Functional Architecture For The Application Of Supervised Machine Learning In Naval Monitoring And Control Systems

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Abstract
The increasing complexity of platforms on modern warships necessitates the implementation of advanced control and monitoring systems to ensure operational efficiency, safety, and availability. In this context, the present research endeavor focuses on identifying the critical components and causes of failures through a detailed analysis of the reliability of the system and the diagnosis. In the domain of ship machinery control and monitoring systems, the integration of machine learning – encompassing functions ranging from anomaly detection to decision assistance – signifies a disruptive innovation with the capacity to transform decision-making processes within the complex and challenging environment of a warship. The present document delineates a functional architecture for the implementation of supervised machine learning (ML) algorithms, encompassing data preprocessing, feature extraction, model training, and evaluation. The integration of classification and regression techniques in the context of supervised machine learning for the purpose of anomaly detection and decision support within control and supervision systems of ship machinery is hereby proposed. This integration of techniques represents a disruptive innovation in the operational management of warships. Furthermore, it delves into the integration of machine learning (ML) into the ship's engineering console, with the objective of processing data from sensors that monitor critical parameters. These parameters include, but are not limited to, temperature, pressure, vibration, revolutions per minute (RPM), frequency, and voltage. These sensors are utilized in various components of the ship, such as engines, generators, and other equipment. The implementation of the ML allows for the planning of preventive and corrective maintenance, thereby extending the useful life of the machinery and subsystems. This, in turn, ensures stability, efficiency, and control of the Navy's resources. The anticipated outcomes of this initiative include a substantial enhancement in technical availability, a notable decrease in unplanned failures, and an augmentation in the autonomy of complex systems supervision.
Keywords: Machine learning, supervised learning, naval architecture, automation, anomaly detection, decision making

INTRODUCTION

The contemporary shipbuilding industry is undergoing a period of technological transformation, driven by the imperative to enhance the efficiency, safety, and sustainability of its operations. In particular, Integrated Supervision and Control Systems (SISC) on warships play a critical role in the management of critical subsystems, including, but not limited to, propulsion, power generation, HVAC, and ancillary systems.

However, these systems encounter substantial challenges related to operational reliability, data traceability, and failure responsiveness. In this context, the incorporation of emerging technologies, such as Machine Learning (ML), is presented as an innovative solution to anticipate failures, optimize maintenance, and improve decision-making in real time.

In recent years, there has been a notable surge in the adoption of machine learning (ML) techniques within the domain of monitoring and control systems on a global scale. In Europe, projects such as MARISA have demonstrated the potential of machine learning (ML) to enhance maritime situational awareness by integrating data and identifying anomalies in real time.

Universities such as the Delft University of Technology (TU Delft) and the Rheinisch-Westfälische Technische Hochschule Aachen (RWTH Aachen) have developed hybrid models for the diagnosis of faults in offshore turbines, thereby reinforcing the applicability of machine learning (ML) in complex electromechanical environments. In the United States, research initiatives have been spearheaded by institutions such as DARPA and the MIT Lincoln Laboratory. These initiatives focus on the utilization of deep neural networks and SCADA data analysis to predict failures in military platforms. Japan has been a leader in the field of naval automation, as evidenced by initiatives such as the Smart Ship Project and the developments of the National Maritime Research Institute (NMRI). These initiatives have led to the integration of algorithms, including CNN and LSTM, for the monitoring of conditions in marine engines.

Notwithstanding these advances, significant gaps persist in the extant literature, particularly with regard to the practical and contextualized implementation of machine learning (ML) algorithms on warships from developing countries, where technological, budgetary, and interoperability constraints represent additional barriers. In the case of the Colombian Navy, these limitations are manifested in the following ways: first, there is a lack of data traceability; second, there is fragmentation of systems; and third, there is an absence of robust predictive tools.

Confronted with this extensive operational context, it is imperative to develop technological solutions that are adapted to the operational environment of the Colombian Navy. The incorporation of machine learning (ML) algorithms within ship information systems (SISCs) holds the potential to enhance several facets of naval operations. This integration would facilitate the anticipation of failures, thereby reducing periods of downtime. Additionally, it would contribute to a more streamlined management of the naval asset lifecycle, a development that has the capacity to improve safety, reduce expenditures, and fortify the response to critical situations.

From a scientific perspective, this study contributes to the body of knowledge on the application of machine learning (ML) in real-time control systems. From a technological perspective, it proposes a replicable model for other naval forces with similar conditions.

The central objective of this study is to explore and evaluate the integration of machine learning algorithms in the supervision and control systems of warships. The ultimate goal is to improve the efficiency of maintenance and operation of their electromechanical systems.

The hypothesis that guides this research is that the implementation of real-time machine learning (ML) algorithms significantly improves early fault detection and maintenance planning compared to traditional methods.

The application of machine learning techniques is gaining traction in the maritime industry, although its adoption is more limited compared to other sectors (Akyüz et al., 2019). The analysis of extensive data, including ship performance metrics, climatic and environmental conditions, allows the ML to offer innovative solutions to improve efficiency and promote cleaner transport by reducing harmful emissions (Vorkapić et al., 2024).

The utilization of machine learning (ML) methodologies enables the processing, interpretation, visual representation, and analysis of the aforementioned information. This,

in turn, facilitates the development of data-driven predictive models for physical phenomena.
The following text is intended to provide a comprehensive overview of the subject matter. Consequently, the following specific objectives are established for this research:

- Develop a theoretical-practical framework for the integration of ML algorithms in the warship engineering console.
- Identify the most suitable ML algorithms for real-time sensor data analysis and prediction of critical component failures.
- Evaluate the performance of such algorithms in terms of accuracy, efficiency, and responsiveness within a real-world operating environment.
- Propose recommendations for the implementation of ML-based control and supervision systems, which optimize maintenance and operational efficiency on warships.

1. THEORETICAL FRAMEWORK

Technological developments in the naval field have engendered a mounting demand for intelligent systems that are capable of monitoring, diagnosing, and controlling in real time the multiple subsystems that comprise a modern naval platform.
In this context, Machine Learning (ML), and in particular supervised learning, has established itself as a key tool to transform Integrated Supervision and Control Systems (SISC), allowing a more efficient, autonomous, and predictive management of critical electromechanical systems. Machine learning (ML) is defined as a subfield of artificial intelligence that allows machines to learn from data without being explicitly programmed (Lambrou et al., 2019).
Supervised learning, a primary branch of machine learning (ML), involves training a model from a dataset that has been labeled, with each input data point being associated with a specific output (Panda, 2022).

2.1 Specialized document review

An examination of the scientific and technical literature reveals a growing interest in the application of machine learning techniques in the naval field, especially in areas such as anomaly detection, failure prediction, and maintenance optimization. This includes scientific articles, doctoral theses, relevant international projects, and technical reports from institutions such as DARPA (USA), NMRI (Japan), and the European Union. The following conclusions were derived from the aforementioned review:

- ML algorithms most commonly used in industrial and naval environments (e.g., neural networks, SVM, LSTM, CNN).
- Key metrics for evaluating the performance of ML models in real-time.
- Limitations and challenges of the application of ML on warships.
- Success stories in predictive maintenance, anomaly detection and autonomous control.
- Technical and operational requirements for deploying ML in critical systems.

From this review, relevant applications are considered for a SISC with ML technology described in Table 1.
Table 1. Relevant International Projects on ML in Integrated Supervision and Control Systems (SISC) on Naval Platforms

Country / Region	**Project/ I am a student**	**Institution**	**Technologies**	**Application**	**Relevance**
USA	Sea Hunter	DARPA/U.S. Navy	ML for autonomous navigation,	Autonomous control of unmanned	Demonstrates ML integration into real-time monitoring and

			fault detection	naval platform	control systems in harsh naval environments
USA	JAIC Naval Predictive Maintenance	Joint Artificial Intelligence Center (DoD)	Neural networks, predictive analytics	Critical machinery monitoring and fault prediction	Apply ML in predictive maintenance and control of electromechanical systems on warships
Japan	NMRI Smart Ship Project	National Maritime Research Institute	Hybrid ML (fuzzy logic + neural networks)	Propulsion and power system monitoring	Focus on energy efficiency and intelligent control of complex naval systems
Japan	SATREPS Naval AI Initiative	JICA / JST	Supervised and unsupervised learning	Fault diagnosis and condition-based maintenance	Promotes ML integration into engineering consoles for continuous monitoring and decision-making
Europe	SURPRISE	Spanish Navy / INDRA / CITIC	ML with Spark, Time Series Analysis	Monitoring of engines and auxiliary systems	Applied case of ML in SISC for predictive maintenance in naval fleets
Europe	Digital Twin Naval Systems	Navantia / European Union	Digital twin + ML (regression, classification)	Simulation, monitoring and control of critical systems	Enables ML integration into engineering consoles for failure prediction and operational optimization

The comparative analysis of these projects reveals essential common elements for the effective implementation of ML in naval SISC, i.e. the need for real-time processing, integration with distributed sensors, adaptability of algorithms to changing conditions, and robustness in the face of demanding operating environments. These factors form the basis for the development of a functional architecture that enables intelligent monitoring, failure prediction and maintenance optimization on naval platforms.

The application of machine learning is revolutionizing various fields of engineering and science, particularly those involving the analysis of large datasets derived from high-fidelity numerical experiments and simulations (Panda, 2022).

2. METHOD

This study employs an exploratory and conceptual methodological approach, with the objective of developing a theoretical and functional framework for the application of Machine Learning (ML) techniques in the Integrated Supervision and Control Systems (SISC) of naval platforms. The research is grounded in a systematic review of scientific and technical literature, complemented by a functional analysis of existing naval systems and the formulation of a conceptual proposal adapted to the operational environment of warships.

The central objective of this study is to propose a functional architecture that allows for real-time data analysis, anomaly detection, and failure prediction in critical electromechanical systems. This will contribute to the improvement of operational efficiency and maintenance planning.

