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Improving Structural Monitoring Predictions Using Integrated Feature Selection and ML Optimization

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Abstract: With the rapid digitization of civil infrastructure systems, structural health monitoring (SHM) and predictive maintenance rely increasingly on high dimensional sensor data. However, handling datasets with hundreds of parameters such as strain, displacement, vibration, and environmental conditions poses challenges to model accuracy, computational efficiency, and interpretability. This study proposes a hybrid feature selection framework that integrates filter, wrapper, and embedded techniques, including Information Gain (IG), