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Optimization of Machine Learning Methods for Fault Diagnosis in Photovoltaic Systems: A Hybrid Approach

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ABSTRACT

Reliable fault diagnosis in photovoltaic systems is compromised when measurement data are corrupted by noise. This study assesses the robustness of Support Vector Machine-based hybrid classifiers SVM+KNN, SVM+LR, SVM+MLP, SVM+DT, and SVM+RF subjected to controlled Gaussian noise injection. A dataset of 13,767 records collected at the Ngaoundéré weather station was used, partitioned 80%/20% for training and testing. The hybridization strategy relies on a parallel probabilistic fusion scheme in which prediction probabilities from each base classifier are averaged. Model performance was evaluated along three complementary axes: F1-score, empirical error rate, and temporal stability of the classification rate. Results show that the SVM+RF hybrid achieves the best overall accuracy (91.7%) and AUC (0.991), with the greatest resilience to noise, while SVM+KNN exhibits the weakest robustness. Importantly, probabilistic fusion does not consistently outperform the strongest individual model; it mainly moderates instability when the base classifiers offer genuine complementarity. One-way ANOVA confirms that the performance differences between individual and hybrid configurations are statistically significant. Temporal analysis further reveals that fused models maintain a more regular classification rate across samples, a key advantage in unstable PV operating environments. This work contributes to the development of robust and reliable hybrid systems for real-world diagnostics.

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1. Introduction

In recent years, interest in renewable energy has grown due to increasing environmental concerns and the gradual depletion of conventional energy sources [1], [2]. Among all renewable energy sources, solar energy has stood out for its efficiency [3], [4], [5], [6], thanks to its abundance, sustainability, and renewable nature. Photovoltaic (PV) systems have played a crucial role in the energy transition [7], [8]. For example, electricity generation from photovoltaic systems would reduce carbon dioxide emissions by approximately 69 to 100 million tons by 2030 [9]. Since 2011, the installed capacity of the solar sector has been steadily increasing. According to the International Renewable Energy Agency (IRENA), new solar installations reached 438 GW between 2017 and 2022. Ground-mounted and rooftop solar installations were capable of generating electricity and powering various types of loads [10], [11]. However, their efficiency and durability were compromised by various malfunctions and environmental disturbances. Among these factors, Gaussian noise affecting measurement data, as well as nonlinear loads, were highlighted by Kerrouche et al. [12]. Furthermore, Lodhi et al. demonstrated that factors such as thunderstorms, shading, or physical and thermal stresses on cable insulation could cause defects in photovoltaic arrays. These defects could significantly reduce the energy yield and power output of photovoltaic systems [13]. For example, study [14] revealed, during a monitoring campaign of a photovoltaic system, an estimated annual energy loss of 18.9% due to the presence of multiple faults. Anomalies in photovoltaic arrays can also present critical safety risks, such as fires or explosions, endangering people and infrastructure; for example, a grounding fault caused a fire in Bakersfield, California. Furthermore, the authors mentioned that a large-scale photovoltaic power plant in the same state experienced a similar incident following a short circuit [15], [16]. Early and accurate detection of these anomalies was essential to maintaining optimal performance and extending the lifespan of photovoltaic installations. Therefore, researchers have increasingly focused on the detection and diagnosis of faults in photovoltaic systems.

Traditionally, fault detection relied on physical models or manual inspections, methods that were often costly and poorly suited to complex installations [17], [18], [19]. The emergence of artificial intelligence (AI) and machine learning (ML) has enabled the development of more efficient approaches. For example, the study in [20] combined convolutional neural networks (CNNs), the AlexNet architecture, and an SVM classifier, but with limited accuracy (69.39% to 73.53%). The study in [21] used a multilayer perceptron under specific winter conditions. Other work, such as that by Mellit et al. [22], combined the Internet of Things (IoT) and machine learning to achieve a detection accuracy of 98%. Similarly, in [23], the authors proposed a hybrid model based on thermographic images analyzed using CNN and ML techniques. In parallel, ensemble learning approaches have demonstrated their effectiveness for anomaly detection, fault diagnosis, and photovoltaic power generation forecasting [24], [25], [26]. These approaches, based on the combination of several classifiers, offer better generalization capabilities than individual models. In [27], an ensemble method showed improved performance for forecasting photovoltaic power generation in smart grids, despite limitations with time-series data. The study [28] tested bagging and stacking methods, achieving accuracies of 79.50% and 94%, respectively. Other researchers, such as the authors of [29], have proposed algorithms combining ELM, RBF, and simulated annealing (SA) optimization, capable of detecting different types of faults, albeit at a higher computational cost. Finally, a combination of decision trees, quadratic discriminant analysis and Extra Trees proposed in [24] achieved an accuracy of 97.67% after optimization.

However, many of these methods still require manual feature extraction, which is time-consuming and involves expertise in signal processing. Recent studies [30] highlight the advantages of machine learning models for fault detection and isolation, as well as for predictive maintenance. Study [31] introduced a voting system combining SVM, logistic regression, and decision trees, achieving better results than individual approaches on several indicators. Similarly, [32] proposed a combination of PCA, an LSTM network for energy consumption prediction, and CatBoost for fault diagnosis, with an accuracy exceeding 98%.

Despite these advances, the robustness of machine learning models in noisy environments remains a major challenge. The dynamic weather conditions to which PV systems are exposed introduce noise in the measured data, potentially compromising diagnostic reliability. One of the strategies explored to enhance model resilience is hybridization. In this work, hybridization refers to the parallel combination of probabilistic outputs from several models, using an unweighted fusion strategy. Previous studies [23], [33], [34], [35] suggest that hybridization improves performance. However, few works have systematically assessed its robustness under increasing levels of Gaussian noise. This study thus raises the following question: can hybridization improve the robustness and stability of PV diagnostic models in the presence of significant noise?

In this context, we propose to evaluate the robustness of several machine learning models, particularly the Support Vector Machine (SVM) and its hybridized versions with k-Nearest Neighbors (KNN), Logistic Regression (LR), Multilayer Perceptron (MLP), Decision Tree (DT), and Random Forest (RF), subjected to increasing levels of Gaussian noise. The originality of this work lies in the comparative analysis of these hybridizations in terms of stability, average performance, and diagnostic reliability in a realistic setting.

The subsequent sections of this paper are organized as follows: Section 2 outlines the data employed, the methodology used, and the hybridization strategy implemented. Section 3 showcases the results derived from numerical simulations, evaluated in terms of robustness and time stability. Lastly, Section 4 wraps up with the contributions of this research and presents future directions for PV diagnostic methodologies.

2. Materials and Methods

2.1. Datasets

The data used in this study come from a numerical simulation and comprise a total of 13,767 records, incorporating meteorological variables such as temperature and irradiance. To enhance the realism of our analysis, these variables were collected at the Ngaoundéré weather station (Fig.1), in Cameroon, over the period from January 1 to December 31, 2023, with a sampling interval of 5 seconds. This dataset includes both normal observations, serving as a reference, and perturbed records, reflecting the presence of faults. These records were then used as inputs to train machine learning models, with the aim of enabling them to effectively detect new, including previously unseen, anomalies. We chose to split the dataset into 80% for training and 20% for testing.

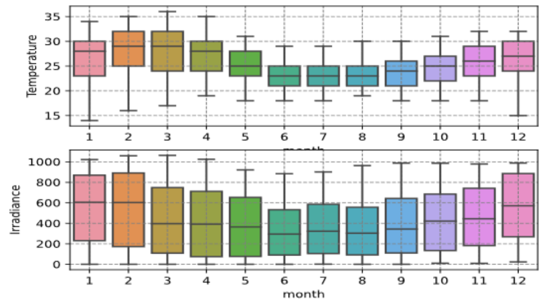


Figure 1. Monthly distribution of solar irradiance and ambient temperature measurements collected in Ngaoundéré (Cameroon) during the year 2023

The figure illustrates the seasonal variations of the meteorological conditions used to simulate the photovoltaic system and generate the dataset employed in this study.

2.2 Hybrid Modeling

According to [36], the term" hybrid" is a product of the historical evolution of recommender systems, where certain sources of knowledge were initially exploited, leading to well-established techniques that were later combined. The goal is to leverage multiple sources of knowledge, selecting the most appropriate for a given task in order to use them as effectively as possible. The hybridization of machine learning models aims to combine the strengths of multiple algorithms to achieve performance superior to that of each model taken individually. This approach helps improve accuracy, robustness to noise, generalization to new datasets, and resilience to local faults [37], [38], [39], [40], [41], [42]. There are three main categories of hybrid recommender system designs used to develop a hybrid recommendation system [36], [43]: monolithic hybridization design, parallelized hybridization design, and pipelined hybridization design [44].

In this study, we adopt a parallel hybridization strategy based on the probabilistic fusion of the outputs of several supervised classifiers (Fig. 2) [45]. This approach allows us to exploit the complementarity of different machine learning models while enhancing robustness to noisy data, a critical criterion in photovoltaic systems exposed to varying environmental conditions. This type of architecture enables more stable predictions in uncertain environments, which aligns with the goals of soft computing: providing flexible, adaptive, and imprecision-tolerant solutions. Unlike serial or hierarchical approaches, parallel hybridization executes multiple models independently and simultaneously on the same input data [46]. Each classifier mi, belonging to a set of M models (e.g., SVM, Random Forest, Logistic Regression), generates for each sample x a probability distribution over the target classes:

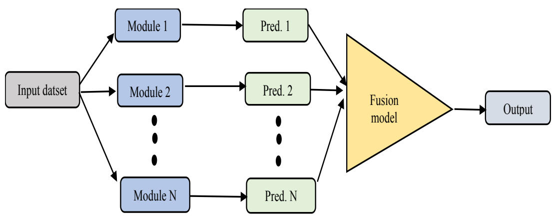


Figure 2. Block diagram of a stacking method with *n* models and a fusion model

$$P_{m_i}\left(y \mid x\right), i=1,\ldots,M \qquad (1)$$

The probability distributions generated by each model are then combined using an arithmetic mean, resulting in a more robust final prediction:

$$P_{fusion}\left(y \mid x\right)=\frac{1}{M}\sum_{i=1}^{M}P_{m_i}\left(y \mid x\right) \qquad (2)$$

This unweighted fusion assumes that all models have an equal influence. This choice is justified here by the desire to maintain the simplicity of the hybridization scheme while benefiting from the diversity of classifiers. The predicted class for the sample x is the one that maximizes the fused probability, according to the Maximum A Posteriori (MAP) rule:

$$\hat{Y}=\arg_{y}^{\max} P_{m_i}\left(y \mid x\right) \qquad (3)$$

This approach is particularly well-suited for fault detection in photovoltaic systems, where the multi-source nature of noise (sensors, weather conditions, partial shading, etc.) makes the use of a single model potentially fragile. Figures 3 and 4 provide a structured and complementary view of the intelligent diagnostic process implemented in this study. Figure 3 presents the overall flowchart of the experimental framework, from loading the PV data to evaluating robustness.

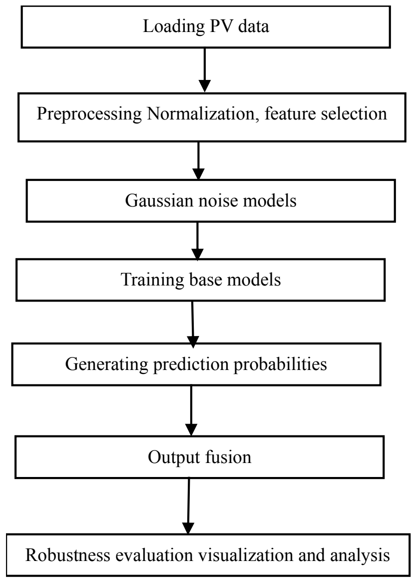


Figure 3. Flowchart of the overall steps developed for this study

It details the successive steps: data preprocessing, Gaussian noise injection, training of base models, generation of prediction probabilities, output fusion, and performance analysis. Meanwhile,

Figure 4 highlights the two main phases of the diagnostic: detection (preprocessing and feature extraction) and classification (supervised learning, prediction, and evaluation). Together, these two figures offer a better understanding of the architecture of the proposed hybrid approach, emphasizing the central role of parallel fusion in the robustness of PV diagnostics against noise. To our knowledge, few studies have systematically evaluated the effect of this fusion under different levels of Gaussian noise in the context of PV diagnostics, which distinguishes this contribution.

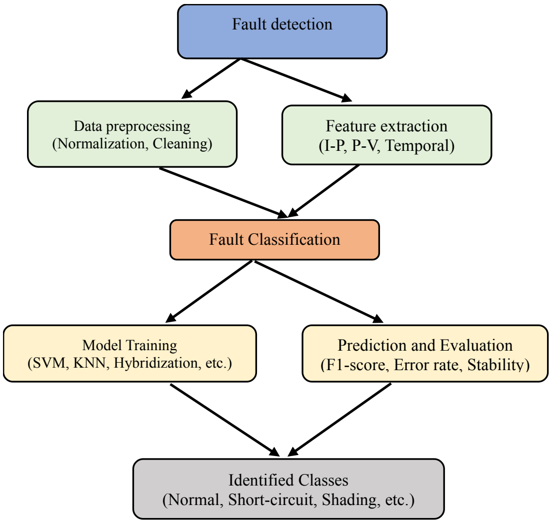


Figure 4. Steps for fault detection and classification in photovoltaic systems

3. Results and Discussion

Our simulations were conducted in Python using open-source machine learning libraries, including scikit-learn, matplotlib, seaborn, numpy, and pandas.

3.1. Feature Selection

The heatmap allowed for a quick visualization of which variables are strongly correlated (positively or negatively). This is crucial for: detecting redundancy between variables, and better understanding the data structure before selecting or building a model. Figure 5 illustrates a heatmap revealing a clear structure: the maximum voltage values are strongly interdependent, while the average values vary more independently. This suggests that voltage peaks are synchronized between modules, but average behaviors may reveal imbalances or localized faults. This observation is valuable for fault detection and optimization in modeling PV systems.

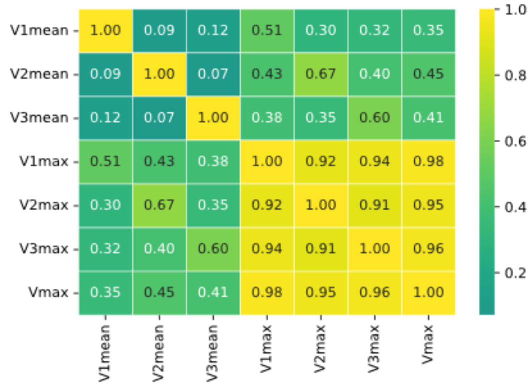


Figure 5. Correlation matrix of the selected electrical variables

By examining the distribution of the extracted variables (Fig. 6) from the photovoltaic panels, we notice that the original data exhibits irregular shapes, with marked asymmetries and sometimes multiple peaks, particularly in the average voltages (V1mean, V2mean, V3mean). This type of distribution suggests the presence of atypical behaviors, likely related to faults or saturation phenomena. In contrast, once Gaussian noise was added, the curves became much smoother, often centered, with a shape resembling a normal curve. This smoothing effect has the advantage of reducing extreme concentrations and spreading the values more evenly, which can be beneficial for certain machine learning methods sensitive to extreme values. Overall, the noise acts as a balancing factor: it mitigated the pronounced irregularities of the raw data and allowed for a more continuous and realistic representation of the distributions.

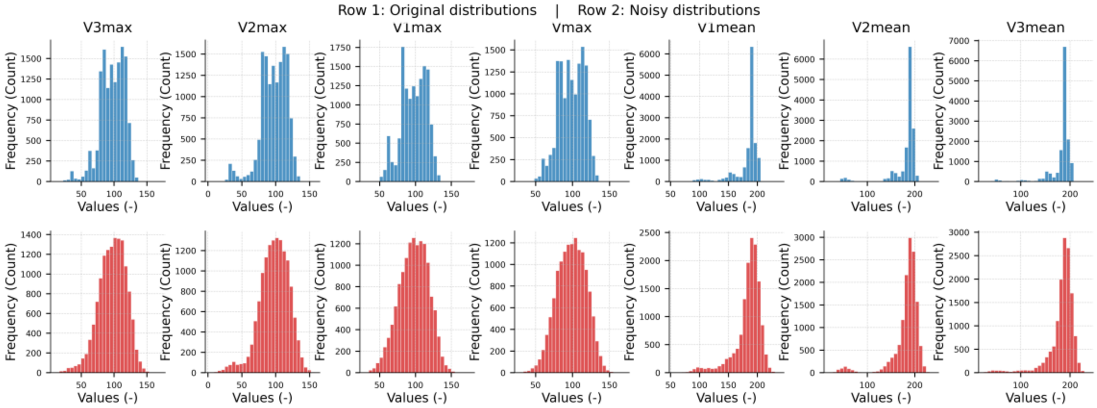


Figure 6. Distribution of the selected quantitative variables before and after Gaussian noise injection (σ). The first row shows the original feature distributions, whereas the second row illustrates the corresponding noisy distributions used for robustness evaluation

3.2. Model Performance

The five SVM-based ensemble classifiers achieve overall accuracies ranging from 89.7% (SVM+KNN) to 91.7% (SVM+RF), with consistent class-level trends observed across all configurations. Shading faults are most reliably detected (92.7–96.3% recall), while the Normal class exhibits the greatest misclassification rate (83.4–86.9% recall), indicative of feature space overlap with fault conditions. SVM+RF emerges as the optimal configuration, delivering the best overall accuracy and Shading recall (96.3%), attributable to the variance-reducing properties of Random Forest aggregation, whereas SVM+KNN underperforms due to its sensitivity to local density irregularities in high-dimensional feature spaces. These findings underscore that the choice of secondary classifier meaningfully influences fault detection reliability, with ensemble diversity proving critical to classification robustness.