The present study employs a non-experimental research design of a qualitative and documentary nature. The primary objective of this design is to facilitate a comparative analysis of existing technological approaches and the conceptual synthesis of a viable solution for the Colombian naval context. This approach enables the identification of best practices, algorithms, and technological architectures that have proven effective in analogous environments, and the adaptation of these to the specific needs of the Colombian Navy.

This methodological framework is designed to address the specific objectives of the study, particularly the development of a conceptual architecture based on machine learning (ML) and the evaluation of its applicability in naval engineering consoles. The proposal is structured around the integration of supervised algorithms, selected for their predictive capacity, accuracy, and ease of validation in critical environments.

The conceptual validation of the proposal will be carried out through the analysis of representative use cases in naval systems, the review of performance metrics reported in the specialized literature, and the evaluation of the technical and operational feasibility in the context of the Colombian Navy.

The experimental implementation of the proposed architecture is suggested as a future research direction, along with its empirical evaluation in real or simulated scenarios.

The mounting emphasis on contemporary vessel autonomy is predicated on intricately interconnected subsystems that facilitate coordinated operational decision-making, thereby diminishing the necessity for human intervention (Hatledal et al., 2020).

3.1 Conceptual proposal: Supervised Machine Learning applied to Supervision and Control Systems

achine learning (ML) has firmly established itself as a potent instrument within the domain of artificial intelligence. This technological capability empowers systems to process substantial volumes of data, identify intricate patterns, and acquire knowledge from operational experience.

In the context of Integrated Monitoring and Control Systems (SISC) on platforms, where continuous monitoring and rapid, precise decision-making are imperative, Machine Learning (ML) offers an adaptable and predictive solution. The system's capacity to analyze data in real time and identify anomalies enhances operational efficiency and reduces maintenance expenditures.

3.2 Justification for the exclusive use of supervised learning

In this research, it is chosen to use only supervised learning techniques, due to the following reasons:

- Availability of labeled data: In naval environments, there are historical records of failures, maintenance and normal operation of the systems, which allows supervised models to be trained with inputs (sensor data) and known outputs (system status, presence or absence of failures).
- Predictive objective and clear diagnosis: The focus of the work is on detecting anomalies, classifying system states and predicting failures, tasks that fit naturally into the supervised approach, as they have well-defined objectives.
- Accuracy in critical environments: Control systems on warships cannot tolerate significant errors or ambiguous decisions. Supervised learning allows you to tune models with precise and controlled performance metrics such as accuracy, sensitivity, or false positive rate.

- Ease of validation: By using labeled data, it is possible to evaluate and compare the performance of different algorithms quantitatively, which is crucial for the acceptance of technological solutions in military environments.

3.3 Selected supervised models for naval systems

In the context of naval systems, where reliability and availability are critical, it is essential to select supervised learning models that offer a good balance between predictive accuracy, interpretability, and computational efficiency (Magena, 2024). The following models have proven to be effective in similar applications and are considered suitable for integration into the proposed architecture:

- Vector Support for Regression (SVR): suitable for nonlinear relationships in continuous data; useful for predicting the progressive deterioration of components.
- k-Nearest Neighbors (k-NN): intuitive and effective model in conditions with clearly differentiable operating patterns.
- Bayesian networks: allow probabilistic predictions to be made with interpretability, facilitating decision-making under uncertainty.
- Regression with Gaussian Processes: useful for systems where not only a prediction is required, but also an associated confidence interval.
- Artificial Neural Networks (ANN): powerful for modeling complex relationships between multiple operational variables, especially with large volumes of data.
- The selection of these models is based on their versatility, interpretability and ability to handle high-dimensional data, essential characteristics in the context of naval systems.

Integrating machine learning models into predictive maintenance strategies is critical to anticipating equipment failures and scheduling maintenance activities efficiently, minimizing downtime and associated costs.

3.4 Application to Marine Engineering Console

The marine engineering console constitutes a centralized system that collects and displays real-time information regarding the status and performance of various propulsion plant systems and the ship's auxiliary equipment. The implementation of machine learning techniques within this console holds the potential to effect a transformative shift in the manner in which operators engage with the system and make critical decisions.

Figure 1. Application of machine learning to the engineering console
Source: Own elaboration

The integration of supervised learning algorithms into the marine engineering console would allow:

● Intelligent Data Visualization: Highlight relevant information and anomalous patterns in the displayed data, making it easier to detect problems early.
● Automated diagnostics: identify possible causes of failures or deviations in performance, providing recommendations to the operator.
● Prediction of the future state: anticipate the behavior of the systems and warn of possible imminent failures, allowing proactive intervention.
● Performance optimization: suggest adjustments to operating parameters to maximize efficiency and reduce energy consumption. By training the marine engineering console with machine learning capabilities, the efficiency, reliability, and safety of vessel operations can be significantly improved. These models can be valuable in predictive maintenance to identify subtle warning signs of problems that might not be apparent through standard monitoring methods (Magena, 2024).
● Assisted diagnostics: By combining the information provided by sensors with the expert knowledge stored in the database, ML models could help operators quickly diagnose the root cause of a problem and select
● Classification of the condition of the equipment.
● Prediction of expected failure.
● Generation of intelligent alerts and suggestions for corrective or preventive maintenance. It is possible to implement machine learning algorithms, such as artificial neural networks, to model and predict the performance of maritime systems, mitigating the computational load associated with numerical simulations (D'Agostino et al., 2022).
In the context of performance optimization, Machine Learning can be leveraged to analyze real-time and historical operational data to identify patterns and relationships that optimize the performance of naval systems. The implementation of this approach will improve operational efficiency and reduce the cognitive load of naval personnel. Furthermore, it will increase the availability of critical systems.

