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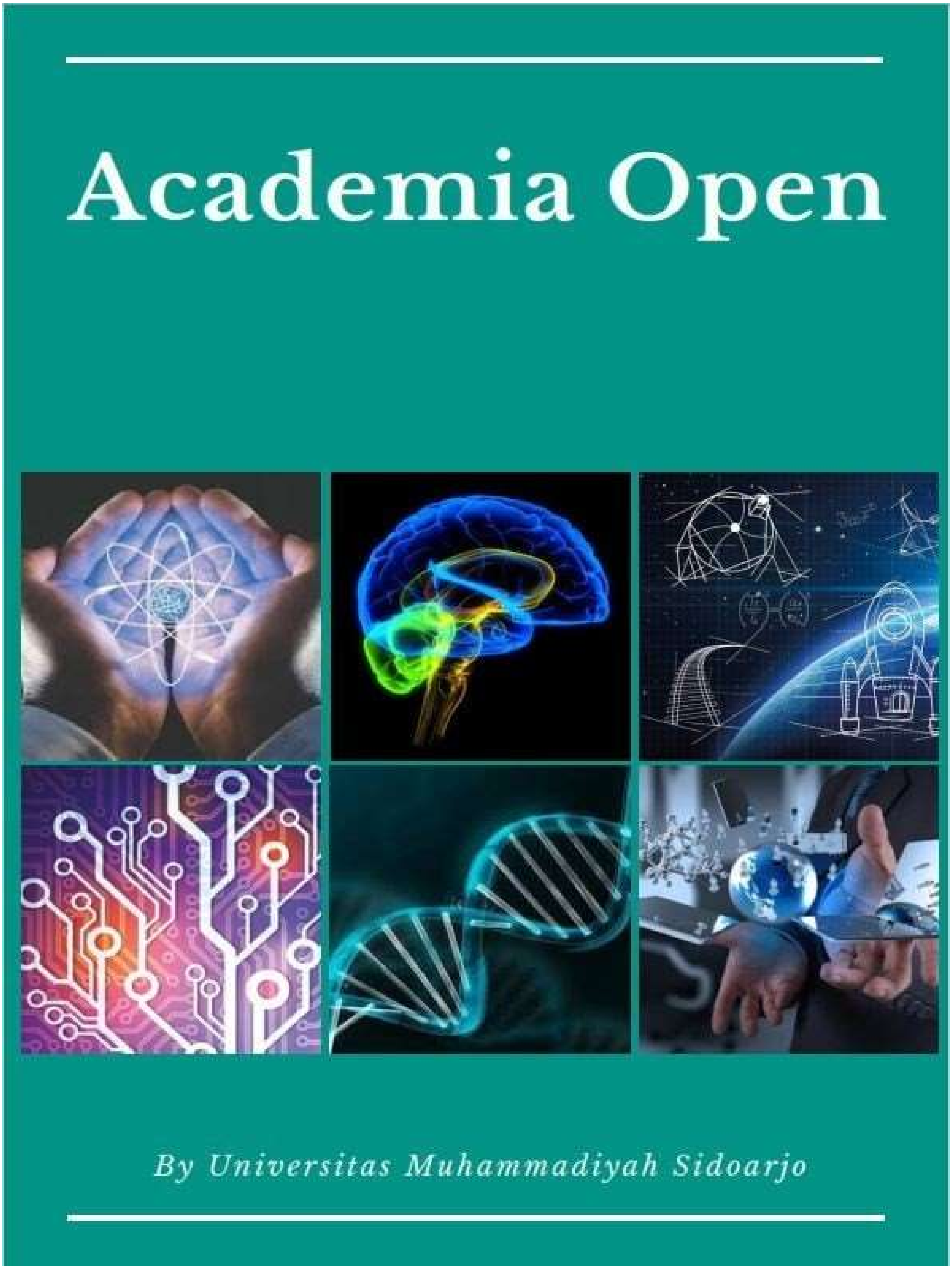

