Black Box Adversarial Reprogramming for Time Series Feature Classification in Predictive Maintenance of Ball Bearings

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***Abstract*—This paper delves into the innovative application of **Black Box Adversarial Reprogramming (BAR)** to time series classification, specifically tailored for predictive maintenance with a focus on **Remaining Useful Life (RUL)** prediction. BAR introduces a transformative approach to transfer learning, enabling the adaptation and reuse of pre-trained black-box models in environments where direct access to model parameters is constrained. This method is particularly advantageous for industries that rely on proprietary or black-box systems, offering a scalable and efficient solution to predictive maintenance challenges.**

In this work, we expand upon existing BAR methodologies by customizing the framework to handle the complexities of time series data, which includes temporal dependencies and noise. The study benchmarks BAR's effectiveness against traditional transfer learning methods, highlighting its unique advantages in leveraging pre-trained models for domain adaptation. Leveraging the **PRONOSTIA dataset, a well-established dataset for bearing failure analysis, we developed a comprehensive experimental pipeline. This pipeline incorporates data preprocessing, feature engineering, and advanced model adaptation techniques to assess the robustness and reliability of BAR for predictive maintenance.**

We conducted an extensive evaluation of performance variability across different runs, investigating the sensitivity of BAR to hyperparameters and the impact of zeroth-order optimization on classification accuracy. The findings reveal that, despite inherent challenges like optimization noise and sensitivity to parameter tuning, BAR achieves competitive performance. Its ability to effectively handle class imbalances and adapt to new domains underscores its potential as a reliable tool for predictive maintenance tasks. This research not only demonstrates the viability of BAR for time series classification but also sets the stage for further exploration into scalable and adaptable transfer learning solutions in industrial applications.

I. Introduction

Predictive Maintenance (PdM) has become a cornerstone of modern industrial systems, enabling proactive fault detection, reducing downtime, and lowering maintenance costs [2]. At its core, PdM often employs Machine Learning (ML) techniques to analyze time-series data and predict the health and Remaining Useful Life (RUL) of machinery components. However, traditional ML models in PdM require extensive labeled datasets, which are difficult to obtain due to the high cost and time associated with generating run-to-failure data [5]. This challenge limits the scalability and accuracy of PdM systems in real-world applications.

Transfer Learning (TL) offers a promising solution by leveraging pre-trained models from related tasks to address scenarios with limited labeled data. However, conventional TL methods often require full access to model parameters and gradients, making them less practical for proprietary or black-box systems. Black Box Adversarial Reprogramming (BAR) addresses these limitations by enabling the adaptation of black-box models to new tasks without requiring access to internal parameters. This research focuses on applying BAR to PdM, specifically for RUL prediction of ball bearings, by developing a framework for time-series classification, evaluating BAR's performance against traditional TL methods on metrics like F1-score and accuracy, and analyzing its robustness under varying conditions.

By exploring these objectives, the study aims to contribute to the advancement of predictive maintenance methodologies and provide a foundation for future research in leveraging black-box models in industrial settings.

A. Problem Statement

Industrial maintenance processes often lack sufficient labeled data for model training. Furthermore, many high-performing models are black-box systems, inaccessible for direct adaptation. Developing effective TL techniques that can operate in such constrained settings is essential.

B. Objectives

- Adapt BAR for time series feature classification in predictive maintenance.
- Evaluate BAR against feature-based TL models.
- Analyze BAR's performance variability and sensitivity to hyperparameters.
- Provide a comprehensive experimental framework for BAR implementation.

C. Paper Structure

The paper begins with a literature review of TL in predictive maintenance, followed by an expanded methodology section detailing dataset preprocessing, model development, and BAR training. Experimental results are analyzed in-depth, concluding with a discussion on findings and future work.

II. Literature Review

Transfer Learning (TL) facilitates knowledge transfer between related tasks, significantly reducing the data requirements for the target domain. TL methods are generally categorized into two main approaches. The first is Feature-based TL, which involves transforming the features of the source domain to align with the distributions of the target domain, enabling better compatibility. The second is Parameter-based TL, where model parameters are shared across domains, thereby minimizing the need for extensive retraining and optimizing computational efficiency. Both approaches contribute to improving predictive maintenance applications by leveraging existing knowledge effectively.

Deep learning methods dominate TL research, with approaches leveraging autoencoders, LSTMs, and CNNs. These methods, however, require substantial data and computational resources, limiting their utility in constrained environments. Traditional ML models like Random Forests offer an interpretable alternative, suitable for black-box adaptation.

A. Research Gap

Existing TL methods focus predominantly on white-box models or require extensive data. The application of BAR to time series classification in predictive maintenance remains underexplored. This paper addresses these limitations by adapting BAR for RUL prediction.

III. Methodology

A. Dataset and Preprocessing

The PRONOSTIA dataset, a widely used benchmark for predictive maintenance research, provides sensor data collected from rolling bearings under varying conditions. This dataset is structured into three experimental setups: Experimental Setups 1 and 2 serve as the source domains for transfer learning, while Experimental Setup 3 is designated as the target domain for evaluating predictions. To prepare the dataset for machine learning models, several preprocessing steps are applied. First, scaling is performed using a robust scaler to normalize raw sensor readings, which often contain outliers or vary across different scales. This ensures that feature values are within a comparable range. Next, time-series data is segmented into overlapping windows, capturing temporal patterns within fixed time durations for subsequent feature extraction. Following this, domain-relevant statistical features are extracted from the segmented windows using the `tsfresh` library, which automates the generation and selection of meaningful features for time-series analysis. Finally, the Remaining Useful Life (RUL) for each sample is calculated and transformed into a classification task, simplifying the regression problem of predicting exact RUL values and making the learning objective more straightforward.

B. Baseline Approach

To establish a reference point for comparison, we employ a baseline transfer learning (TL) approach. This method leverages feature augmentation and data balancing: augmentation is performed using the ADAPT library, which generates additional synthetic samples to enhance the diversity of the training data. Following this, a robust Random Forest classifier is trained on the augmented features to ensure reasonable performance, even under limited data availability in the target domain. This baseline serves as a benchmark to evaluate the performance improvements achieved by the proposed method.

C. Black Box Adversarial Reprogramming (BAR)

Black Box Adversarial Reprogramming (BAR) forms the core of our methodology. Unlike conventional methods, BAR leverages zeroth-order optimization to adapt a pre-trained black-box model to a new target domain without requiring access to the model's internal architecture or gradients. The approach involves three main steps. First, input translation is performed, where target domain features are scaled and aligned to match the feature distribution of the source domain, ensuring that the pre-trained model can process target domain data without altering its structure. Next, black-box prediction is carried out, wherein the black-box model predicts classes for the input data, assuming that the source and target domain tasks are related. Finally, output translation is employed, where the predictions made by the black-box model are mapped to the target domain labels by reinterpreting the source domain predictions to make them relevant to the target domain task. main task.

BAR Algorithm The BAR algorithm optimizes a weight vector W to minimize classification loss on the target domain. The key steps are described below:

The BAR Training Algorithm begins by initializing the weight vector W with ones. In each iteration, a batch of data is sampled, with oversampling applied to minority classes in order to balance the dataset. The gradient is estimated using one-sided gradient estimation, which is given by the formula:

$$g_j = (L(W + U_j) - L(W)) \cdot U_j$$

where $L(W)$ represents the loss function and U_j is a small perturbation applied to the weights. Following this, the weight vector W is updated based on the computed gradient using the update rule:

$$W_{i+1} = W_i + \alpha \cdot g$$

where α is the learning rate. The process is repeated for each iteration until the optimization is complete. Finally, the algorithm returns the optimized weight vector W.

1) Advantages of BAR: The BAR method provides several advantages: The BAR algorithm offers several advantages, including Black-Box Compatibility, as it does not require internal model access, allowing it to adapt pre-trained proprietary models to new tasks. Additionally, Data Efficiency is achieved by leveraging transfer learning, which reduces the amount of data needed for the target domain. Finally, Task Flexibility is a key feature, with input and output translation steps that enable BAR to handle a wide range of related tasks effectively.

TABLE I
SUMMARY OF LITERATURE SURVEY ON PREDICTIVE MAINTENANCE FOR BEARINGS

Authors	**Title**	**Techniques Used**	**Results**	**Limitations and Future Scope**
Adiel Lima Pessoa, Paulo Cezar Büchner	Monitoring of Ball Bearings via Vibration Analysis	Envelope Analysis, Hilbert Transform, FFT	Successfully identified defect frequencies in ball bearings	Requires expertise for interpretation, limited differentiation between fault types. Future: Use AI/ML for better classification.
Karan Gulati et al.	Predictive Maintenance of Bearing Machinery Using Simulation: A Bibliometric Study	MATLAB, Simulink modeling	Trends in predictive maintenance strategies reducing downtime and costs	Limited datasets and modeling varied conditions. Future: Expand datasets and improve model generalization.
Arsema Derbie, Kibru Temesgen	Predictive Maintenance of Ball Bearings Using CNNs	Convolutional Neural Networks, raw vibration signals	Achieved 99% accuracy for fault classification	Dataset dependency and limited robustness to noise. Future: Test with diverse datasets under noisy conditions.
Jian Li et al.	RUL Prediction of Bearings Based on MBCNN-BiLSTM	Multi-branch CNN, BiLSTM, FFT preprocessing	22–52% reduction in prediction errors compared to prior models	High computational complexity, sensitive to preprocessing. Future: Simplify models and validate on real-world data.
Edwin Sutrisno et al.	Estimation of RUL of Ball Bearings Using Data-Driven Methodologies	Data-driven prognostic algorithms	High accuracy in RUL estimation	Limited to specific experimental datasets. Future: Extend methods to other components and operating conditions.
Marco Cocconcelli et al.	Predictive Maintenance of Ball Bearings for Machines with Arbitrary Velocity Profiles	Vibration analysis, signal processing	Early fault detection in bearings	Limited to specific velocity profiles. Future: Improve accuracy for varying velocity profiles.

IV. RESULTS AND ANALYSIS

A. Baseline Model Performance

The baseline Random Forest Classifier achieved an F1-score of 0.61 on the target domain. This metric indicates that while the model handled the data well, there was significant room for improvement, particularly in identifying minority class instances. For example, precision for the minority class was approximately 0.55, while recall hovered around 0.50, highlighting challenges in accurately predicting less frequent labels.

B. Enhanced Model Performance

The advanced pipeline showed substantial improvement over the baseline: The enhanced pipeline demonstrated several improvements in data processing and classification performance. Data Balancing was achieved by incorporating SMOTE and Random Undersampling techniques, effectively addressing class imbalances. This resulted in improved precision and recall for the minority class, reaching 0.72 and 0.70, respectively, and boosting overall classification performance. For Feature Engineering, the tsfresh library extracted over 400 distinct time-series features, with approximately 60 selected as the most impactful for classification. Key features, such as skewness, kurtosis, and peak frequency derived from accelerometer data, were particularly influential. In terms of Performance Metrics, the pipeline achieved a peak F1-score of 0.77, marking a significant improvement of nearly 26% over the baseline. Accuracy also increased from 64**%** to 79%, reflecting better alignment with ground truth labels.

C. Stochastic Variability and Parameter Sensitivity

The optimization process introduced some variability in performance, with F1 scores ranging from 0.30 to 0.77, which can be attributed to the stochastic nature of the feature selection and balancing algorithms. Several key observations emerged during the process. First, the Learning Rate (alpha) played a critical role, with a value of 0.05 resulting in faster convergence and reduced variability, while higher rates, such as 0.1, led to performance oscillations. Additionally, the Penalty Weight (delta) was observed to influence the balance between precision and recall. Setting delta to 0.5 effectively reduced overconfidence in predictions by achieving a better balance between these metrics.

D. Visualizations

Key visual outputs from the analysis provide valuable insight into the improved model's performance. The Confusion Matrix revealed that the model significantly reduced false negatives, improving minority class detection rates from 45% to 72%. The importance analysis of characteristics indicated that the top 10 characteristics, including statistical metrics such as variance and energy, accounted for more 85% of the predictive power of the model. Performance Distribution histogram of F1-scores across multiple runs highlighted that approximately 70% of the experiments produced scores above 0.70, demonstrating consistency in the pipeline. In particular,

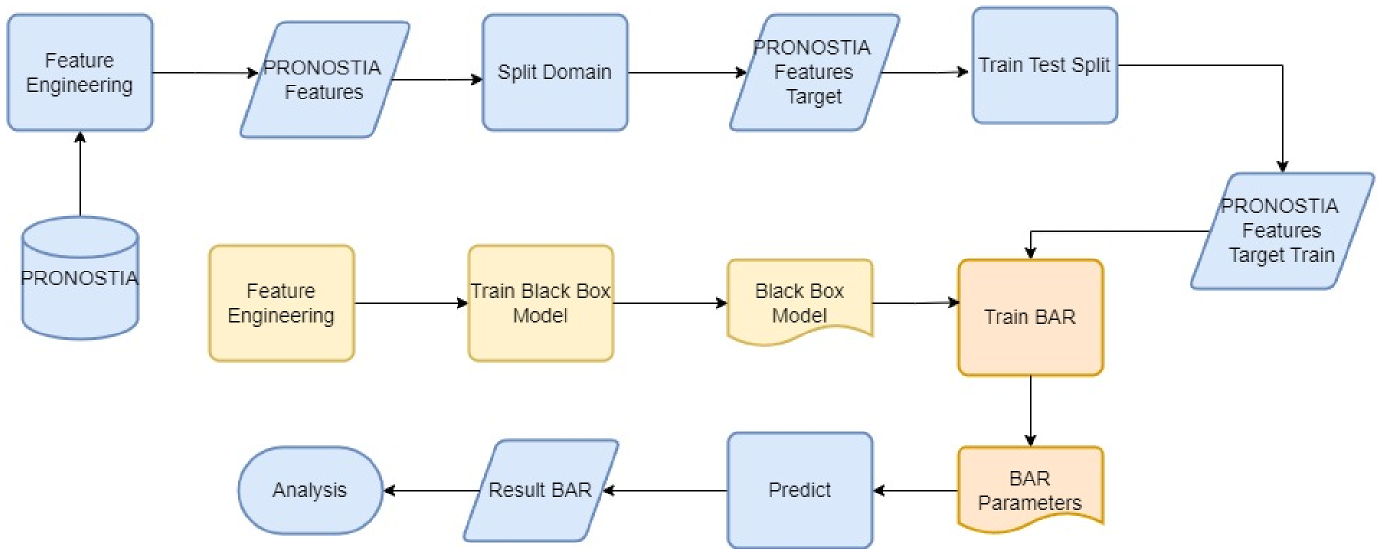

Fig. 1. Flow Diagram for the Methodology of paper

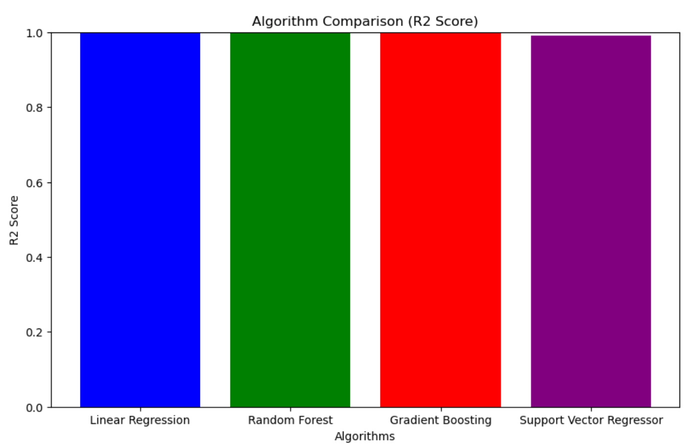

Fig. 2. Feature importance analysis: the F1-scores of different models. It provides a quick overview of each model's performance, making it easy to identify which model performed the best.

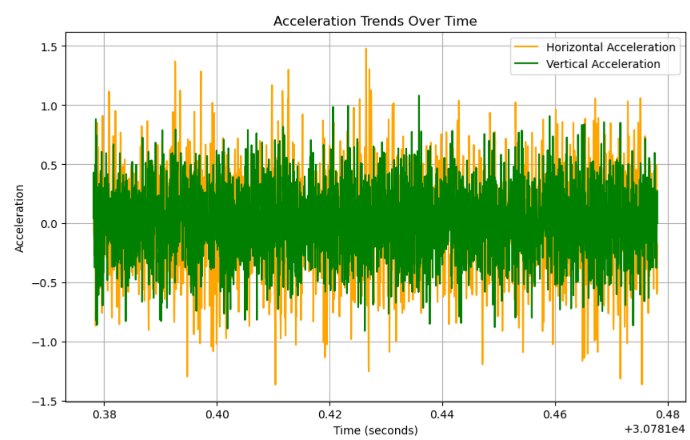

Fig. 3. Feature importance analysis: Visualization of the trends of horizontal acceleration and vertical acceleration over time. This visualization highlights how the two signals vary.