3.5 Design of the Functional Architecture of Supervised Learning in Supervision and Control Systems (SISC)

The functional architecture of supervised learning in a warship's Integrated Supervision and Control Systems (SISC) is structured in a logical sequence of stages, each aimed at ensuring predictive effectiveness, operational reliability, and effective integration into the engineering console. The architecture under consideration enables real-time data processing, intelligent alerts, and recommendations for maintenance and operation decision-making.

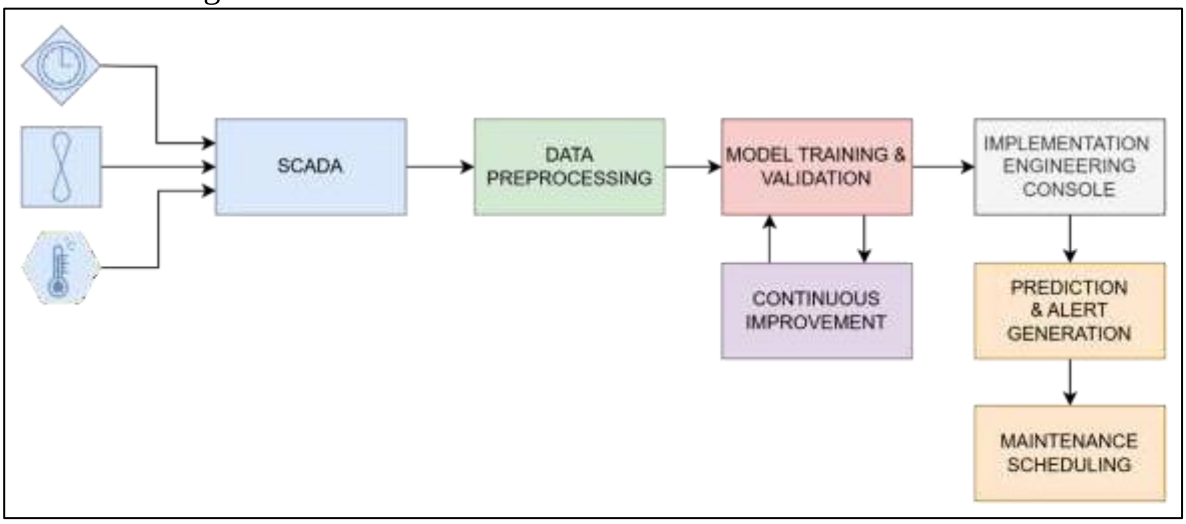

Figure 2. Functional architecture of supervised learning
Source: Own elaboration

3.6 SCADA Data Acquisition

The process commences with the aggregation of data from multiple sensors distributed in critical systems, including propulsion, power generation, air conditioning, hydraulics, and auxiliaries. These sensors are designed to collect operating parameters, including but not limited to temperature, pressure, vibration, revolutions per minute, current, and voltage. The data is transmitted to the SCADA system, which functions as a platform for the acquisition and centralized storage of information.

3.7 Data pre-processing

Before being used by supervised models, the data goes through an essential pre-processing stage that includes:

- Data cleansing: Detecting and correcting outliers, imputing missing data, smoothing noise, and verifying consistency between sensors.
- Feature Reduction and Selection: Redundant records are eliminated, relevant variables are identified, and techniques such as Principal Component Analysis (PCA) are applied to reduce dimensionality while maintaining critical information.
- Data segmentation: Historical data is divided into training, validation, and testing sets to ensure rigorous evaluation of the models.

3.8 Model Training and Validation

The selected supervised models—including Vector Support for Regression (SVR), k-Nearest Neighbors (k-NN), Bayesian Networks, Regression with Gaussian Processes, and Artificial Neural Networks (ANN)—are trained using the labeled data.

Each model is meticulously calibrated to predict specific failures, classify operating states, or estimate mean time to failure (RUL). During this phase, critical metrics such as accuracy, sensitivity, specificity, and the false positive rate are evaluated to optimize performance. Furthermore, the implementation of regularization and cross-validation techniques is essential for the purpose of avoiding overfitting and ensuring the generalization of the model.

