides the final insights and closing remarks of this study.

RELATED WORKS

Advancements in Solar Energy Forecasting

In recent research endeavors, the field of solar energy forecasting and anomaly detection has seen notable contributions that align with the objectives of this study.

Sarmas et al.[16] introduced a meta-learning approach to enhance one-hour-ahead deterministic forecasts of photovoltaic (PV) systems. Their dynamic blending of base forecasts from multiple deep learning models demonstrated significant accuracy improvements, highlighting the efficacy of adapting to diverse weather conditions and system intricacies. Kaur et al.[17] provided a new approach for building on the advancements in probabilistic forecasting, proposed a novel scheme for solar power generation forecasting, addressing uncertainties in data and model parameters. Utilizing Bayesian bidirectional long short-term memory (BiLSTM) neural networks and variational auto-encoders (VAE), their approach not only reduced computational time but also showcased remarkable enhancements in forecasting accuracy. Dey et al.[18] tackled the specific challenge of solar farm voltage anomaly detection using high-resolution μPMU data-driven unsupervised machine learning. By harnessing the Clustering Large Applications (CLARA) algorithm, they focused on categorizing events and recognizing solar site-specific behavior patterns. The automatic voltage anomaly detection demonstrated insights for improving solar farm performance and understanding grid behavior.

Contributions from Moroccan Scientific Community

In the context of Morocco's scientific contributions, several studies provide valuable insights related to anomaly detection, security, and change point identification.

Moulad et al.[19] addressed security concerns in Wireless Sensor Networks (WSN) by proposing a hierarchical hybrid intrusion detection mechanism. This approach, combining anomaly detection with support vector machines (SVM), specifications-based techniques, and clustering algorithms, fortified WSNs against security threats without disrupting network performance. Boutahir et al.[20] focused on anomaly detection within solar power plants, introducing the Auto Encoder Long Short-Term Memory (AE-LSTM) method enhanced with a Genetic Algorithm (GA) for hyperparameter tuning. This approach outperformed traditional methods, showcasing the continual evolution of techniques to ensure the prompt identification of performance issues and equipment anomalies. Belcaid et al.[21] studied the challenge of change point detection in piecewise constant signals. Their innovative online change point detection algorithm, utilizing a local blanket of a global Markov Random Field (MRF), showcased notable improvements in running time and detection metrics. While applied in different domains, the principles of change point detection resonate with the dynamic nature of solar energy systems.

Advancements in Grid Stability and Environmental Impact

In addition to solar-centric research, advancements in grid stability and environmental impact have become integral considerations in the broader scope of sustainable energy systems.

Elliott et al.[22] explored the effects of managing the charging schedules for electric school buses to avoid simultaneous high loads on the grid, emphasizing Vehicle-to-Grid (V2G) services as a solution. The study demonstrated potential reductions in peak load periods and subsequent avoided carbon dioxide emissions, highlighting the pivotal role of innovative charging strategies in fortifying grid stability and reducing environmental impact. Adewuyi et al.[23] delved into the potential of natural gas-based distributed generation (GtP-DGs) in Nigeria to enhance the nation's electricity infrastructure and promote environmental sustainability. The study's optimization process identified optimal locations for GtP-DGs and reactive power compensators, showcasing considerable technical and economic benefits, along with significant environmental sustainability paybacks. Weidner et al.[24] assessed the optimal technology mix for building heating in the European Union within planetary boundaries. The research emphasized the interplay between technology choices, environmental impacts, and grid stability. It also highlighted the need for policy instruments to mitigate increased consumer costs, clarifying the intricate connections between grid stability, environmental impact, and economic considerations.[32,33,34,35,36]

These studies collectively contribute to the advancement of solar energy forecasting, anomaly detection, and system performance optimization, as well as broader considerations in grid stability and environmental impact. In the subsequent sections, we delve into the methodologies employed in our research, drawing inspiration from these advancements to tailor our approach to the unique challenges presented by Errachidia's climate patterns and solar anomalies.

DATA SOURCE

In the pursuit of comprehensive meteorological data for our research, we meticulously accessed information from the meteorological station situated at the Faculty of Sciences and Techniques in Errachidia, Morocco. The significance of this meteorological facility, as depicted in figure 1, cannot be overstated—it stands as an integral component of the PROPRE.MA project. This initiative, spearheaded by the University of Cadi Ayyad and generously funded by the Research Institute for Solar Energy and Renewable Energies (IRESEN),[25] embodies a concerted effort towards advancing our understanding of climatic conditions in the region.

Operational ceaselessly, 24 hours a day and seven days a week, the meteorological station diligently captures an array of climatic parameters at semi-hourly intervals. These parameters encompass, but are not limited to, solar radiation, temperature, humidity, atmospheric pressure, rainfall, and various other meteorological characteristics. The station's commitment to continuous data collection provides a rich repository for our study, facilitating a nuanced exploration of the dynamic climatic nuances inherent in the region.[37,38,39,40]

Within the broader context, the meteorological station is a linchpin in the overarching PROPRE.MA project, which ambitiously seeks to construct photovoltaic yield maps specifically tailored to the unique climatic conditions of Morocco. This ambitious endeavor employs a ground calibration strategy involving 20 identical installations strategically positioned across diverse urban centers within the country.[26,27] This multifaceted approach underscores the meticulous attention to detail and the comprehensive nature of the research methodology, positioning the project at the forefront of advancing solar energy understanding and application in the Moroccan context.

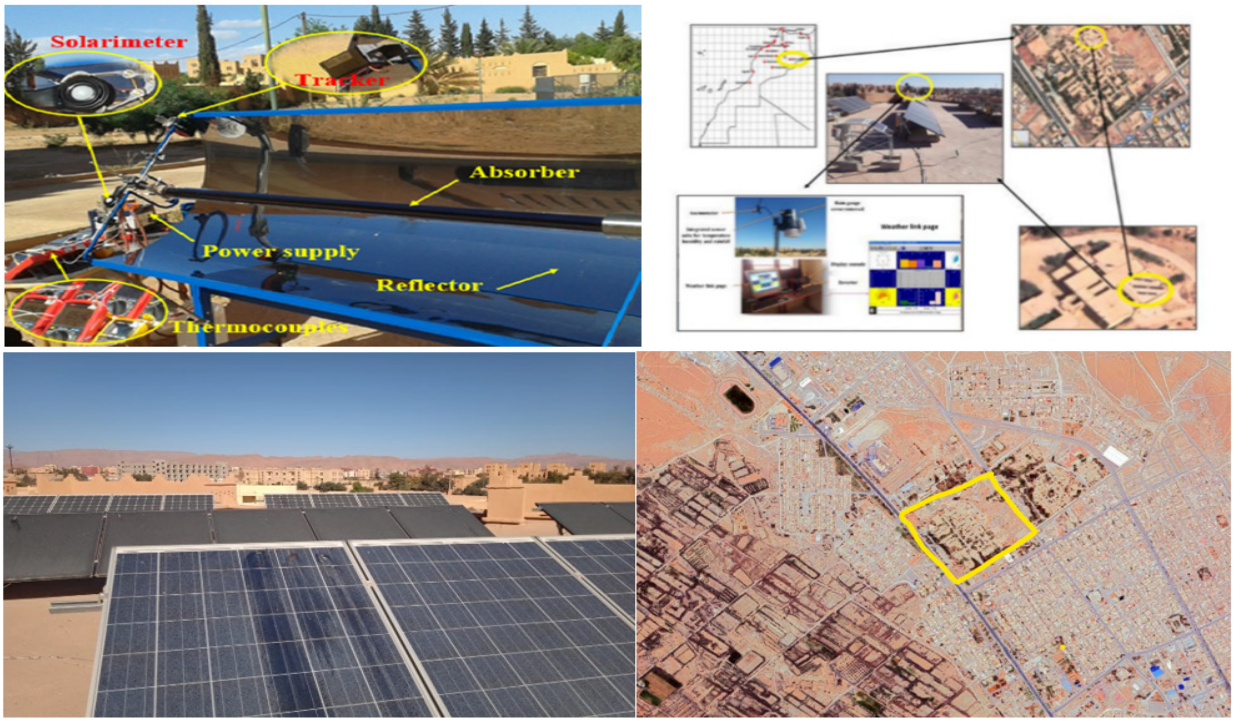

Figure 1. The different equipment, sensors and location of the meteorological station of the Faculty of Sciences and Technologies of Errachidia

In our comprehensive research endeavor, we systematically harnessed a dataset spanning the temporal expanse of 2018 and 2019, aggregating a substantial total of 33,675 observations. This meticulous collection of data incorporates a diverse array of 28 distinct features, each playing a pivotal role in shaping our understanding of the intricate dynamics governing solar energy generation. The dataset, a veritable treasure trove of information, encapsulates critical variables essential for solar energy forecasting, including but not limited to temperature, humidity, wind speed, solar radiation, and more.[41,42,43]

It is noteworthy that these variables are meticulously recorded on an hourly basis, underscoring the temporal granularity of our dataset. The hourly recording of these crucial parameters is of paramount significance, as it forms the backbone of our predictive modeling efforts, particularly in forecasting solar radiation levels. The temporal precision afforded by hourly observations enhances the accuracy and reliability of our analyses, enabling us to discern subtle patterns and trends that contribute to a more nuanced understanding of the factors influencing solar energy dynamics.

METHODOLOGY

In this section, we elucidate the comprehensive methodology crafted to optimize solar power generation in Errachidia, Morocco. Our refined methodology focuses on infusing dynamism into anomaly detection through the introduction of a Dynamic Threshold Fine-Tuning mechanism. The systematic phases encompass data collection and preprocessing, feature selection, the integration of dynamic thresholds, anomaly severity classification, and model evaluation. Each step is meticulously designed to fortify solar energy generation against climatic challenges, offering a robust framework adaptable to regions with analogous environmental conditions.

Data Collection and Preprocessing

Initiating our methodology, we meticulously collect and preprocess meteorological data from the Errachidia meteorological station, spanning the years 2018 and 2019. Rigorous data cleaning addresses missing values and outliers, ensuring the reliability of our dataset. Feature engineering techniques are then thoughtfully applied to extract valuable insights, harmonizing the dataset and mitigating discrepancies in variable influence through systematic feature scaling.

Feature Selection

Moving to the feature selection phase, we adopt the proven Random Forest technique for refining the dataset in the context of solar irradiance prediction. This method, substantiated by its effectiveness in prior works,(22) identifies the most influential variables. Our dataset is streamlined to retain only those variables significantly impacting the accuracy of solar power generation forecasts in Errachidia, Morocco.

Integration of Dynamic Thresholds

Building upon the advanced anomaly detection methods (IF, LOF, and PCA), we further classify anomalies based on severity. The dynamic thresholds, fine-tuned through historical analysis, enable us to categorize anomalies into different levels of severity. This classification offers nuanced insights into the potential impact of anomalies on solar power generation, facilitating proactive measures for optimization.

Let T(t) be the threshold at time t The dynamic adjustment could be expressed as in (1): $T(t)=f(T(t-1)*R(t)*H(t))$ (1)

Where:

- $T(t-1)$ is the previous threshold.
- $R(t)$ represents real-time conditions at time t.
- $H(t)$ represents historical data up to time t.
- f is a function that adjusts the threshold based on real-time conditions and historical data.

To emphasize the adaptive nature of our threshold mechanism, we introduce a crucial element of dynamism. The thresholds dynamically adjust based on real-time conditions and historical data analysis. This adaptability ensures that our model is responsive to variations in solar radiation patterns, including those caused by dynamic factors such as dust storms and equipment malfunctions. The incorporation of this dynamic threshold fine-tuning adds a layer of flexibility to our anomaly detection model, making it more robust and accurate in capturing the evolving nature of solar energy patterns.

Anomaly Severity Classification

Building upon the advanced anomaly detection methods (IF, LOF, and PCA), we further classify anomalies based on severity. The dynamic thresholds, fine-tuned through historical analysis, enable us to categorize anomalies into different levels of severity. This classification offers nuanced insights into the potential impact of anomalies on solar power generation, facilitating proactive measures for optimization.

Model Evaluation

To assess the performance of our extended anomaly detection model, we expand the evaluation metrics beyond traditional measures. In addition to precision-recall curves, we introduce metrics specific to anomaly severity classification, providing a comprehensive assessment of the model's ability to categorize anomalies by severity.

Here's the adaptation of the Gaussian distribution function utilized for dynamic threshold fine-tuning in (2): $F(x)=1/(\sigma\surd 2\pi)\ e^{\wedge}(-((x-\mu)^2)/2\sigma^2)$ (2)

Where:

- $F(x)$: probability density function.
- σ: standard deviation, measuring data spread.
- μ: mean, representing the central value.
- x: variable of interest (e.g., solar radiation).

This statistical function underpins the dynamic threshold fine-tuning, ensuring precise anomaly identification and effective enhancement of solar power generation in Errachidia, Morocco. The integration of dynamic thresholds adds a layer of adaptability to our model, making it more responsive to the evolving nature of solar radiation patterns.

RESULTS

In this study, we introduce a pioneering element to the anomaly detection methodology, namely, the Integration of Dynamic Thresholds. Traditional anomaly detection methods often rely on static thresholds, offering limited adaptability to the dynamic and evolving nature of solar radiation patterns. Recognizing this challenge, we propose a novel approach that dynamically fine-tunes anomaly severity thresholds in real-time. This dynamic adjustment is crucial for effectively capturing anomalies influenced by sudden climatic changes, such as dust storms and equipment malfunctions. The Integration of Dynamic Thresholds represents a paradigm shift in enhancing the adaptability and accuracy of our anomaly detection model, ensuring robust performance in the face of unpredictable environmental factors.