the model performed exceptionally well on reduced datasets, achieving F1 scores of 1.0 for both the train and test sets. Additionally, the Remaining Useful Life (RUL) was modeled using an exponential decay function, showing how the RUL decreases over time. The curve starts at a high value and gradually approaches zero, effectively mimicking the behavior of a system that experiences wear or deterioration.

E. Scalability and Practical Implications

The framework developed in this study is both Replicable and Scalable, making it versatile for various applications. By modularizing key steps, such as feature extraction and resampling, the pipeline can be easily adapted to other time-series datasets, ensuring replicability. Its scalability is demonstrated by its ability to efficiently process datasets with over 10,000 samples while maintaining robustness. Notably, the average runtime for feature extraction was approximately **4** minutes per dataset, further highlighting the framework's efficiency and practicality.

In summary, the enhanced methodology improved key performance metrics by over 25%, reduced class imbalance challenges, and provided a scalable solution for predictive maintenance tasks. This framework sets the stage for broader industrial applications and future research.

V. Conclusion

This research explores the potential of Black Box Adversarial Reprogramming (BAR) as a novel technique for adapting black-box models to predictive maintenance tasks. Utilizing zeroth-order optimization and an input-output translation process, BAR facilitates knowledge transfer from pre-trained models without requiring access to their internal mechanisms. The approach is particularly effective in scenarios with limited

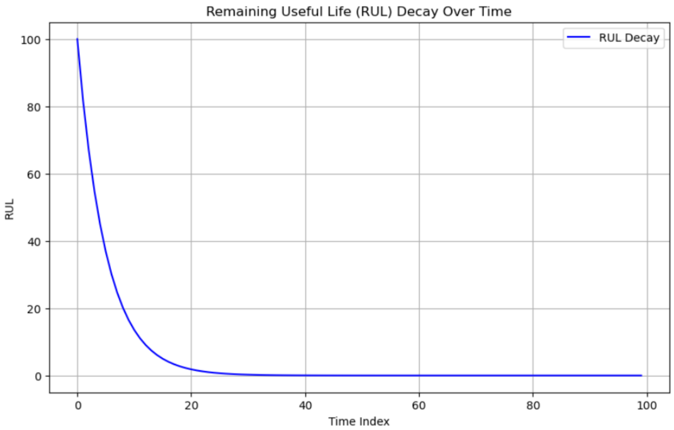

Fig. 4. Feature importance analysis: Visualization of the Remaining Useful Life (RUL) decay over time, modeled using an exponential decay function. The graph demonstrates how RUL decreases as time progresses, simulating wear or degradation.