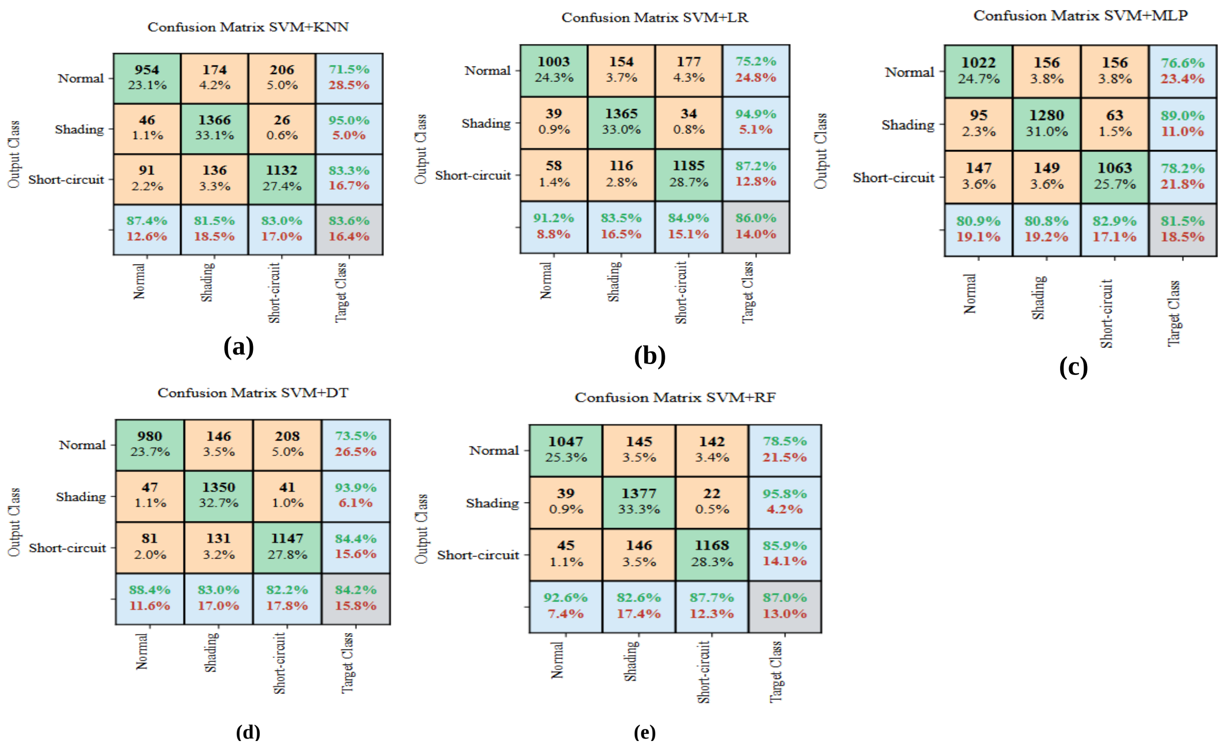


Figure 7 confusion matrices for three-class fault detection in the presence of noise: (a)SVM+KNN, (b)SVM+LR, (c)SVM+MLP, (d)SVM+DT, (e) SVM+RF

3.3. Robustness Evaluation Results

In this study, we examined the robustness of several machine learning models hybridized with SVM in the face of increasing levels of Gaussian noise injected into the input data, using the F1-score as a performance indicator (Fig. 8). The adopted hybridization relies on parallel fusion based on the average of the prediction probabilities (Eq. 2). In general, the results reveal that this strategy does not consistently lead to an improvement in robustness. Indeed, the analysis of the different combinations highlights contrasting behaviors. On the one hand, the SVM + KNN pair (Fig. 8a) shows a slight performance increase at low noise levels (variance < 0.1), but this improvement quickly fades as the noise increases, highlighting a limited complementarity in disturbed environments. On the other hand, hybridization with logistic regression (SVM + LR) in Fig. 8b shows a more marked benefit at the start of the curve: the natural stability of LR initially compensates for the rapid drop of SVM. However, this effect is transient, and beyond a certain noise threshold, the hybrid model simply aligns with LR, without any synergistic gain. Similarly, the SVM + MLP pair in Fig. 8c exhibits an intermediate behavior with no real advantage: although MLP can theoretically capture noisy structures, its shared sensitivity with SVM to nonlinear noise cancels out any potential benefit. In contrast, the SVM + DT pair in Fig. 8d stands out slightly for its ability to temporarily smooth performance at low and medium noise levels, but this stabilization remains insufficient in the face of high variance, where performance collapse is abrupt for all models.