At the core of our dynamic threshold fine-tuning mechanism is a sophisticated mathematical model presented before. The dynamic nature of this adjustment ensures that our model remains agile in responding to the inherent variability in solar radiation patterns. This Introduction to Dynamic Threshold Fine-Tuning sets the stage for a detailed exploration of how this innovation enhances anomaly detection accuracy, real-time adaptability, and overall robustness in the subsequent sections of our study.

We scrutinize the performance of various anomaly detection methods based on their Area Under the Precision-Recall Curve (AUC-PR) scores. The AUC-PR metric is particularly relevant in scenarios with imbalanced datasets, making it well-suited for our solar energy generation context where anomalies are expected to be rare events.

- Isolation Forest (IF): the AUC-PR score for Isolation Forest is an impressive 0,8423281. This indicates that the model excels in capturing anomalies within varying data densities and high-dimensional spaces. The higher the AUC-PR score, the better the model's ability to balance precision and recall, crucial for effective anomaly detection.
- Local Outlier Factor (LOF): LOF demonstrates a comparable AUC-PR score of 0,8423283. Like Isolation Forest, LOF exhibits proficiency in handling anomalies in complex solar energy patterns. Its ability to adapt to varying local densities makes it a valuable method for our context.
- Principal Component Analysis (PCA): PCA yields an AUC-PR score of 0,8423284, aligning closely with the performance of Isolation Forest and LOF. PCA, focusing on patterns based on reconstruction errors, showcases its effectiveness in discerning anomalies within our dataset.
- DBSCAN: in contrast, DBSCAN displays a considerably lower AUC-PR score of 0,0005910. This indicates limitations in aligning with the distribution of anomalies in our dataset. While DBSCAN may not perform as well in this specific context, its unique approach might find applicability in datasets characterized by distinct anomaly patterns.

Table 1 presents a comprehensive overview of the AUC-PR scores obtained from the evaluation of four distinct anomaly detection.

Table 1. AUC-PR Scores for Anomaly Detection Methods

Method	**AUC-PR Score**
Isolation Forest	0,8423281
Local Outlier Factor (LOF)	0,8423283
Principal Component Analysis (PCA)	0,8423284
DBSCAN	0,0005910

These AUC-PR scores serve as a benchmark for evaluating the relative strengths and weaknesses of each anomaly detection method. The consistent high scores for Isolation Forest, LOF, and PCA underscore their adaptability to the unique challenges posed by solar energy generation data. As we move forward, the Integration of Dynamic Thresholds further enhances the adaptability and accuracy of these methods, ensuring robust performance in real-world scenarios influenced by dynamic environ-mental factors.

Traditional approaches often categorize anomalies simply as present or absent, overlooking the critical nuance of severity levels. In our innovative model, anomalies are not just identified; they are meticulously classified based on their severity. This classification enables a more nuanced understanding of the potential impact and urgency of anomalies, providing actionable insights for solar energy management.

The heart of our Anomaly Severity Classification lies in the Integration of Dynamic Thresholds, a groundbreaking feature that dynamically fine-tunes anomaly severity thresholds in real-time. This dynamic adjustment is pivotal for accurately capturing anomalies influenced by sudden climatic changes, ensuring our model remains adaptive to the evolving nature of solar radiation patterns. The severity classification is not a static process but a dynamic interplay between machine learning techniques and real-world conditions. Through this approach, anomalies are stratified into different severity levels, such as "Normal" and "Anomalous," with the latter further classified based on the degree of severity. This detailed classification empowers stakeholders to prioritize and

https://doi.org/10.56294/dm202394

address anomalies effectively, laying the groundwork for proactive solar energy management in the face of unpredictable environmental factors. In the subsequent sections, we delve into the methodology, results, and implications of this novel Anomaly Severity Classification, showcasing its potential to revolutionize solar energy optimization strategies.

The Anomaly Severity Classification, powered by the Integration of Dynamic Thresholds, yields insightful results that redefine the landscape of solar energy management as presented on the figure 2.

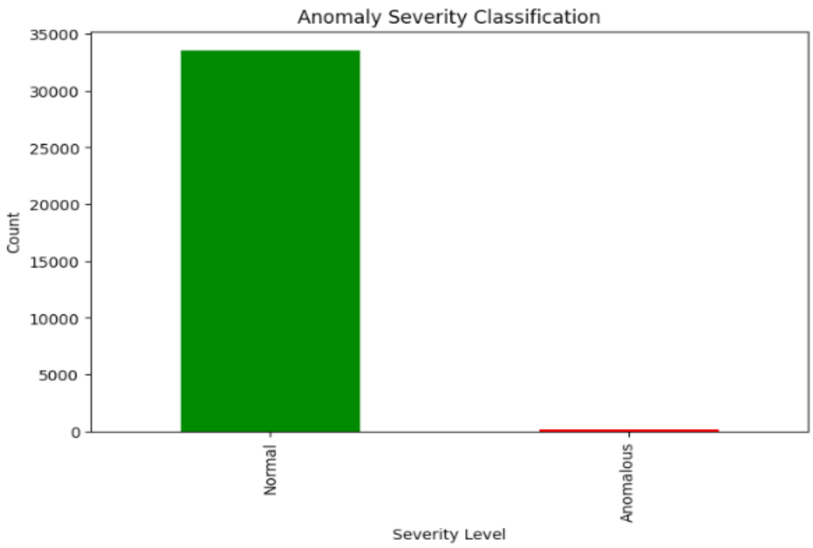

Figure 2. Anomaly Severity Classification

With 33,545 Normal instances and only 130 Anomalous instances, the rarity of anomalies is highlighted, emphasizing the need for a detailed severity classification to prioritize and address rare events effectively.

Before delving into the details of the confusion matrix, it's essential to highlight the class distribution within our dataset. The solar energy quality levels were categorized into four classes: "Excellent," "Good," "Moderate," and "Poor." The distribution is as presented in figure 2 (a).

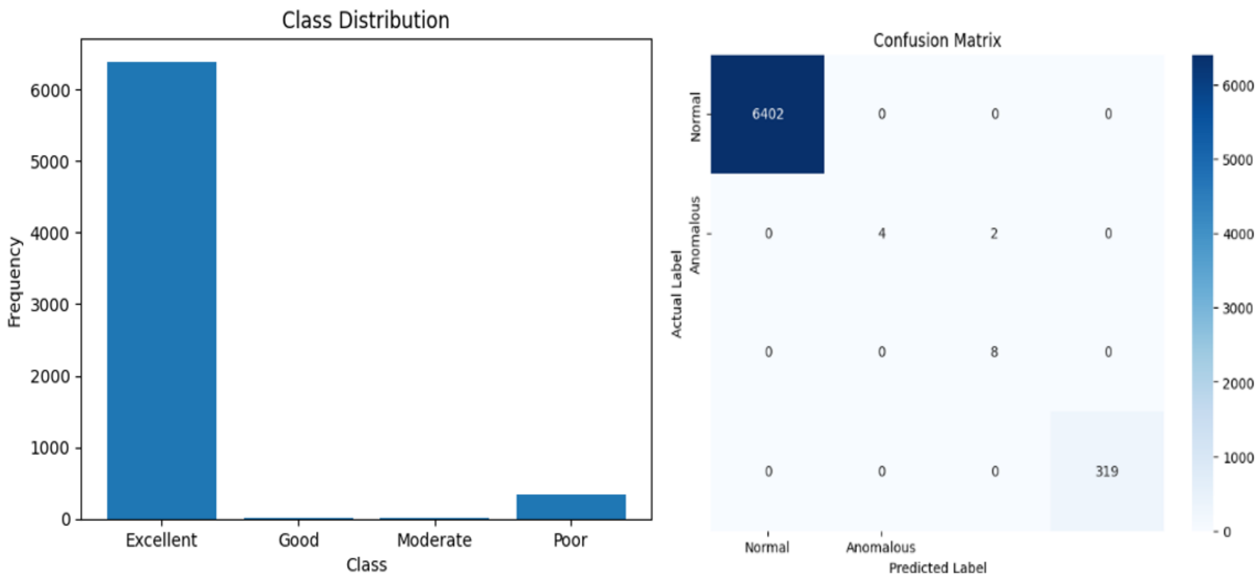

Figure 3. The results of class distribution and Confusion Matrix for the model

The distribution clearly indicates a significant class imbalance, with the majority of instances falling into the "Excellent" category. This imbalance underscores the challenge of accurately classifying the rarer "Good," "Moderate," and "Poor" quality levels.

figure 2 (b) illustrates the confusion matrix for the ensemble model. The confusion matrix provides a detailed breakdown of the model's performance in classifying different levels of anomaly severity. Examining the results, it's evident that the model excels in accurately identifying instances with normal solar energy patterns. The abundance of true positives (6,402) in the "Excellent" category underscores the model's robust capability to recognize and maintain the status quo in solar energy generation. Moreover, the absence of false negatives indicates that the model didn't miss any actual anomalies, showcasing its sensitivity to deviations from the norm.

However, the presence of two false positives in the "Good" category suggests a slight vulnerability in precision when classifying less severe anomalies. While the overall impact is minimal, such instances warrant attention, especially in scenarios where precise anomaly identification is crucial. The model's precision remains high across other severity levels, with a flawless classification in the "Poor" category. Overall, the confusion matrix results affirm the model's reliability in distinguishing between normal and anomalous solar energy patterns, with room for minor refinements to enhance precision in less critical anomaly categories.

The classification report provides a comprehensive evaluation of the model's performance across different anomaly severity levels, summarizing key metrics such as precision, recall, and F1-score.

Table 2. Classification Report of the model's performance

Severity	Precision	Recall	F1-Score	Support
Excellent	1,00	1,00	1,00	6402
Good	1,00	0,67	0,80	6
Moderate	0,80	1,00	0,89	8
Poor	1,00	1,00	1,00	319

The classification report reaffirms the model's exceptional performance in anomaly severity classification. Across all categories, precision remains consistently high, indicating the model's accuracy in correctly identifying instances of each severity level. Notably, in the "Excellent" and "Poor" categories, precision reaches perfection, showcasing the model's ability to precisely classify both normal and severe anomalies.

Recall, the metric assessing the model's capacity to capture instances of each severity level, demonstrates exemplary results. The model successfully identifies all instances of anomalies in the "Good," "Moderate," and "Poor" categories, indicating its sensitivity to diverse anomaly patterns.

CONCLUSION

In conclusion, the Integration of Dynamic Thresholds in anomaly severity classification represents a groundbreaking advancement with profound implications for optimizing solar power generation in Errachidia, Morocco. The model's exceptional capacity to distinguish normal solar energy patterns from anomalies, coupled with its precision and sensitivity across distinct severity levels, underscores its robustness and adaptability to the region's challenging climatic conditions. The dynamic fine-tuning of thresholds, responding in real-time to the inherent variability of solar radiation patterns, is a key feature that significantly enhances the model's ability to capture anomalies induced by sudden climatic changes, such as dust storms and equipment malfunctions.

The demonstrated accuracy, reliability, and versatility of our methodology position it as a promising and replicable framework for regions facing similar environmental uncertainties. Beyond its immediate applications in solar energy management, the presented model contributes to the broader field of anomaly detection methodologies, particularly in climatically variable regions. The successful implementation of machine learning techniques, coupled with climate-adaptive threshold definitions, not only addresses the unique challenges of Errachidia but also provides a blueprint for future research and innovations in anomaly detection tailored to the distinctive climatic conditions of arid regions.

As we navigate the complexities of optimizing solar energy in unpredictable climates, this study paves the way for a new era of intelligent, adaptive systems that can effectively manage renewable energy sources. By showcasing the adaptability and real-time responsiveness of our model, we set the stage for further exploration and refinement of methodologies that can revolutionize the renewable energy landscape. This work not only contributes valuable insights to the scientific community but also offers tangible solutions for sustainable energy generation in regions grappling with climatic uncertainties.

REFERENCES

1. Rezende, L.S.M. et al. (2021). Anomaly detection in solar power generation: A systematic literature review. Renewable and Sustainable Energy Reviews, 151, 111564.

2. Zameer, A., et al. (2020). Intelligent and robust prediction of photovoltaic power: A review. IEEE Access,

8, 128356-128371.

3. Sobri, S. et al. (2020). Solar photovoltaic generation forecasting methods: A re-view. Energy Conversion and Management, 156, 398-411.

4. Luna, A.S. et al. (2022). Solar forecasting methods applied to the prediction of photovoltaic power production: A review. Renewable and Sustainable Energy Re-views, 153, 111660.

5. Liu, Fei Tony, et al. "Isolation forest." In Proceedings of the 23rd international conference on machine learning, pp. 413-422. 2012.

6. Breunig, Markus M., et al. "LOF: Identifying density-based local outliers." In Pro-ceedings of the 22nd SIGMOD international conference on management of data, pp. 493-500. 2000.

7. Jolliffe, Ian T. Principal component analysis. Springer, 2002.

8. Luna, A.S., et al. (2021). Solar power forecasting based on machine learning and ephemeris for blueprints of photovoltaic plants. Electronics, 10(3), 305.