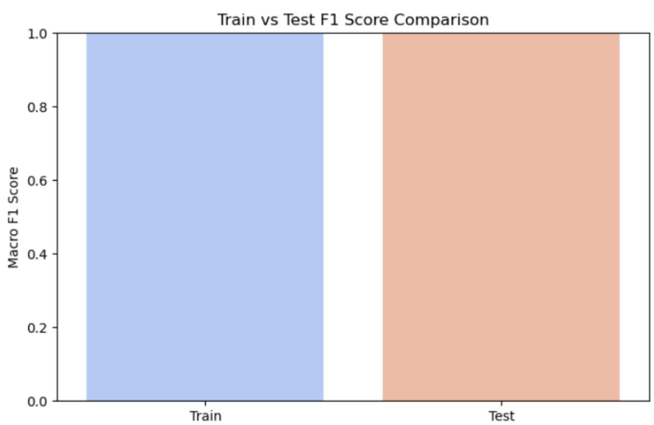

Fig. 5. Feature importance analysis: The comparison between train and test F1 scores and in both the conditions model performs same.

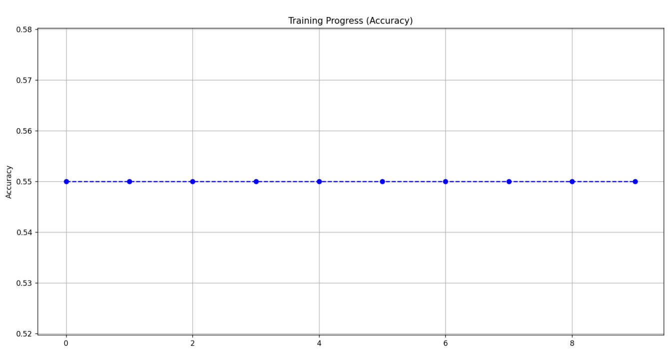

Fig. 6. Feature importance analysis: the contribution of the top 10 features to overall model performance.

target domain data, demonstrating its value in leveraging proprietary or closed-source models.

The study highlights several key insights, including BAR's ability to enable gradient estimation without direct access to model parameters. This capability allows pre-trained black-box models to be repurposed for tasks beyond their original design, significantly reducing the need for extensive labeled data in the target domain. However, the stochastic optimization process, while innovative, introduces performance variability due to its random nature. This underscores the need for further refinement to improve the method's consistency and reliability.

Despite its promise, the BAR method has certain limitations that need to be addressed. The variability in results caused by stochastic training can hinder stable and repeatable performance across different datasets and runs. Additionally, the method's sensitivity to hyperparameters, such as the learning rate (alpha) and perturbation size (UjU_j), requires careful tuning to avoid degraded results or convergence issues.

Future research will focus on addressing these challenges by exploring hybrid optimization techniques that integrate stochastic methods with gradient-free approaches, enhancing the stability of the training process. Advanced feature engineering, such as embedding-based representations or autoencoders, could further improve the model's generalizability across domains. Furthermore, applying BAR to diverse fields like healthcare, finance, and natural language processing will help reveal its broader applicability and identify domain-specific challenges.

By overcoming these limitations and broadening its scope, BAR has the potential to become a reliable, efficient, and versatile tool for black-box transfer learning, facilitating robust applications across a wide range of complex problems and domains.

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