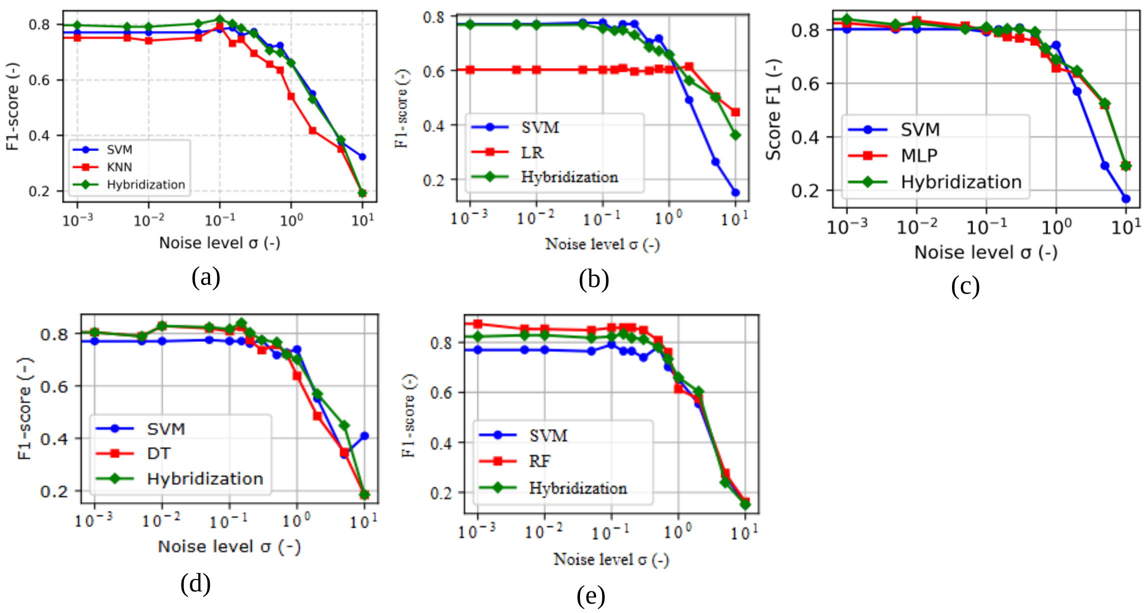


Figure 8 Evolution of the weighted F1-score of the standalone classifiers and the proposed hybrid models under increasing Gaussian noise levels (σ ranging from 0 to 10), illustrating the robustness of each model to measurement perturbations

Conversely, the SVM + RF combination in Fig. 8e proves to be the most robust: Random Forest, naturally stable against disturbances, maintains high performance, and the hybridization allows for a slight increase in stability in some cases, particularly at moderate noise levels. However, even in this case, the hybrid model does not truly exceed the standalone RF, suggesting that the robust model dominates the fusion, without any real collaborative effect. Thus, these observations lead to a nuanced view of the interest in systematic probabilistic hybridization. The effectiveness of hybridized models strongly depends on the nature of the base models and their actual complementarity. When one of the models is particularly vulnerable to noise, as is often the case with SVM in the configurations studied, it can pull down the overall performance. Conversely, when a model dominates in robustness, like RF, hybridization merely follows its performance without surpassing it. These findings highlight the need to rethink fusion strategies, particularly by considering more flexible approaches such as dynamic weighting, weighted voting, or adaptive ensemble methods, to better exploit the structural complementarities between models and enhance their resilience to uncertainty.

$$Precision = \frac{T_H}{T_H + F_H} \qquad (4)$$

$$Recall = \frac{T_H}{T_H + F_H} \qquad (5)$$

$$F1-score = 2\frac{Precision * Recall}{Precision + Recall} \qquad (6)$$

where T_H represents a correct estimation of the healthy state,
T_F a correct estimation of the faulty state,
F_H a false estimation of the healthy state, and
F_F a false estimation of the faulty state [48].

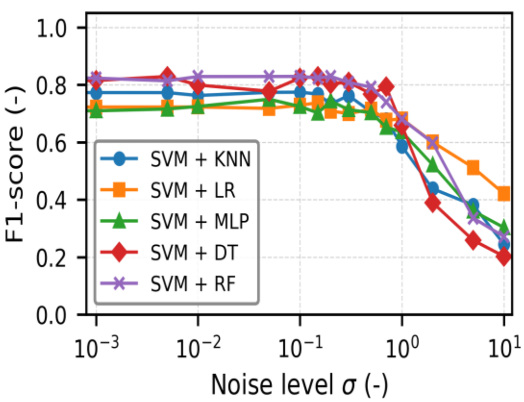


Figure 9. Comparison of F1-scores of SVM hybrid models under different levels of Gaussian noise

The analysis of Fig. 9 highlights a decreasing robustness of the hybrid models as the noise level increases. Among them, the SVM + RF hybrid appears to be the most robust overall, particularly in low or moderate noise scenarios, where it outperforms the others thanks to its ability to handle data variability. SVM + DT follows a similar trend, also benefiting from its tree-based nature to resist initial disturbances effectively.

The study of the impact of Gaussian noise on model performance shows a general trend of progressive degradation in the error rate as the noise variance increases, as shown in Fig. 10. This empirical error rate is defined by the formula (7) [49].

$$\hat{R}(h) = \frac{1}{n}\sum_{i=1}^{n} 1\left(h(x_i) \neq y_i\right) \qquad (7)$$

where $\hat{R}(h)$ is an empirical error rate of the classifier h,
n a total number of training examples,
x_i the ith input (example),
y_i the true label of xi,
$h(x_i)$ the model's prediction for xi, and
$1(h(x_i) \neq y_i)$*: indicator function, equal to 1 if the prediction is incorrect, 0 otherwise.*

At low levels of perturbation (variance < 0.3), all models maintain a relatively stable and low error rate, with values generally ranging between 0.15 and 0.25. In this regime, the parallel hybridization between SVM and a second model (KNN, LR, MLP, DT, or RF) exhibits comparable, or slightly lower, stability, reflecting a moderate regularization effect. This hybridization is based on a probability fusion defined by Eq. 2. When the noise variance exceeds 0.5, differences between models become more noticeable. SVM, in particular, shows greater sensitivity to noise, with its error rate increasing more sharply than that of its counterparts. Conversely, some models, such as Random Forest (RF) in Fig. 10e or Logistic Regression (LR) in Fig. 10b, maintain better stability in intermediate noise regimes. In these cases, hybridization does not systematically improve performance; it often merely follows an intermediate trajectory, occasionally benefiting from a slight reduction in the error rate, but without surpassing the most robust individual model. At very high noise levels (variance > 1.5), all models, including hybrid models, experience a marked increase in error rate, generally converging toward values above 0.7. This phenomenon illustrates the robustness limit reached when noise becomes predominant in the data. In certain cases, a differential weighting strategy could be considered to enhance hybridization performance, by assigning greater weight to the most robust model under highly noisy conditions. In summary, probability averaging-based hybridization can, in some cases, moderate the instability of a standalone model (notably SVM), but it does not consistently provide a substantial gain in overall robustness to noise. This observation highlights the importance of carefully selecting the models to be hybridized, favoring complementary approaches rather than simply merging models with similar performance levels.