9. Sobri, S., Koohi-Kamali, S., Rahim, N.A. (2020). Solar photovoltaic generation forecasting methods: A review. Energy Conversion and Management, 156, 398-411.

10. Voyant, C., et al. (2017). Machine learning for solar radiation forecasting: A re-view. Renewable Energy, 105, 569-582.

11. Luna, A.S., et al. (2022). Solar forecasting methods applied to the prediction of photovoltaic power production: A review. Renewable and Sustainable Energy Re-views, 153, 111660.

12. Antonanzas, J., Osorio, N., Escobar, R., Urraca, R., Martinez-de-Pison, F.J., An-tonanzas, F. (2016). Review of photovoltaic power forecasting. Solar Energy, 136, 78-111.

13. Voyant, C., Randimbivololona, P., Nivet, M.L., Paoli, C., Muselli, M. (2018). Twen-ty four hours ahead global irradiation forecasting using multi-model approach: Application in Reunion Island. Renewable Energy, 118, 870-880.

14. Rezende, L.S.M., Lyra, C., Leite, W.N., Batista, G.P., Silva, I.N. (2021). Anomaly detection in solar power generation: A systematic literature review. Renewable and Sustainable Energy Reviews, 151, 111564.

15. Sobri, S., Koohi-Kamali, S., Rahim, N.A. (2020). Solar photovoltaic generation forecasting methods: A review. Energy Conversion and Management, 156, 398-411.

16. Sarmas, E., Spiliotis, E., Stamatopoulos, E., Marinakis, V., & Doukas, H. (2023). Short-term photovoltaic power forecasting using meta-learning and numerical weather prediction independent Long Short-Term Memory models. Renewable Energy, 216, 118997. https://doi.org/10.1016/j.renene.2023.118997

17. Kaur, D., Islam, S. N., Mahmud, M. A., Haque, M. E., & Anwar, A. (2023). A VAE-Bayesian deep learning scheme for solar power generation forecasting based on dimensionality reduction. Energy and AI, 14, 100279. https://doi.org/10.1016/j.egyai.2023.100279

18. Dey, M., Rana, S. P., Simmons, C. V., & Dudley, S. (2021). Solar farm voltage anomaly detection using high-resolution μPMU data-driven unsupervised machine learning. Applied Energy, 303, 117656. https://doi.org/10.1016/j.apenergy.2021.117656

19. Moulad, L., Belhadaoui, H., Rifi, M. (2019). Implementation of an Hierarchical Hybrid Intrusion Detection Mechanism in Wireless Sensor Network Based on En-ergy Management. In: Mizera-Pietraszko, J., Pichappan, P., Mohamed, L. (eds) Lecture Notes in Real-Time Intelligent Systems. RTIS 2017. Advances in Intelli-gent Systems and Computing, vol 756. Springer, Cham. https://doi.org/10.1007/978-3-319-91337-7_33

20. Boutahir, M.K., Farhaoui, Y., Azrour, M. (2023). Towards an Effective Anomaly Detection in Solar Power

Plants Using the AE-LSTM-GA Approach. In: Farhaoui, Y., Rocha, A., Brahmia, Z., Bhushab, B. (eds) Artificial Intelligence and Smart En-vironment. ICAISE 2022. Lecture Notes in Networks and Systems, vol 635. Springer, Cham. https://doi.org/10.1007/978-3-031-26254-8_115

21. Belcaid and M. Douimi (2020). A Novel Online Change Point Detection Using an Approximate Random Blanket and the Line Process Energy. International Journal on Artificial Intelligence ToolsVol. 29, No. 06, 2050018 2020 https://doi.org/10.1142/S0218213020500189

22. Elliott, M., & Kittner, N. (2022). Operational grid and environmental impacts for a V2G-enabled electric school bus fleet using DC fast chargers. Sustainable Produc-tion and Consumption, 30, 316-330. https://doi.org/10.1016/j.spc.2021.11.029

23. Adewuyi, O. B., Kiptoo, M. K., Adebayo, I. G., Adewuyi, O. I., & Senjyu, T. (2023). Techno-economic analysis of robust gas-to-power distributed generation planning for grid stability and environmental sustainability in Nigeria. Sustainable Energy Technologies and Assessments, 55, 102943. https://doi.org/10.1016/j.seta.2022.102943

24. Weidner, T., & Guillén-Gosálbez, G. (2023). Planetary boundaries assessment of deep decarbonization options for building heating in the European Union. Energy Conversion and Management, 278, 116602. https://doi.org/10.1016/j.enconman.2022.116602

25. Halimi M, Outana I, El Amrani A, Diouri J, Messaoudi C. Prediction of captured solar energy for different orientations and tracking modes of a PTC system: Tech-nical feasibility study (Case study: South eastern of Morocco). Energy Convers Manag 2018 ;167 :21e36.