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Artificial Intelligence Techniques for Computer System Failure Prediction: Ensemble and Gradient Boosting Analysis

ALaa KHudhair ali, alla_khdair99@mtu.edu.iq,(1)
Middle Technical University, Iraq
Zeinh Sabeeh Jaseem, zeinh.sabeeh@mtu.edu.iq,(2)
Middle Technical University, Iraq
Ruaa Kadhim Jabir, ruaa-kadhim@mtu.edu.iq,(3)
Middle Technical University, Iraq

(1) Corresponding author

Abstract

General Background: The growing dependence on computer systems across industrial and service sectors has increased the need for reliable early failure prediction to ensure operational continuity. **Specific Background:** Recent advances in artificial intelligence, particularly ensemble methods, gradient boosting algorithms, Automated Machine Learning (AutoML), and Explainable AI (XAI), have demonstrated strong potential in analyzing complex operational data for predictive maintenance. **Knowledge Gap:** Existing studies largely address these techniques in isolation, with limited focus on their integrated application and interpretability in real-world, dynamic environments. **Aims:** This review examines recent AI-based approaches for computer system failure prediction, emphasizing ensemble learning, gradient boosting, AutoML, and XAI. **Results:** The analysis indicates that gradient boosting and ensemble models offer superior predictive accuracy, while AutoML reduces development effort and XAI enhances model transparency and trust. **Novelty:** The review highlights the combined role of performance-driven and explainability-focused techniques within a unified predictive framework. **Implications:** Integrating these approaches supports more reliable, interpretable, and cost-effective predictive maintenance strategies in modern computing systems.

Keywords : Computer System Failure Prediction, Artificial Intelligence, Ensemble Methods, Gradient Boosting, Explainable Artificial Intelligence

Highlight :

- Combined model strategies consistently outperform conventional monitoring by capturing complex operational patterns.
- Sequential tree-based learners demonstrate strong suitability for large-scale, noisy, and heterogeneous operational data.
- Interpretation frameworks strengthen practitioner trust by clarifying decision rationales for preventive maintenance actions.

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Introduction

Today, computer systems constitute the basic infrastructure that supports the vast majority of the mundane day-to-day processes of business organizations and enterprise even in advanced high data rate processing fields, networked storage and cloud applications, IoT services, and even in extremely sensitive data center, telecommunications network, or investi gation environments. As systems are used increasingly by organizations as the core of their operations units, the failure of such a system may result in the entire business being affected, resulting in severe losses not only to business but also to society or services or to the reliability of the institution. Recent studies have reported the devastating effect of critical system down time on business survival [1], [2]. Considering the increasing complexity of components of computer systems, the diversity of their architectures and their deployment at different levels, e.g. cloud, hybrid and virtualized infrastructures, the applicability of traditional techniques for fault monitoring is very limited. Such techniques are increasingly unable to keep up with the dynamic nature of process data. This has spurred the development of a novel attack which power on the potential of intelligent techniques based on presuming breaches ahead of events by analyzing operational behavior data, e.g., system logs, memory usage, processor performance, temperatures, network load, etc [2]. Recent evidences suggest that Artificial Intelligence is able to capture deeper and latent patterns which are not easily visible by human eye and hence it is possible to build very accurate and reliable predictive models more so when sophisticated algorithms are used which can deal with complex and real time data [3]. The literature also suggests that the combined use of methodologies like gradient boosting and ensemble techniques has drastically enhanced the failure forecasting as compared to conventional procedures which mainly depend on threshold monitoring or direct performance measures [4]. This scope of research is strongly motivated by the demanding requirements of improving the operation stability, reducing unexpected failure of systems, improving the policy of the preventive maintenance, and enhancing the risk management when the new generation high availability, continuous-operation computing environment comes to realization.