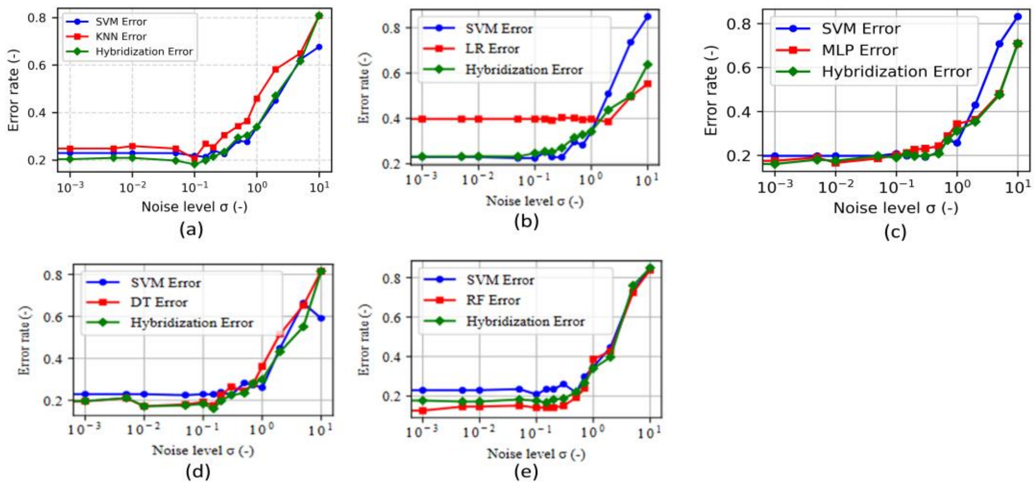


Figure 10. Evolution of the classification error rate of the standalone and hybrid classifiers under increasing Gaussian noise, highlighting the degradation of classification performance as the noise variance increases

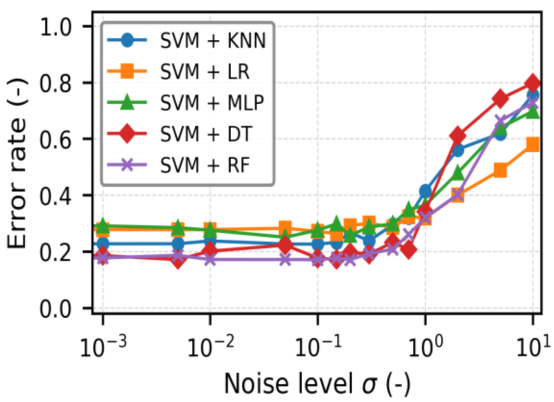


Figure 11. Comparison of error rates of SVM hybrid models under different levels of Gaussian noise

Figure 11 shows the error rate of hybrid models combining SVM with various classifiers (KNN, LR, MLP, DT, RF) as a function of increasing levels of Gaussian noise injected into the input data. In the low-noise region $\left(\sigma \prec \frac{0.1}{\sigma} \prec 0.1\sigma \prec 0.1\right)$, all models exhibit a stable and relatively low error rate (around 0.2 to 0.3). The SVM + RF model (purple) shows the best performance, closely followed by SVM + DT (red). In the moderate noise range $\left(0.1 \approx \frac{0.1}{\sigma} \approx 0.1\sigma \approx 0.1 to 0.5\right)$, a slight increase in the error rate is observed for most models. However, SVM + RF and SVM + DT maintain their relative robustness, with error rates lower than those of the other combinations. Finally, in the high-noise region $\left(\sigma \succ \frac{0.1}{\sigma} \succ 1\sigma \succ 1\right)$, all models experience a significant performance degradation. The error rate exceeds 80% for most models around $\sigma = \frac{10}{\sigma} = 10\sigma = 10$. SVM + KNN is the most affected, with an error rate approaching 100%. SVM + RF retains some level of stability, although it too eventually collapses under intense noise. Overall, the SVM + RF and SVM + DT hybridizations appear to be the most noise-resistant, likely due to the natural ability of random forests and decision trees to handle variability in the data. The analysis of the evolution of the classification rate over the course of the samples, conducted on various pairs of hybrid models (SVM + KNN, SVM + LR, SVM + MLP, SVM + DT, SVM + RF) in Fig. 11, clearly highlights the impact of injected Gaussian noise on the temporal performance of the classifiers. Unlike traditional static evaluation, this study relies on deliberately perturbed data, simulating an uncertain context such as that encountered in industrial environments or under fluctuating weather conditions, particularly relevant for photovoltaic systems. In this context, the value of a hybrid strategy becomes especially apparent. Indeed, while SVM-type models are known for their robustness to linear disturbances, their performance degrades when the noise introduces more complex distortions. Conversely, models like KNN in Fig. 12a or DT in Fig. 12d, which are more sensitive to local variations, exhibit strong instability in the presence of noise, compromising their reliability. Hybridization thus consistent performance across all samples. robustness and consistency of classification systems in uncertain environments.