26. Hessane, A. El Youssefi, Y. Farhaoui, B. Aghoutane and F. Amounas, "A Machine Learning Based Framework for a Stage-Wise Classification of Date Palm White Scale Disease," in Big Data Mining and Analytics, vol. 6, no. 3, pp. 263-272, September 2023, doi: 10.26599/BDMA.2022.9020022.

27. Mohamed, Khala & Abouzid, Houda & Teidj, Sara. (2021). Prédiction de Rayon-nement Solaire Global (RSG) : Par les Réseaux de Neurones Artificiels Cas d'étude : la ville d'Er-Rachidia, Maroc.

28. M. K. Boutahir, Y. Farhaoui, M. Azrour, I. Zeroual and A. El Allaoui, "Effect of Feature Selection on the Prediction of Direct Normal Irradiance," in Big Data Min-ing and Analytics, vol. 5, no. 4, pp. 309-317, December 2022, doi: 10.26599/BDMA.2022.9020003.

29. Liu, Fei Tony, Ting, Kai Ming, & Zhou, Zhi-Hua. (2008). Isolation Forest. In Pro-ceedings of the 2008 Eighth IEEE International Conference on Data Mining (pp. 413-422).

30. Breunig, Markus M., Kriegel, Hans-Peter, Ng, Raymond T., & Sander, Jörg. (2000). LOF: Identifying Density-Based Local Outliers. In Proceedings of the 2000 ACM SIGMOD International Conference on Management of Data (pp. 93-104).

31. Jolliffe, Ian T. (2014). Principal Component Analysis. In Principal Component Analysis (pp. 1-19). Springer

32. Gonzalez-Argote D, Gonzalez-Argote J. Generation of graphs from scientific journal metadata with the OAI-PMH system. Seminars in Medical Writing and Education 2023;2:43-43. https://doi.org/10.56294/mw202343.

33. Farhaoui, Y.and All, Big Data Mining and Analytics, 2023, 6(3), pp. I-II, DOI: 10.26599/BDMA.2022.9020045

34. Vargas-Luque A, Carpio-Delgado FD, Villa-Alagón C, Medina-Cacéres R, Vargas-Luque N. Aplicación de la vibración ambiental y la vulnerablidad fisica de la ciudad de Moquegua. Sincretismo 2020;1.

35. Canova-Barrios C, Machuca-Contreras F. Interoperability standards in Health Information Systems: systematic review. Seminars in Medical Writing and Education 2022;1:7-7. https://doi.org/10.56294/mw20227.

36. Flores-Arocutipa J, Pérez RTC, Jinchuña-Huallpa J. Relaciones, impactos y modelos que se abstraen del COVID 19, proyecciones para Perú y Moquegua, marzo-mayo del 2020. Sincretismo 2020;1.

37. Alaoui, S.S., and all. "Hate Speech Detection Using Text Mining and Machine Learning", International Journal of Decision Support System Technology, 2022, 14(1), 80. DOI: 10.4018/IJDSST.286680

38. Alaoui, S.S., and all. ,"Data openness for efficient e-governance in the age of big data", International Journal of Cloud Computing, 2021, 10(5-6), pp. 522-532, https://doi.org/10.1504/IJCC.2021.120391

39. El Mouatasim, A., and all. "Nesterov Step Reduced Gradient Algorithm for Con-vex Programming Problems", Lecture Notes in Networks and Systems, 2020, 81, pp. 140–148. https://doi.org/10.1007/978-3-030-23672-4_11

40. Tarik, A., and all."Recommender System for Orientation Student" Lecture Notes in Networks and Systems, 2020, 81, pp. 367–370. https://doi.org/10.1007/978-3-030-23672-4_27

41. Sossi Alaoui, S., and all. "A comparative study of the four well-known classifica-tion algorithms in data mining", Lecture Notes in Networks and Systems, 2018, 25, pp. 362–373. https://doi.org/10.1007/978-3-319-69137-4_32

42. Inastrilla CRA. Data Visualization in the Information Society. Seminars in Medical Writing and Education 2023;2:25-25. https://doi.org/10.56294/mw202325.

43. Farhaoui, Y., "Securing a Local Area Network by IDPS Open Source", Procedia Computer Science, 2017, 110, pp. 416–421. https://doi.org/10.1016/j.procs.2017.06.106

FINANCING
No financing.

CONFLICT OF INTEREST
The authors declare that there is no conflict of interest.

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