The importance of research

Importance Here we study a topic of high relevance in current computing, where the cost of unexpected system downtime can be very high, potentially in the scale of millions of dollars for large enterprises, in addition to the impact in institutional reputation and quality of services. New perspectives: Encouraged by the exponential developments in artificial intelligence, new asp Criteriapects of designing predictive systems for terabytes of multifaceted operational data emerge.Ensemble methods represent the current state-of-the-art technique in obtaining high-precision prediction as they can accomodate noisy data and complex relationships among variables, as well as gradient boosting algorithms, and AutoML simplifies the model building process for the users even for non-expert ones [5]. The importance of this work is even underpinned by the inclusion of XAI approaches for interpreting predictive decisions, which at its core is crucial in gaining trust and acceptance for adoption in critical business context. Hence, the work presented in this paper does lead to a scientific underpinning for anticipating developments in predictive maintenance which facilitate efficient take on challenges due to continuing operation.

Research objectives

This paper is an attempt to review the science of the most influential artificial intelligence techniques applied to computer system failure prediction and explain how each technique works with its pros and cons. A general overview of ensemble methods is presented, along with how they can be used to improve predictive performance by fusing multiple decision sources, followed by the discussion of gradient boosting methods, which are potent predictive modeling toolsover high-accuracy. This is to emphasize the fact that the study on how AutoML can contribute towards the automation of the model selection and the hyperparameter optimization while saving significant time and effort is novel [6]. Also, it tries to emphasize the explosive for Explainable AI (XAI) in order to have much higher transparency of prediction results, particularly for directed application domains which require explicit reasoning behind decisions (i.e., data centers, financial systems). The end result of the research is anticipated to be the development of a "big picture" view that enables fostering more effective strategies for control of operational risk and system failure [7].

Literature review

Evaluation of the science output shows that computer system failure prediction methods have matured in the past decade, particularly with the proliferation of AI embedded in complex operational environments. In the article, the authors present an overview of predictive maintenance methodologies applied to high performance computing systems, highlighting the use of machine learning and deep learning for processing operational data and detecting trends related to failures [8], . Enhanced system capabilities in the face of novel algorithmic developments for early failure prediction of the systems were reported in this study, but also challenges related to variability of operational data and difficulty of validating models in real environments were emphasized, as they impair transferability of research findings across different scenarios.

Also included were the findings from another recently published study in Applied Sciences reviewing different ML techniques applicable in predictive maintenance for several industry domains. Based on the results showing model performance influence by the quality and availability of the features and the benefit of using multisource data, such as sensor data and operational logs, to enhance prediction performance. The research also brought out an important issue: the scarcity of existing studies that relate predictive performance to model interpretability, signifying the potential for more integrated research incorporating XAI methods into predictive maintenance strategies.

In the same way, the Sci-Direct study investigated the use of machine learning and deep learning to predict failures in industrial systems. We conduct an empirical analysis on production data in the wild to demonstrate that gradient boosting models and deep neural networks can identify signs of failure with high accuracy far in advance of actual failures . The study also underscored the importance of addressing data-driven issues of imbalance and noise and of employing interpretability methods to build trust on model outputs, especially in safety-critical applications.

Another related research is the work of Antici et al. for job failure prediction in high performance computing systems with machine learning and Natural Language Processing. The authors analyzed job features and text information in execution logs to identify jobs that may fail prior to submission. These findings showed that the approach might improve the utilization of the computational power and the processing time and the power consumption, which can be an indication that the models with sequential and numerical data are more powerful than those without any data type.

Meanwhile, Zhao et al. focused on the application of machine learning (ML) algorithms in the smart manufacturing context for failure prediction

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and variable influence analysis via methods including SHAP. They stated that XGBoost and RF obtain the best predictive performance, and interpretability analysis can help to find the most important variables for engineers to understand the reasons of failures and make more precursor maintenance decisions. The research also suggested that by combining interpretability and prediction the system availability and operation risk can be improved.

