GA-Stacking for Predictive Maintenance

Tien Dat Nguyen[1*]

[1*]Computer Science Department, University of Information Technology.

Corresponding author(s). E-mail(s): 21520707@gm.uit.edu.vn;

Abstract

Predictive Maintenance (PdM) is a crucial problem of the industry, using data analytics to detech operational anomalies and potential machine defects. However, implementing PdM is challenging due to limited datasets, significant effort and expertise required, and strong foundation of machine data and detail analysis of failure mechanisms. To incorperate this, a novel method named GA-Stacking was researched, and it shows promising results comparing to state-of-the-art methods.

Keywords: predictive maintenance, genetic algorithm, stacking

1 Introduction

Predictive Maintenance (PdM) represents a transformative approach to equipment management, using data analytics to detect operational anomalies and identify potential machinery defects before failures occur. This proactive maintenance strategy enables timely repairs, reducing the likelihood of unexpected equipment breakdowns and optimizing operational efficiency [1]. The primary objective of PdM is to minimize maintenance frequency while avoiding unplanned outages and unnecessary expenses, thereby enhancing overall productivity and cost effectiveness.

The significance of Predictive Maintenance lies in its multifaceted benefits. By minimizing the time equipment is off-line for maintenance, it reduces disruptions to production schedules and increases operational efficiency. PdM also reduces the costs associated with spare parts and supplies by ensuring that repairs are performed precisely when needed rather than on a fixed schedule. In addition, it extends the life cycle of assets, optimizes maintenance activities, and supports effective spare parts management. Together, these advantages contribute to a more efficient and sustainable approach to industrial operations. [2]

However, implementing Predictive Maintenance is not without challenges. A successful PdM system is highly dependent on accurate, high-quality data obtained from sensors installed on machinery. Unfortunately, access to comprehensive and freely available datasets remains limited, making the development and testing of PdM models more challenging [3]. Additionally, integrating PdM into existing operational workflows and digital ecosystems often requires significant effort and expertise, as well as a detailed understanding of each asset's failure modes and operational history. Developing a robust predictive model requires a strong foundation of machine data and a detailed analysis of failure mechanisms, underscoring the importance of expertise and infrastructure in the deployment of PdM [4].

To address some of these challenges, the GA-based Stacking (GA-Stacking) approach emerges as a novel method for enhancing predictive model performance. This method combines the strengths of multiple machine learning algorithms through an ensemble learning framework, where a genetic algorithm (GA) is used to optimize the weights and parameters of the stacking model. By leveraging the exploration capabilities of GA, the approach identifies the most effective combination of base learners and meta-learners, resulting in a robust and accurate predictive model. The GA-Stacking technique not only improves prediction accuracy but also supports adaptability across diverse operational conditions, offering a promising solution to overcome the limitations of conventional PdM strategies.

2 Related Work

2.1 Predictive Maintenance

Predictive Maintenance (PdM) has been a significant focus of research in recent years, leading to the exploration of diverse methodologies to address this critical problem. Among the most prominent approaches are the use of machine learning (ML) models and explainable artificial intelligence (XAI) techniques, both of which aim to improve predictive accuracy and enhance user trust in the systems. In 2020, Matzka [5] introduced a comprehensive study that detailed the development and utilization of the AI4I Predictive Maintenance dataset. This dataset facilitated the application of various AI techniques, including the implementation of explainable AI approaches, which provided valuable insights into model decision-making processes. Their work emphasized the importance of interpretability in AI systems, particularly for industrial applications, where understanding the rationale behind predictions is crucial for adoption and implementation.

In 2023, Pruckovskaja et al. [6] proposed a novel algorithm based on Federated Learning (FL), a distributed system framework that preserves data privacy while enabling collaborative model training across decentralized data sources. Their study presented Federated Learning as an innovative and practical alternative to traditional centralized approaches, addressing privacy concerns and demonstrating its efficacy across various PdM scenarios. This work represents a significant step forward in applying advanced distributed computing techniques to industrial problems, allowing organizations to harness the power of collective data without compromising confidentiality.

In 2024, two significant reviews contributed to the understanding of state-of-the-art PdM methodologies. First, Ucar et al. [7] published a comprehensive report summarizing leading approaches applied to different datasets, industries, and machine types. Their work provided a panoramic view of the PdM landscape, identifying trends, challenges, and opportunities for future research. Second, Cummins et al. [8] conducted a specialized review focusing exclusively on explainable AI (XAI) in PdM. The survey highlighted current methods, challenges, and opportunities for integrating XAI into predictive maintenance. Their study was particularly notable for its focus on the interplay between interpretability and the industrial contexts of Industry 4.0 and Industry 5.0, offering critical insights for advancing interpretable machine learning applications in PdM.

Furthermore, systematic reviews have played a pivotal role in consolidating knowledge and providing an overarching view of the field. For instance, Abd Wahab et al. [9] conducted an extensive review of PdM methodologies, synthesizing findings from diverse studies to identify common trends, strengths, and limitations. These reviews are instrumental in offering a holistic understanding of the domain, enabling researchers to identify promising directions and avoid redundant efforts.

Collectively, these studies illustrate the rapid evolution of PdM research, showcasing a blend of innovative algorithms, comprehensive datasets, and systematic reviews that have significantly contributed to the advancement of this field.

2.2 GA-Stacking

In recent years, Genetic Algorithm-based Stacking (GA-Stacking) has emerged as a promising and innovative approach within the field of machine learning, demonstrating exceptional robustness, accuracy, and effectiveness when compared to traditional methodologies. GA-Stacking is a hybrid technique that leverages the optimization capabilities of genetic algorithms to enhance the performance of ensemble models. By optimizing the combination and weights of base learners within a stacking framework, GA-Stacking achieves a superior balance between bias and variance, leading to improved predictive performance across diverse applications. This methodological advancement has made it a preferred choice in addressing complex, high-dimensional, and non-linear problems that challenge conventional machine learning approaches.

The practical applications of GA-Stacking have been extensively explored across a variety of real-world domains, showcasing its versatility and adaptability. For instance, Dostmohammadi et al. [10] successfully employed GA-Stacking to enhance the accuracy of energy consumption forecasting, a critical task in energy management and optimization. Similarly, this approach has proven to be highly effective in the medical field, where it has been utilized to predict Alzheimer's disease with greater precision, as demonstrated by Khoei et al. [11].

The potential of GA-Stacking has also been recognized in addressing contemporary global challenges. For example, researchers have applied it to forecast the spread and impact of COVID-19, yielding insights that support public health decision-making [12]. In another study, GA-Stacking was utilized for diabetes prediction, delivering robust results that underscore its value in personalized medicine and disease prevention strategies [13]. Beyond these applications, its utility extends into geosciences, as evidenced by Hao Yan and Bai's work [14], where GA-Stacking was implemented to predict vertical well inclination angles, an essential factor in optimizing drilling operations.

These applications not only highlight the adaptability of GA-Stacking to diverse problem domains but also underscore its capacity to address both predictive and decision-support challenges. As an evolving field, GA-Stacking continues to attract attention for its potential to push the boundaries of machine learning, driven by the synergy of genetic algorithms and ensemble learning frameworks. This growing body of evidence suggests that GA-Stacking holds significant promise for addressing increasingly complex and multidisciplinary challenges in the future.

3 Methodology

3.1 Stacking method

Stacking is a robust ensemble learning method that combines predictions from multiple base models to enhance overall predictive performance. Initially introduced by Wolpert [15], this technique employs a meta-model to learn an optimal aggregation strategy for the outputs of diverse base models. By incorporating a variety of model types, such as decision trees, support vector machines (SVMs), and neural networks, stacking effectively capitalizes on the complementary strengths of individual models. Moreover, it provides flexibility by allowing any machine learning algorithm to serve as either a base model or a meta-model.

Despite its advantages, one of the primary challenges in stacking lies in selecting appropriate base models to maximize ensemble performance. To address this, several strategies have been proposed, including incremental or greedy approaches [16], max-margin selection methods [17], the super learner framework [18], and, more recently, Bayesian hierarchical stacking [19]. These approaches aim to systematically identify and combine models that contribute most effectively to the ensemble.

3.2 Genetic Algorithms

Genetic Algorithms (GAs) are optimization techniques inspired by the principles of natural selection and Darwinian evolution. They are particularly effective for solving computational problems with large or complex search spaces where finding an optimal or near-optimal solution is challenging [20]. Over time, GAs have undergone significant advancements, resulting in notable breakthroughs in their application and performance [21].

In this study, Genetic Algorithms are employed to optimize the combination of base models in the stacking ensemble. Each individual in the population is represented as a binary array, where a value of 1 indicates that the corresponding base model is selected, and 0 indicates that it is excluded.

3.3 GA-Stacking

GA-Stacking leverages Genetic Algorithms (GA) to optimize the combination of base models in a stacking ensemble. Each individuals in GA is evaluated using a predefined performance metric (or its negative) as the fitness function. This method reduces manual effort in finding the best ensemble setup, allowing for efficient hyperparameter tuning, and also encourages exploration of diverse base model configurations for robust stacking ensembles.

In this study, the workflow is in the figure 1.

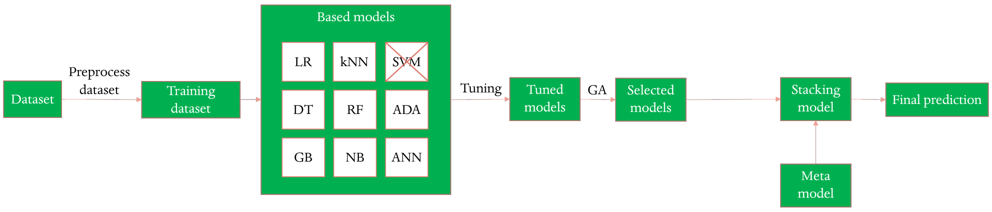

Fig. 1 Workflow of GA-stacking

4 Experiment and Result

4.1 Datasets

4.1.1 AI4I 2020 Predictive Maintenance Dataset

The AI4I 2020 Predictive Maintenance Dataset [5] [6] [22] is a synthetic dataset designed to simulate machine failure scenarios, aiming to approximate real-world predictive maintenance data. The dataset comprises 14 variables, including 6 features and 5 target variables. For the purpose of this study, the task was simplified to a binary classification problem: predicting whether a machine will fail. The dataset contains 10,000 instances, of which 339 represent machine failures.

The dataset was partitioned into three subsets: 80% for training, 10% for validation and tuning of the Genetic Algorithm, and 10% for testing. Evaluation of model performance was based on metrics including Precision, Recall, F1-score, and F30-score. The F30-score was specifically utilized for comparison with Federated Learning approaches [6].

4.1.2 Microsoft Azure PdM Dataset

The Microsoft Azure PdM Dataset [23] is a time-series dataset consists of multiple datas, including machine condition and usage, failure history, maintenance history and machine features. It focuses on real-time sensor data from industrial machines, consists of 875381 non-failure data points and 761 failure data points in total of all machines. It allows evaluating predictive maintenance models in a real-world context, focusing on failure prediction and remaining useful life (RUL) estimation. For this dataset, we convert it to the regression task of predicting how much time before the machine fails, and we only choose machine 3 for simplicity.

4.2 Experiments and Results

4.2.1 AI4I 2020 Predictive Maintenance Dataset

The AI4I 2020 Predictive Maintenance Dataset was utilized for all experiments. This dataset, designed to support predictive maintenance tasks, underwent basic preprocessing steps to ensure data quality and suitability for modeling. Preprocessing included data cleaning to handle missing or inconsistent values (if any) to standardize feature magnitudes, facilitating model performance and comparability.

A diverse set of machine learning models was employed as base learners to construct a robust ensemble framework. The models included Logistic Regression, k-Nearest Neighbors (KNN), Decision Tree, Random Forest, AdaBoost, Gradient Boosting Tree, Naïve Bayes, and Neural Networks. These models were selected for their complementary strengths and varied algorithmic foundations, providing a broad spectrum of predictive capabilities.

To enhance the predictive power of the ensemble, a stacking framework was optimized using a Genetic Algorithm (GA). This setup involved experimenting with various meta-models to identify the optimal combination for final predictions. The GA parameters were configured as follows:

- Crossover Probability: 0.2
- Mutation Probability: 0.2
- Generations: 20
- Population Size: 10 individuals

The fitness function was based on the F1-score, which is particularly suitable for imbalanced datasets. Fitness evaluations were conducted on validation data to ensure model generalizability and performance consistency. This approach aimed to identify an optimal meta-model and combination of base learners to maximize the ensemble's predictive accuracy.

We conduct our test under three conditions: Default parameters, tuned parameters and tuned parameters with SMOTE technique. The result is in the table 1 and the comparison result with Federated Learning is in the table 2.

4.3 Microsoft Azure PdM Dataset

For Microsoft Azure PdM Dataset, a different set of base models is used, which is ElasticNet, Decision Tree, Random Forest, KNN, Gradient Boosting Tree, and AdaBoost. For GA parameters, a fewer number of generations (10) is needed due to computational limit. The result is in the table 3.

5 Conclusion

GA-Stacking demonstrates robust performance in predictive maintenance tasks, particularly when its parameters are carefully tuned. This approach proves to be a strong alternative to state-of-the-art methods, offering both flexibility and consistent performance across varying settings. These findings suggest that GA-Stacking is

Table 1 GA-Stacking result for AI4I dataset

	Metrics	LR	KNN	DT	RF	ADA	GB	NB	ANN	GA-stacking
Default	Precision	0.7	0.57	0.63	0.87	0.53	0.72	0.32	1	0.79
	Recall	0.21	0.11	0.7	0.59	0.47	0.62	0.18	0.09	0.76
	F1-score	0.32	0.19	0.67	0.7	0.5	0.67	0.23	0.16	0.78
Tuned	Precision	0.78	0.47	0.69	0.8	0.55	0.77	0.32	1	0.83
	Recall	0.21	0.21	0.71	0.59	0.5	0.71	0.18	0.24	0.71
	F1-score	0.33	0.29	0.7	0.68	0.52	0.74	0.23	0.38	0.76
Tuned + SMOTE	Precision	0.35	0.24	0.4	0.59	0.36	0.59	0.24	0.91	0.62
	Recall	0.65	0.5	0.68	0.65	0.59	0.76	0.32	0.29	0.68
	F1-score	0.46	0.32	0.5	0.62	0.45	0.67	0.28	0.44	0.65

Table 2 Comparing with Federated Learning

F30-score	Federated Learning [6]						
	#client	Central	Local	FedAvg	FedProx	qFedAvg	FedYogi
	5	0.95	0.89	0.93	0.93	0.48	0.67
	10	0.95	0.8	0.77	0.78	0.39	0.39
	15	0.95	0.78	0.75	0.75	0.42	0.42
	GA-stacking						
	Default	0.76					
	Tuned	0.71					
	Tuned + SMOTE	0.68					

Table 3 GA-Stacking result for Microsoft Azure PdM dataset

	ElasticNet	KNN	DT	RF	ADA	GB	GA-stacking
MSE	0.0111	0.0283	0.0235	0.0202	0.0131	0.0219	0.0111

well-suited for a range of predictive maintenance scenarios, with potential for further improvements through optimization and broader testing.

6 Future Work

To enhance the applicability and performance of GA-Stacking, future research should focus on further tuning of its genetic algorithm parameters and base models, as well as exploring alternate fitness functions to achieve improved outcomes. Additionally, integrating GA-Stacking with other state-of-the-art methodologies, such as Federated

Learning models, could enable the development of scalable and decentralized systems. Finally, evaluating GA-Stacking on real-world datasets is essential to assess its generalizability and robustness in practical predictive maintenance applications.

References

[1] J., R., M., V.S.: Security challenges prospective measures in the current status of internet of things (iot). In: 2022 International Conference on Connected Systems & Intelligence (CSI), pp. 1–8 (2022). https://doi.org/10.1109/CSI54720.2022.9923984

[2] Çınar, Z.M., Abdussalam Nuhu, A., Zeeshan, Q., Korhan, O., Asmael, M., Safaei, B.: Machine learning in predictive maintenance towards sustainable smart manufacturing in industry 4.0. Sustainability **12**(19) (2020) https://doi.org/10.3390/su12198211

[3] Achouch, M., Dimitrova, M., Dhouib, R., Ibrahim, H., Adda, M., Sattarpanah Karganroudi, S., Ziane, K., Aminzadeh, A.: Predictive maintenance and fault monitoring enabled by machine learning: Experimental analysis of a ta-48 multistage centrifugal plant compressor. Applied Sciences **13**, 1790 (2023) https://doi.org/10.3390/app13031790

[4] Nunes, P., Santos, J., Rocha, E.: Challenges in predictive maintenance – a review. CIRP Journal of Manufacturing Science and Technology **40**, 53–67 (2023) https://doi.org/10.1016/j.cirpj.2022.11.004

[5] Matzka, S.: Explainable artificial intelligence for predictive maintenance applications. In: 2020 Third International Conference on Artificial Intelligence for Industries (AI4I), pp. 69–74 (2020). https://doi.org/10.1109/AI4I49448.2020.00023

[6] Pruckovskaja, V., Weissenfeld, A., Heistracher, C., Graser, A., Kafka, J., Leputsch, P., Schall, D., Kemnitz, J.: Federated learning for predictive maintenance and quality inspection in industrial applications. 2023 Prognostics and Health Management Conference (PHM), 312–317 (2023)

[7] Ucar, A., Karakose, M., Kırımça, N.: Artificial intelligence for predictive maintenance applications: Key components, trustworthiness, and future trends. Applied Sciences **14**(2) (2024) https://doi.org/10.3390/app14020898

[8] Cummins, L., Sommers, A., Ramezani, S.B., Mittal, S., Jabour, J., Seale, M., Rahimi, S.: Explainable predictive maintenance: A survey of current methods, challenges and opportunities. IEEE Access **12**, 57574–57602 (2024) https://doi.org/10.1109/ACCESS.2024.3391130

[9] Abd Wahab, N.H., Hasikin, K., Wee Lai, K., Xia, K., Bei, L., Huang, K., Wu, X.: Systematic review of predictive maintenance and digital twin technologies

challenges, opportunities, and best practices. PeerJ Computer Science **10**, 1943 (2024) https://doi.org/10.7717/peerj-cs.1943

[10] Dostmohammadi, M., Pedram, M.Z., Hoseinzadeh, S., Garcia, D.A.: A ga-stacking ensemble approach for forecasting energy consumption in a smart household: A comparative study of ensemble methods. Journal of Environmental Management **364**, 121264 (2024) https://doi.org/10.1016/j.jenvman.2024.121264

[11] Khoei, T.T., Catherine Labuhn, M., Caleb, T.D., Chen Hu, W., Kaabouch, N.: A stacking-based ensemble learning model with genetic algorithm for detecting early stages of alzheimer's disease. In: 2021 IEEE International Conference on Electro Information Technology (EIT), pp. 215–222 (2021). https://doi.org/10.1109/EIT51626.2021.9491904

[12] Nagy, W., Alsalamah, H., Moahamed, E.: Ga-stacking: A new stacking-based ensemble learning method to forecast the covid-19 outbreak. Computers, Materials & Continua **74**, 3945–3976 (2022) https://doi.org/10.32604/cmc.2023.031194

[13] Li, W., Peng, Y., Peng, K.: Diabetes prediction model based on ga-xgboost and stacking ensemble algorithm. PLOS ONE **19**(9), 1–29 (2024) https://doi.org/10.1371/journal.pone.0311222

[14] Hao Yan, H.C. Shuangjin Zheng, Bai, K.: Prediction of vertical well inclination angle based on stacking ensemble learning. All Earth **36**(1), 1–16 (2024) https://doi.org/10.1080/27669645.2024.2424081

[15] Wolpert, D.H.: Stacked generalization. Neural Networks **5**(2), 241–259 (1992) https://doi.org/10.1016/S0893-6080(05)80023-1

[16] Aldave, R., Dussault, J.-P.: Systematic Ensemble Learning for Regression (2014). https://arxiv.org/abs/1403.7267

[17] Sen, M.U., Erdogan, H.: Max-Margin Stacking and Sparse Regularization for Linear Classifier Combination and Selection (2011). https://arxiv.org/abs/1106.1684

[18] Naimi, A.I., Balzer, L.B.: Stacked generalization: an introduction to super learning. European Journal of Epidemiology **33**(5), 459–464 (2018) https://doi.org/10.1007/s10654-018-0390-z

[19] Yao, Y., Pirš, G., Vehtari, A., Gelman, A.: Bayesian hierarchical stacking: Some models are (somewhere) useful. Bayesian Analysis **17**(4) (2022) https://doi.org/10.1214/21-ba1287

[20] Holland, J.H.: Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence, 2nd

edn. MIT Press, Cambridge, MA (1992)

[21] Scholz, J.: Genetic algorithms and the traveling salesman problem a historical review (2018) https://doi.org/10.13140/RG.2.2.22632.78088/1

[22] AI4I 2020 Predictive Maintenance Dataset. UCI Machine Learning Repository. DOI: https://doi.org/10.24432/C5HS5C (2020)

[23] Barga, R., Fontama, V., Tok, W.H.: Predictive Analytics with Microsoft Azure Machine Learning, (2015). https://doi.org/10.1007/978-1-4842-1200-4