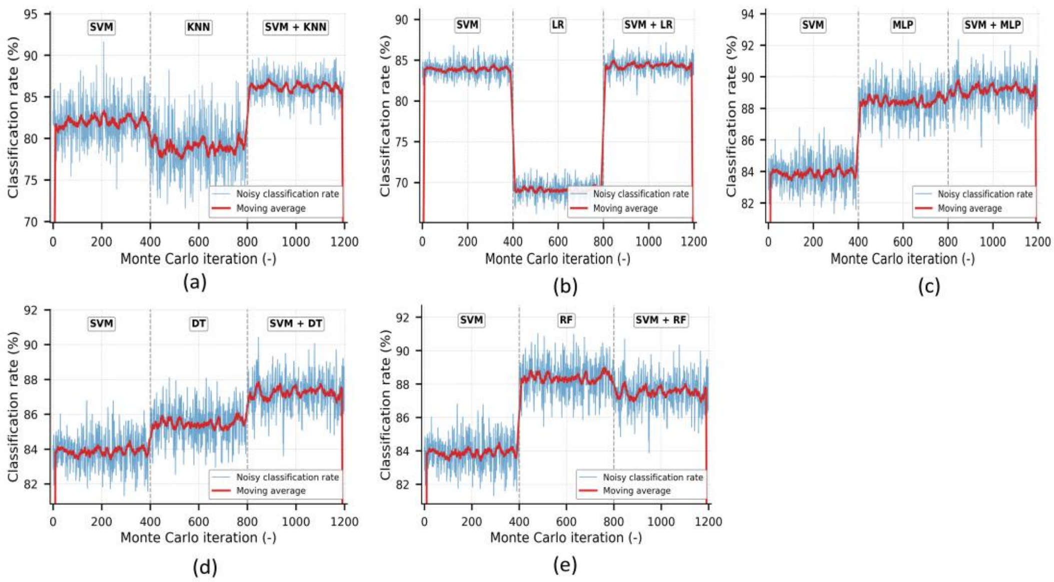
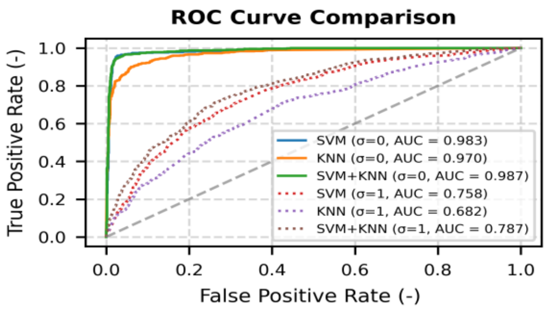


Figure 12. Simulation of the impact of Gaussian noise on the temporal stability of the classification rate for the proposed hybrid models: (a) SVM+KNN, (b) SVM+LR, (c) SVM+MLP, (d) SVM+DT, and (e) SVM+RF. The blue curves represent the noisy classification rate, while the red curves correspond to the moving average, illustrating the stabilizing effect of probabilistic hybridization

Even more strikingly, the SVM + MLP pairing (Fig. 12c) demonstrates an effective synergy, where the precision of the SVM combined with the MLP's ability to model noisy structures leads to a progressive, even upward, improvement in performance. Furthermore, the SVM + DT (Fig. 12d) and SVM + RF (Fig. 12e) pairs clearly illustrate the stabilizing effect of hybridization: while decision tree-based models display highly irregular curves, their fusion with the SVM results in substantial smoothing of variations. Ultimately, this dynamic analysis reinforces previous observations by showing makes it possible to leverage the complementarity of models to mitigate their respective limitations: the performance curves of hybrid models reveal a more regular dynamic, with a moving average that is notably more stable than those obtained with individual models. For instance, the SVM + KNN (Fig. 12a) and SVM + LR (Fig. 12b) combinations, despite being based on models that respond differently to noise, result in hybrid curves capable of smoothing fluctuations and maintaining relatively consistent performance across all samples. robustness and consistency of classification systems in uncertain environments. Even more strikingly, the SVM + MLP pairing (Fig. 12c) demonstrates an effective synergy, where the precision of the SVM combined with the MLP's ability to model noisy structures leads to a progressive, even upward, improvement in performance. Furthermore, the SVM + DT (Fig. 12d) and SVM + RF (Fig. 12e) pairs clearly illustrate the stabilizing effect of hybridization: while decision tree-based models display highly irregular curves, their fusion with the SVM results in substantial smoothing of variations. Ultimately, this dynamic analysis reinforces previous observations by showing that hybrid models offer not only better resilience to noise-induced disturbances but also increased temporal stability. These results therefore confirm the relevance of using probabilistic fusion to enhance the robustness and consistency of classification systems in uncertain environments.



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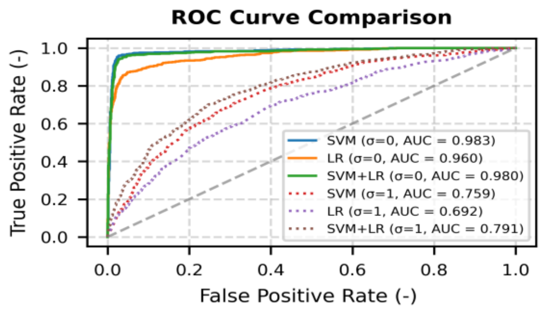

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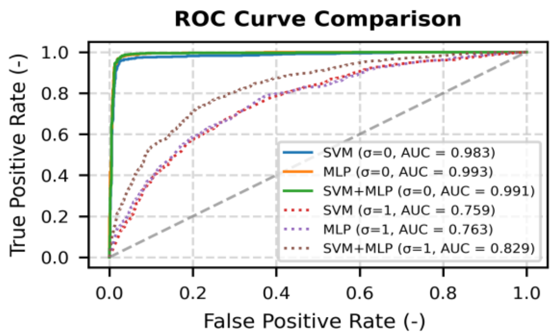

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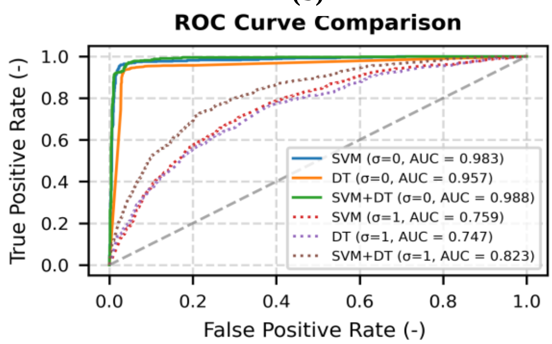

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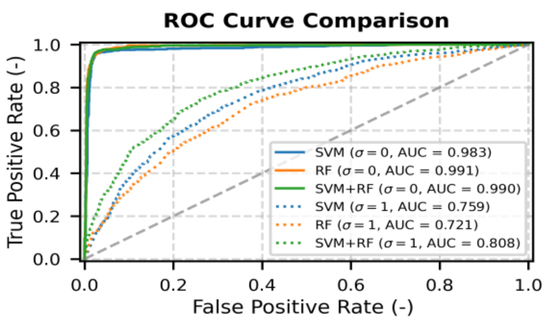

(e)

Figure 13. Comparative ROC Analysis of Standalone and Hybrid Models for Photovoltaic Fault Diagnosis: (a) SVM vs. KNN vs. SVM+KNN, (b) SVM vs. LR vs. SVM+LR, (c) SVM vs. MLP vs. SVM+MLP, (d) SVM vs. DT vs. SVM+DT, and (e) SVM vs. RF vs. SVM+RF

Figure 13 presents the ROC curves of the optimized SVM classifier and the proposed hybrid models (SVM+KNN, SVM+LR, SVM+MLP, SVM+DT, and SVM+RF) under two Gaussian noise levels ($\sigma = 0$ and $\sigma = 1$). Under noise-free conditions ($\sigma = 0$), the optimized SVM consistently achieves an excellent discrimination capability with an AUC of 0.983, while the hybrid models exhibit comparable performance, indicating that the fusion strategy preserves the high classification accuracy of the base classifier. The individual classifiers also show satisfactory performance, although with slightly lower AUC values than the optimized SVM. When the noise level increases to $\sigma = 1$, the performance of all standalone classifiers deteriorates significantly, as evidenced by the noticeable reduction in their AUC values. In contrast, the proposed hybrid models maintain higher ROC curves and consistently achieve better AUC values than their corresponding individual classifiers. This behavior demonstrates that the probabilistic fusion effectively compensates for the weaknesses of the individual learning algorithms and improves the robustness of the classification process in noisy environments.

Among all hybrid approaches, SVM+MLP provides the best performance with an AUC of 0.829, followed by SVM+DT (0.823)**,** SVM+RF (0.808)**,** SVM+LR (0.791)**,** and SVM+KNN (0.787). These results indicate that integrating complementary classifiers with the optimized SVM enhances the overall discrimination capability, particularly under degraded operating conditions. Overall, the ROC analysis confirms that the proposed hybrid models are more resilient to Gaussian noise than the corresponding standalone classifiers, highlighting their suitability for reliable photovoltaic fault diagnosis in the presence of measurement disturbances.

To verify whether the observed improvements for the hybrid models are statistically significant, a one-way analysis of variance (ANOVA) was performed for each comparison between the individual models and their corresponding hybrid version. The results show high F-values and p-values lower than 0.05 in all cases ($p<0.001$), which allows us to reject the null hypothesis of equality of means. Thus, the performances of the hybrid models differ significantly from those of the base models under the studied conditions. More specifically, the SVM/KNN/SVM+KNN, SVM/LR/SVM+LR, SVM/MLP/SVM+MLP, SVM/DT/SVM+DT, and SVM/RF/SVM+RF comparisons all show a statistically significant difference, confirming that the observed gains are not due to chance.

Table 1. Statistical Significance Analysis

Models	ANOVA	
	F-statistic	**p-value**
SVM, KNN, SVM + KNN	1957.8984	0.000000
SVM, LR, SVM + LR	1193.3853	0.000000
SVM, MLP, SVM + MLP	464.9755	0.000000
SVM, DT, SVM + DT	31.7625	0.000000
SVM, RF, SVM + RF	151.4212	0.000000

4. Conclusion

This study has provided an in-depth assessment of the robustness of several machine learning models, whether used individually or hybridized with SVM, in a simulated context involving Gaussian noise applied to input data. By employing a multi-perspective approach—combining static analysis (F1-score), dynamic evaluation (temporal evolution of the classification rate), and average error assessment (Figs. 8 to 12), several key insights emerge. First, it appears that probabilistic hybridization through output averaging does not necessarily guarantee performance improvement, especially when the base models exhibit limited complementarity. While certain combinations, such as SVM + RF or SVM + DT, demonstrate a slight gain under low noise conditions, this advantage tends to vanish as perturbations intensify. When the noise variance exceeds a certain threshold (1.5), even the best-performing models collapse, revealing the structural limitations of simple hybridization. However, this approach should not be reduced to average performance alone. The temporal analysis of results shows that fused models exhibit greater regularity over time, indicating enhanced behavioral resilience in the presence of unstable or highly noisy signals. In the specific context of fault diagnosis in photovoltaic systems, which are often exposed to changing environmental conditions, aging sensors, or measurement errors, this temporal stability represents a major advantage for ensuring reliable and responsive operation. Thus, even though simple probabilistic averaging is not a universal solution, it offers a promising starting point for designing more robust classification systems. In this regard, several avenues for future research emerge. The use of more advanced fusion strategies, such as dynamic probability weighting, adaptive ensembles, or contextual model selection mechanisms, could enable better exploitation of classifier complementarity and adapt fusion to the local characteristics of the noise. Furthermore, a deeper integration of signal processing or noise reduction techniques upstream could also contribute to enhancing the overall robustness of the systems. In summary, this study demonstrates that in uncertain and noisy environments, the average performance of a model is not sufficient. It is by relying on intelligent hybridization, guided by complementarity and temporal dynamics, that the capabilities of machine learning models can be optimized, reinforcing fundamental qualities such as stability, probabilistic reliability, and adaptability.

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Abbreviations

Acronyme	Signification
AI	Artificial Intelligence
ANNs	Artificial Neural Networks
CatBoost	Categorical Boosting
CNNs	Convolutional Neural networks
DL	Deep Learning
DT	Decision Tree
EL	Ensemble Learning
ELM	Extreme Learning Machine
GBoost	Gradient Boosting
IEA	International Energy Agency
IoT	Internet of Things
KNN	K-Nearest Neighbors
LR	Logistic Regression
LSTM	Long Short-Term Memory
ML	Machine Learning
MLP	Multi-Layer Perceptron
NNs	Neural Networks
PCA	Principal Component Analysis
PV	Photovoltaic
RF	Random Forest
SVM	Support Vector Machine
XGBoost	eXtreme Gradient Boosting

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