Research gap

Although the application of artificial intelligence methods for the prediction of computer system failure has advanced greatly, an examination of the scientific literature discloses several result gaps which still hinder the practical utilization of these methods in real environments. At the ensemble and gradient boosting algorithm level, most works are dedicated to increasing the model accuracy through laboratory experiments using benchmark data sets. Therefore, how well they could adapt to dynamic changing environments and react promptly upon real failures is in question. In addition, most of existing work is based on balanced or preprocessed datasets, while failure data in reality are usually very imbalance and heterogeneous–this is also not well handled in existing work.

The literature also clearly shows a gap in exploiting AutoML deep integration for failure prediction. Most studies consider AutoML as a technique for increasing the speed of model building, rather than studying the influences on stability or long-term trustworthiness of predictive decisions. Besides, AutoML-XAI applications are far and few between, since the two are more often than not regarded separately, which hinders predictive systems from reaping the requisite benefits of high performance and interpretive transparency.

Explainable AI (XAI) has been considered but, as in deep learning interpretability tools such as SHAP and LIME gain popularity, most works are limited to explaining model outputs, without investigating how interpretability itself affects maintenance processes and decision-making. Besides that, studies investigating the reception of the outputs from XAI, by engineers and decision makers in live operational environments, are limited, yet such acceptance is vital for technology adoption at the institutional level.

Moreover, we identify a significant research gap in the design of holistic frameworks that integrate the four considered techniques – ensemble methods, gradient boosting, AutoML, and XAI – within a single framework that can harmoniously connect with live production data. Most existing work treats individual technique in isolation, which results in knowledge gap on how to design an integrated and intelligent system to predict and explain failures at run-time with high confidence.

The review also suggests that the lack of studies that offer standardized measures to quantify the performance of the predictive models and the interpretability constitutes a further challenge. In the absence of well-defined criteria for quantifying accuracy, timeliness, explainability, and scalability, it is difficult to compare models or evaluate their usefulness in practice. To close these research gaps, future work needs to focus on advancing integrated models, interpretability, and performance evaluation in operational scenarios.

Theoretical framework

The educational foundation for this work is the understanding of a small number of fundamental concepts of AI and ML. These concepts begin with the notion of failure prediction, which is a technique that utilizes the examination of past and present data to identify the early warning signs of impending system failures. Ensemble methods are core building blocks within this space, since they group together multiple base models – i.e. Random Forests, Bagging and Stacking – to reduce variance and strengthen predictive power. Gradient boosting methods (such as e.g., XGBoost, LightGBM and CatBoost) also extend this functionality, as they construct a sequence of predictors, each one correcting its predecessors errors, and this allows to add further power to the final predictor and making the approach very popular in failure prediction.

Conversely, AutoML approaches have revolutionized predictive modeling by automating stages including algorithm selection, hyperparameter tuning, and data preprocessing, also producing the best models according to specific performance metrics. These approaches are relevant for their ability to accelerate the development of AI-enabled applications that require less expertise. In another perspective, Explainable AI (XAI) is proposed as an essential component to explain the decision-making process of the prediction models especially for more complicated models such as gradient boosting. Tools like SHAP and LIME make it possible for users to investigate how much each feature impacted the model output, making it more transparent, and providing information on what predicted a failure — which can help improve predictive maintenance, if engineers understand the root causes of failure predictions.

1. The concept of predicting computer system failures

The prediction of failure in computer systems is a fundamental aspect of current digital infrastructure management, especially at the pace of growing data volume, work process complexity, and so on. "As the use of computer systems in organizations grows and the continuous delivery of services increasingly depends on them, being able to predict failures in advance has emerged as a strategic enabler for maintaining high reliability and low cost of unexpected downtime. In the light of this background and stated objectives, failure prediction is interpreted by Zhang as a technique which relies on a comprehensive analysis of operational and historical data to identify patterns or early signals of an upcoming failure. The analyst comments that the "/var/log" system logs, and CPU and memory usage levels, component temperature readings, contain a treasure trove of leading indicators that can be mined.