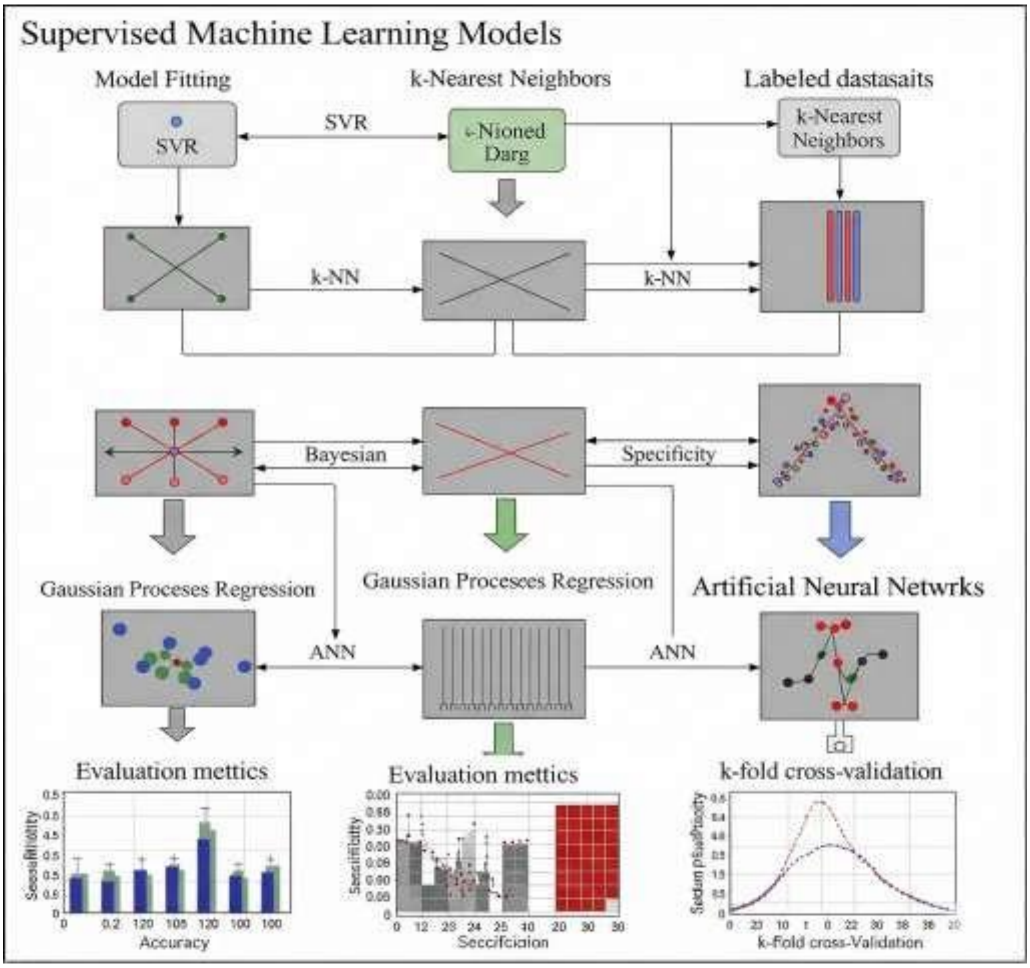

Figure 3. Model Training and Validation Diagram
Source: Own elaboration

The efficacy of machine learning models in predicting failures and optimizing the maintenance of industrial machinery is contingent on the quality of the training data (Jiao et al., 2020).
This data is typically collected from a variety of sources, such as IoT-enabled sensors, control and monitoring systems, and operational records (Reddy Mitta & Ranjan, 2024).

3.9 Feedback and continuous improvement

The system meticulously documents novel operational occurrences and the outcomes of maintenance interventions, thereby enabling the retraining of models with the most recent data. This feedback mechanism ensures a progressive adaptation of the system to changing real conditions, thereby enhancing its accuracy over time.
This architecture ensures an anticipatory, evidence-based, and adaptable response, representing a significant advance over traditional maintenance approaches. The implementation of this flow with supervised models has been demonstrated to enhance the operational reliability of warships and optimize the management of their electromechanical systems in demanding environments.

3.10 Application Flow of Supervised Algorithms

In the context of a naval SCADA system, the implementation of supervised learning algorithms must respond to specific operational needs, including state classification, failure prediction, anomaly diagnosis, and decision-making with controlled uncertainty. The subsequent discussion will delineate the functional flow, while also specifying the particular application of each proposed supervised model.

3.11 Flow Design

The system executes an optimized sequence of algorithms, each of which serves a specialized function

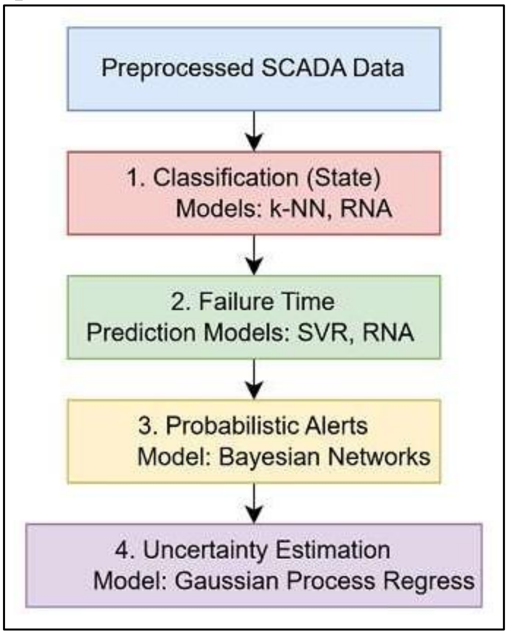

Figure 4. Application flow of the monitored algorithms

The following algorithms are implemented in sequence to achieve specialized functions:

- k-Nearest Neighbors: Initially, this algorithm is used to carry out an agile classification of the operational state of the system, standing out for its efficiency in inference and its structural simplicity.
- Artificial Neural Networks: In parallel, they are implemented to identify complex multivariable patterns, especially useful when normal and anomalous conditions present non-linearity or depend on the interaction of multiple variables. This model acts as a complement to the k-NN in scenarios with high variability.

● Vector Support for Regression: Upon detection of a warning state or anomaly, SVR is used to predict the estimated time to failure of a critical component, facilitating the scheduling of preventive maintenance actions.
● Bayesian networks: These networks are used to infer the probable causes of failure, by analyzing probabilistic relationships between variables. They are essential in situations with multiple possible symptoms, where it is necessary to identify the most likely root cause.
● Gaussian processes: Finally, they are used to make continuous estimates, providing not only a point prediction, but also confidence intervals. Its application is valuable in systems where the quantification of uncertainty is crucial for technical decision-making.

3. EXPECTED RESULTS

The implementation of the conceptual framework based on supervised learning in the Integrated Supervision and Control Systems (SISC) of naval platforms is projected as a transformative solution in the management of the operating condition, technical reliability and optimization of maintenance in highly critical environments. The expected results, evaluated based on key performance indicators (KPIs) and reliability engineering metrics, are as follows:

Reduction of Mean Time to Fault Detection (MTTD): The ability of supervised models to perform multivariable inferences in real time will reduce MTTD by at least 40%, by identifying subtle deviations from the nominal behavior of critical variables such as pressure, vibration, frequency or temperature. This represents an increase in the sensitivity of the system to incipient failures.

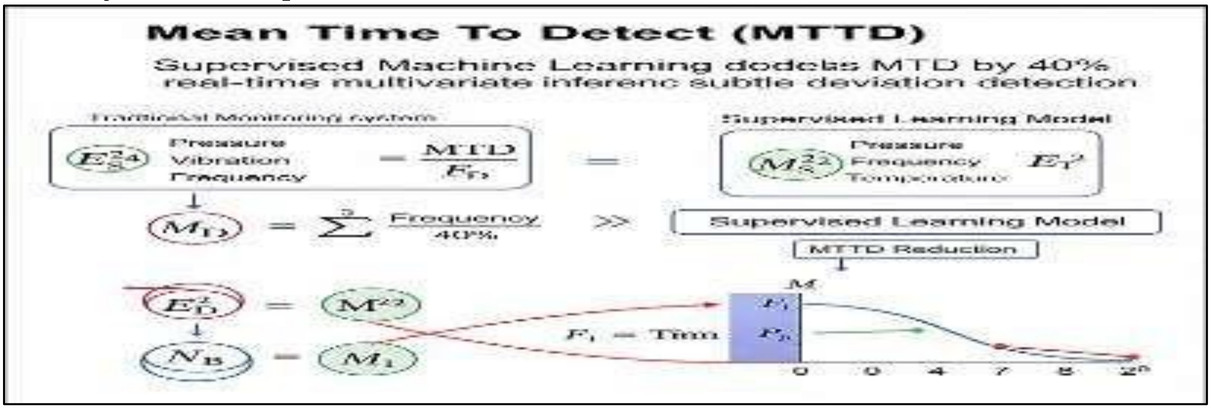

Figure 5. Benefits of Early Fault Detection

Accurate estimation of the Remaining Time of Useful Life (RUL): Algorithms such as SVR and Gaussian Process Regression will provide robust models for the estimation of the RUL of electromechanical components. This estimate will include adjusted confidence bands, which will enable maintenance planning under controlled probabilistic scenarios, improving the Planned Maintenance Compliance (PMC) rate above 90%.