The importance of this approach is that it uncovers behavior details that would have been disguised by observing with traditional thresholds. Particularly, using machine learning algorithms, it is possible to link minor performance changes to prior operational contexts to become more accurate and proactive. Tan, Wang, Qian, Dou found that the development from traditional procedural methods to intelligent techniques based on deep learning models and advanced statistical analysis significantly improves the prediction quality and reduces unexpected failures. The study also states that taking system failures predicted in a realistic time frame ahead of failure occurrence to the organizations to act upon with preventive measures such as load balancing, or service stress-prone modules, increases overall system efficiency and continuity of operations."

This development enables the design of surveillance systems based on constant intelligent processing, allowing the monitoring systems to be used not only to detect faults but also to suggest actions for the enhancement of their performance over time. As such, failure prediction is a vital element of predictive maintenance, which is emerging as one of the most important system management strategies in contemporary digital environments.

2. Ensemble methods in fault prediction

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Ensemble methods are known as one of the most powerful contemporary techniques for failure prediction since they improve the predictive performance by aggregating predictions from multiple base models that are generated by operating independently. The method is based on the belief that the collective decision in a group of multiple models is more reliable than that of an individual model, especially in the situations with complicated and variant operations. Breiman, in his pioneering paper on the Random Forest algorithm states that the issue of variance and overfitting can be handled by averaging a great number of trees to obtain a more stable and generalizable model.

This view has been the basis for many follow-up works that typically constrained the application of ensemble methods to the cloud and data center environments, which are indeed subject to the evolution and streaming of large-scale data for operation. In the research of Rahman, it was demonstrated that the application of Bagging and Stacking led to substantial enhancement in failure prediction by over 20% in particular operational systems. This enhancement is related to the capacity of ensemble models to combine different perspectives represented in the data, allowing to unveil latent patterns, hidden relationships and complex interactions that a single model may not be able to discover. The literature also suggests that this superiority can be attributed to some essential properties of ensemble algorithms, such as the very high flexibility to work with multidimensional and heterogeneous data, which is the type of data that naturally appears in current day operational environments that includes a mixture of performance logs, sensor data and process streams. They can also be adapted to sudden changes in the nature of workloads, which makes them suitable for use in failure prediction on systems that involve high demands of reliability and proactive decision making.

Moreover, studies have progressed on more sophisticated ensemble algorithms like Boosting in its different versions (AdaBoost, Gradient Boosting, XGBoost) and these have attained high effectiveness in enhancing prediction accuracy and capturing nonlinear associations among variables. These methods have been demonstrated that can be more effective in identifying anomalies and small changes that could be linked to latent system failures, which also makes the idea of using ensembles as a general blueprint for building intelligent monitoring systems grounded on predictive analytics more compelling.

3. Gradient Boosting algorithms

Gradient Boosting is considered one of the best prediction methods for structured data analysis and regular monitoring of computer system log data. Theoretical basis Friedman's work on “greedy function approximation” provided the theoretical basis for this strategy by explaining how to build a sequence of weak learners, in most cases small decision trees, in such a way that each subsequent model corrects the errors or residuals of the former model. This approach is distinguished by its capacity to iteratively enhance performance with repeated learning phases, which allows the ultimate model to identify minute and intricate patterns which conventional methods commonly overlook. An approach of this nature is especially appropriate for data from operational systems, which is often subject to variation and noise.

As data sizes continue to grow and data streaming speeds increase in cloud computing environments and data centers, the demand has increased for meaningful improvements that would enhance training efficiency while preserving accuracy. They answered this need with the XGBoost algorithm, which was one of the greatest breakthroughs in gradient boosting applications. XGBoost presented a high performance framework that can process large scale data efficiently by system optimization techniques such as parallel processing and regularization to control over-fitting as well as to handle missing values more efficiently. These extensions have turned XGBoost into a serving model for failure prediction problems, especially those involving servers and storage where the operational data sets are large and fast-changing.

The development of gradient boosting did not end. Prokhorenkova et al. the CatBoost algorithm was proposed – a new way of how treating categorical data such as an integral part of system logs, which are made of descriptive text, code that status, process identifiers, and non-numerical error messages should be treated. By integrating internal transformation procedures based on ordered target statistics (which reduce bias and other information leakage), CatBoost was able to prove superior. This method leads to a radical improvement in model quality on real traffic, as real life traffic usually involves bringing up many categories, which are moreover not ordered.

Recent studies have demonstrated that gradient boosting has more and more become the kernel of ML-based intelligent monitoring systems owing to its high predictive performance, the stability, scalability, and the generalization for various operation conditions. These approaches enable the development of more proactive models that detect subtle changes associated with imminent failures, leading to more dependable digital infrastructure and reducing the financial impact associated with unexpected outages.

4. Automated machine learning (AutoML) techniques and their role in automation

Automated machine learning (AutoML) is a significant step towards enabling artificial intelligence in the automation domain, since it facilitates construction of predictive models with reduced reliance on expert human data scientists.The importance of the approach stems from that it can solve the problems formulated with the complexity of models in the present time, where models are not only simple algorithms any more, but also need to know how to select proper algorithms, evaluate the quality of features and tune learning parameters exactly. In this light, Hutter et al. mentioned that AutoML is considered as an all-encompassing framework that allows organizations to automate all phases of the model building process, from selecting the data representations to the most appropriate learning algorithm to applying automated hyperparameter optimization. This leads to methods that can reach high performance with little human involvement.

This is especially welcome in fields for which traditional failure prediction is crucial and in which raw operational data are usually complex and multiform and needed to be processed to discover features related to system faults. AutoML provides a way to build more models while analyzing large numbers of operational variables to arrive at multiple candidate models from which a most efficient model can be identified based on performance metric. Thornton et al. discuss the impact of AutoML methods, such as Auto-WEKA, that are applicable to this both showing that they can achieve performance that is comparable to what a machine learning expert would do in selecting algorithms and configuring models – and in so doing reducing the burden for companies that do not necessarily have the same level of expertise in data science and machine learning.

The influence of AutoML is not limited to making model building easier; it also breathes new air in the development cycle and allows more experiments with more models and configurations in way less time than it takes using traditional manual way. Besides, AutoML also helps to reduce human mistakes like applying unsuitable parameters or forgetting which features contain the most predictive information. This makest AutoML a crucial component in a failure prediction application since reliable and prompt decisions must be taken based on accurate processing of the operation data.

The advantages of AutoML are more significant in case of small and medium enterprises for their pertinent data is valuable, but they are not empowered by technology to produce complicated predictive models. In these bodies may apply AutoML to generate high-quality models also in

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their own right, ... and predictive failure functionalities parallel to those of the larger organization. In short, AutoML propagates the ideal of technological parity by providing powerful machine learning tools even for those with a small amount of knowledge and resources.

5. Explainable Artificial Intelligence (XAI)

As modern systems increasingly depend on complex machine learning models such as Gradient Boosting and deep neural networks, there is a strong demand to offer interpretability mechanisms to interpret how these models make decisions. This consideration is even more important in sensitive environments (e.g., computing systems and data centers) where an accurate failure prediction is not only requested but also the knowledge of why and how the model arrived to its output is crucial to performing proper maintenance actions and not adding operational risk.

In this regard, Lundberg and Lee proposed the SHAP (SHapley Additive exPlanations) framework, which has become one of the leading approaches for model interpretation on tree-based models and ensemble methods such as Gradient Boosting. SHAP is based on Shapley values from game theory, which provides an axiomatic-based method to fairly determine each feature s contribution to the model s output. There is evidence in the literature to demonstrate that this approach not only provides global interpretation of the model, but also, to a certain degree, provides an evaluation of feature importance per instance, becoming critical when dealing with infrequent or anomalous failure cases in the field.

Ribeiro et al. also show with LIME that the complex machine learning model should be complemented by these tools that approximate the model behavior around a particular prediction, from a local perspective. Such reasoning leads to a better understanding of the elements that influence a specific prediction, even though the overall model is too complicated to be understood. LIME helps provide fine grained local explanations that allows system administrators and engineers to trace and analyze alerts, particularly when decisions are based on non-intuitive and difficult to observe operational variables [9].

In failure prediction, Shaposhnikova mentions that the use of XAI methods on predictive models has resulted in advancements for proactive maintenance. With these tools, organizations can determine which variables most influence system failures -- increasing temperatures, lagging response times, or recurring log patterns ahead of a crash. The combination restores confidence in the predictive models because there are well-grounded and traceable reasons, and thus technical teams are empowered to act upon the reasons, e.g. performing maintenance, redistributing workload, or changing system configurations.

Therefore, XAI has played a key role not only in enhancing the quality of prediction but also in satisfying the process transparency for risk management. The quoted works show that meaningful explanations of the decision making process are what makes it possible for the use of machine learning models in high accuracy and high trust requiring application fields [10].

6. The Integrative Relationship Between GBM and XAI in Explaining Failure Predictions

The area of failure prediction is seeing a lot of innovation due to the demand of models with high accuracy and interpretability, an equation hard to satisfy in the past. Against this background, the integration of Gradient Boosting Machines (GBM), specifically the XGBoost algorithm, with Explainable Artificial Intelligence (XAI) methodologies, like SHAP, has recently become a predominant paradigm in order to develop advanced predictive models which can be leveraged by organizations to maximize value of data while keeping interpretability and traceability. Molnar highlights that its fusion is considered one of the most promising trends in AI applications in secretive operational domains, as it brings together efficiency, trustworthiness, and transparency in a unique manner. The advantage of our integration is that GBM models, and especially XGBoost, have been shown to work well with structured data and capture non-linear relationships prior to failure. This power to predict, however had previously come at the expense of understanding of the decision-making process within models, which limited their use in areas requiring a high degree of transparency, such as analysis of operational risks and management of data center logs. This is the point at which XAI comes in: approaches like SHAP leave it possible to see on an individual variable level whether that variable was, for example, temperature, resource usage, or log patterns often are leading indicators of failure [11].

Molnar (2022) also states that trust in the model is strengthened when the outputs of GBM are interpreted by using XAI tools, and trust in a model increases the quality of decisions that are informed and supported by it. Engineers no longer need to rely on context-free predictions; they have an understanding of why the system is predicting a failure and what factors, specifically, led to that prediction. This knowledge enables the formulation of more effective proactive maintenance policies, such as selecting the parts more vulnerable to failure and system designs to stay away from critical operating states [10].

The integration of GBM and XAI has also enabled improved collaboration between the technical and the business teams in the enterprise. SHAP explanations cause the model output to become more interpretable, even for laypeople, which will help to encourage the use of artificial intelligence in the decision-making of "high impact"so without needing an extremely deep knowledge on algorithms. Molnar (2022) sees this as a “great enabler” for predictive systems to transition from being experiment usages, to core enterprise decision support systems where operational risk models of failure prediction are tightly integrated into the very management of operational risk. In short, utilizing the combination GBM model with XAI tool could bring about better prediction power and more significant application value [11]. In this way,failure prediction moves beyond being a technical function to become a critical facet of operational management -- one that is concerned with predicting when systems will fail, not simply when they will fail, but why they fail, based on a thorough understanding of the causes of their degradation or failure.

Research Methodology

The methods include a review of the scientific literature on the prediction of computer system failure using artificial intelligence methods. Papers were retrieved from reputable scientific publishers, i.e., IEEE Xplore, ScienceDirect, Springer, and ACM Digital Library, with a view to a decade's worth of research as this decade has seen the most groundbreaking revolutions in the field of artificial intelligence.