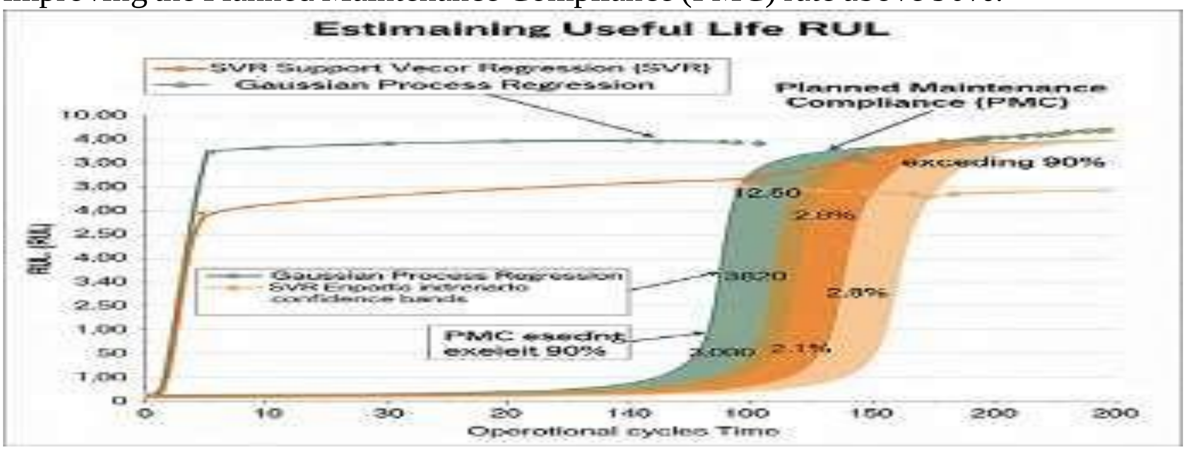

Figure 6. Estimation of the remaining lifetime of components

4.1 Reduced false positive and false negative (FPR/FNR) rate

The implementation of a hybrid inference system (combining RNA, k-NN, and Bayesian Networks) will allow an improvement in the overall accuracy of the classification system of more than 95%, with an expected reduction of the false alarm rate (FPR) below 5%. This will result in a reduction of operational interference and the prevention of superfluous interventions.

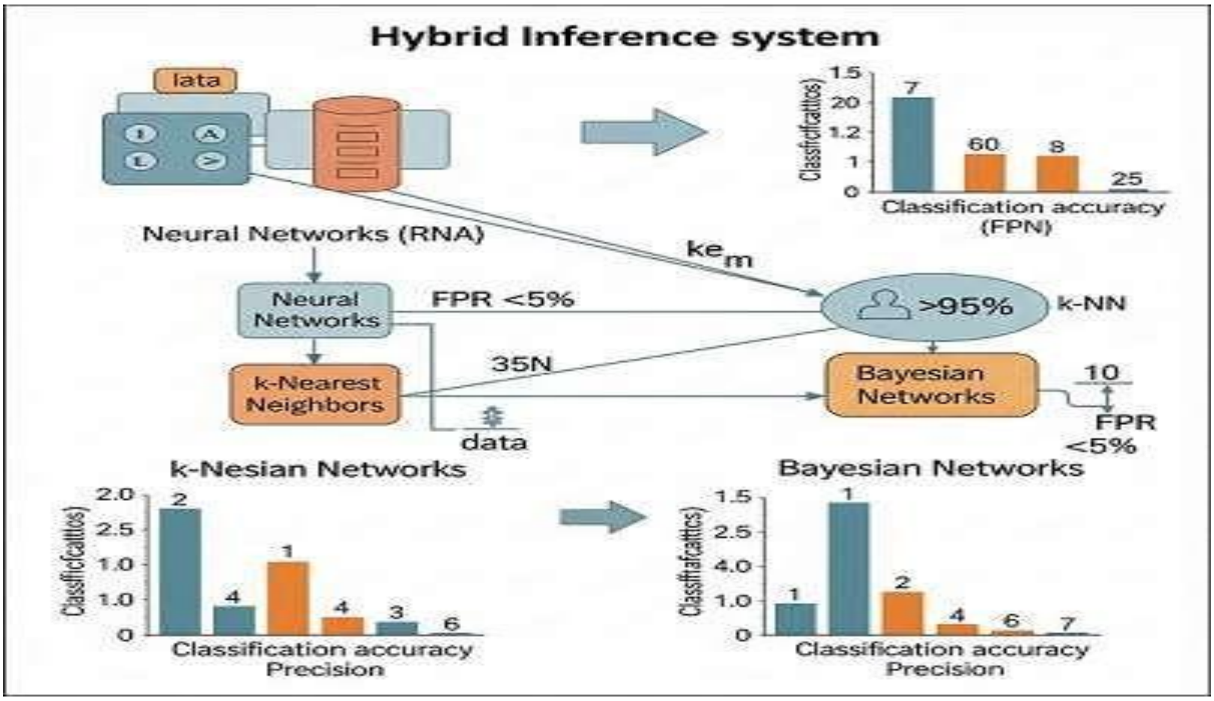

Figure 7. Optimizing decision-making to reduce unnecessary interventions

4.2 Improved Mean Time Between Failures (MTBF) and operational availability

Through condition-based maintenance (CBM), the system will raise the MTBF of key subsystems by at least 25%, increasing the technical availability (A_0) of the overall system, calculated as:

$A_{0}=\frac{MTBF}{MTBF+MTTR}$

This enhancement will have direct implications for the naval unit's mission continuity and tactical response capability.

4.3 Functional integration in real-time SCADA environments

The model anticipates a distributed deployment architecture, wherein the algorithms will be embedded in processing nodes connected to the SCADA through industrial protocols (MODBUS/TCP, OPC-UA). It is anticipated that the system's total latency, encompassing both acquisition and inference phases, will not surpass 20 milliseconds. This ensures a nearly instantaneous response to anomalous events, thereby maintaining operational efficiency and security.

4.4 Implementation of adaptive systems with retraining capability

The system will maintain a policy of incremental learning (online learning) or periodic batch retraining with updated datasets, allowing adaptation to non-stationary conditions, such as the aging of components or changes in operating regime, guaranteeing algorithmic resilience in real conditions.

4.5 Consolidation of a Decision Support System (DSS) oriented to predictive maintenance

The visualization of results through specific dashboards for operators and engineers will include dynamic indicators, intelligent alerts, RUL projections and prioritized maintenance suggestions. This DSS will reduce the operator's cognitive load and standardize technical response protocols to anomalous conditions.

Figure 8. Human-machine interfaces for intelligent monitoring

4.6 Strategic impact on the naval logistics sustainment doctrine

The system's innovation aligns with the principles of I4.0, particularly in the naval environment. This innovation enhances technical traceability, logistics planning, and operational autonomy. A favorable impact on the total life cycle of the assets is projected, accompanied by a sustained reduction in the operating costs (OPEX) of the platform system.

In the domain of naval control and monitoring systems, the integration of artificial intelligence (AI)-driven predictive maintenance systems signifies a paradigm shift, offering a comprehensive understanding of equipment conditions and potential failures through advanced machine learning models (Reddy, Mitta, & Ranjan, 2024).

4. DISCUSSION

The implementation of predictive maintenance systems, founded on machine learning methodologies, signifies a substantial progression in the realm of industrial asset management. This paradigm shift offers the potential for transitioning from a reactive, preventive maintenance strategy to a proactive and optimized approach.

In comparison with preceding studies, the anticipated outcomes of this research are consistent with the successful international experiences of the Sea Hunter (USA), the Smart Ship Project (Japan), and the SOPRENE (Spain) projects. These projects have demonstrated the efficacy of machine learning (ML) in naval environments for diagnostic, prediction, and autonomous control tasks. However, this work is distinguished by its exclusive focus on supervised techniques, its specific application to naval engineering consoles, and its orientation towards operational contexts with technological limitations, such as that of the naval forces of developing countries.

The proposed functional architecture integrates a variety of supervised algorithms, including SVR, k-NN, ANN, Bayesian networks, and Gaussian processes. Each of these algorithms is designed to fulfill a specific function within the analysis flow. This hybrid combination enables the simultaneous classification of operating states and the prediction of failures, as well as probabilistic inference of causes. Consequently, the accuracy of the system is enhanced, and the rate of false alarms is reduced. Furthermore, the incorporation of a continuous feedback and retraining module ensures the system's adaptability to changing conditions, such as component aging or variations in operating regime.

From a theoretical standpoint, this research underscores the viability of supervised learning in critical naval control systems, thereby demonstrating that its implementation can surmount the limitations of conventional approaches predicated on fixed rules or interval maintenance. The proposed system has the practical capacity to reduce the mean time to detect failures (MTTD), improve the estimation of the remaining time of life (RUL), increase the mean time between failures (MTBF), and increase the technical availability (A_0) of the systems under monitoring.
However, it is important to acknowledge the inherent limitations of this approach. Firstly, reliance on labeled data can impede the system's capacity to discern novel or sporadic failures that are not encompassed within the training set. Secondly, the proposal has not yet been empirically validated in real environments; therefore, a future simulation or prototyping phase is required to evaluate its performance under operational conditions. Finally, the integration of the system with existing SCADA systems can present technical challenges related to latency, protocol compatibility, and cybersecurity.

5. CONCLUSIONS

The present study developed a comprehensive framework using supervised machine learning in warships' SCADA systems, with a focus on early fault detection and optimized predictive maintenance. The study's findings indicated that the meticulous selection and integration of supervised models resulted in the effective analysis of operational data, thereby facilitating more precise and timely decision-making processes within marine engineering consoles.
The proposed architecture integrates stages of preprocessing, feature selection, predictive modeling, and visualization of results. This integrated approach enables systematic management of large volumes of data in real time, thereby addressing the inherent challenges associated with such large-scale data management operations.
SVR, k-NN, RNA, Bayesian networks, and Gaussian processes algorithms offer a versatile and adaptable solution to different types of faults and on-board systems. The incorporation of a continuous learning module is instrumental in ensuring that the models are perpetually updated and enhanced, thereby preserving their accuracy and relevance over time.
The findings are relevant from both theoretical and practical standpoints. They demonstrate that a unique approach based on supervised learning can be effectively integrated into complex maritime environments. This integration improves operational readiness and reduces risks and costs associated with unexpected failures. Furthermore, the methodological proposal establishes the foundation for future advancements that will augment automation and efficiency in the maintenance of critical naval systems.
In the realm of future endeavors, it is recommended to undertake the validation of the proposed architecture through experimental implementations in both real and simulated environments. Additionally, it is advised to explore the integration of unsupervised or semi-supervised learning techniques to enhance the detection of both unknown and rare events. It is also advisable to investigate strategies to optimize latency and integration with specific SCADA protocols, in order to maximize system performance on different naval platforms.
This research makes a significant contribution to the field of predictive maintenance in naval SCADA systems. It positions supervised learning as a key tool for modernization and operational safety in warships.
Acknowledgements: The authors would like to express their gratitude to all the participants and the authorities of the University who allowed this investigation to take place.
Funding: Project funded through the Ministry of Science, Technology, and Innovation Colombia, 1022-2020 invitation for R&D&I projects aimed at strengthening the R&D&I

portfolio ARC-2020, Colombian integrated platform supervision and control system project (SISCP-C). Naval School of NCO Officers ARC "Barranquilla".

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