A full-text search was conducted using the following keywords: Failure Prediction, Machine Learn in Comput Systems (MALCS), Ensemble Methods, Gradient Boosting, AutoML and Explainable AIand their equivalent terms in Arabic to cover the search comprehensively. After the preliminary results were ranked down, several more rigorous criteria were introduced, such as date of publication, transparency of methodology, whether it concerned fault prediction directly and whether it employed any of the aforementioned AI methods. This allowed the selection of the most pertinent and important ones, which in turn enabled us to build an overall well-balanced view on the recent research activities. In addition, the selected articles were thoroughly read, analyzed, and synthesized to identify research gaps as well as similarities between diverse approaches (emphasis on data quality, model accuracy, and applicability to different computing environment).

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Previous Studies and Results Analysis

The review of prior work indicates that forecasting of computer systems failures is now attracting significant attention in both academic and industrial communities with the transition of digital infrastructures toward complex systems such as cloud and high-performance computing (HPC). It has been reported in several studies that ensemble methods like Random Forest (RF) and Extra Trees (ET) are good options since they are consistent performers and they can deal with high variance data. Other works have shown that gradient boosting models (e.g., XGBoost) currently constitute the state of the art for precision prediction tasks and surpass the performance of traditional neural networks in multiple studies, particularly when applied to structured data [12]. An increasing number of studies have shown that AutoML is a significant factor driving improvements in the modeling process, which automatically picks up good algorithms in a limited amount of time and requires minimal human input. This enabled predictive methods to gain traction in work environments where artificial intelligence specialization is not available.

In terms of transparency, a combined Explainable Artificial Intelligence (XAI) methodology for applied studies on the model results demonstrated that interpreting model outcomes supports decisions at the operational level and increases trust of system engineers especially in the case of short-term failure prediction. Tools like SHAP have been extremely useful in surfacing the most impactful variables leading to failure, enabling new ways to improve the system itself. The literature on most of the studies shows that the integration of XAI with Gradient Boosting delivers a high performance and interpretable approach, which has motivated several technology organisations to use this technique for data centers and smart monitoring applications[13] .

Discussion

The review results reflect a fundamental change in the treatment of failures in computer systems. Traditional approaches like threshold monitoring are not adequate anymore, there is a demand for more intelligent techniques that investigate deep data for revealing latent indicators of failures ahead of time. The results show that the ensemble and gradient boosting methods remain the most popular solutions as they are very capable to deal with imbalanced datasets, which are very common in failure related problems since the normal conditions are usually way more than the failure conditions [14]. In addition, AutoML makes it feasible to speed up and popularize the use of failure prediction, which brings the chance of using artificial intelligence for small and medium enterprises without too much cost or too much professional knowledge. Conclusion In contrast, the panel emphasized the need for Explainable Artificial Intelligence (XAI) not only to allow for understanding of decisions, but also in order to meet regulatory requirements in “ultra-sensitive” sectors (government datacenters and banking systems). When that decision is that the system is going to fail in a matter of hours, Knowing why becomes far more important than any opaque prediction. Some works suggest to include XAI already during the early phases of model design and not as an afterthought [15].

In addition, the operational data is dynamic, and hence the prediction models need to be updated regularly. Therefore, the predictiveated that the models need to be regularly updated as the patterns in the operating data change, also implying that continuous learning or incremental learning solutions might be needed for the best performance.

Conclusion and Recommendations

In summary, we observe that AI techniques provide a powerful and effective means for predicting the failure of computer systems. The synergy among ensemble algorithms, gradient boosting techniques and AutoML allows a general formation for constructing high-accuracy models that can be applied in different application fields. Moreover, the integration with Explainable Artificial Intelligence (XAI) is a crucial aspect to balance performance and transparency of the decisions, thus making the solution more trustable for the companies that need 100% uptime services.

The review puts forth several major recommendations: to invest in high-quality collection of operational data; to develop more specialized AutoML systems targeted at interpreting computing systems; to improve the interplay between XAI and predictive models so as to enhance understandability and trust; and finally, to adopt continual learning techniques to keep models up to date as the behaviors of systems of systems continually change

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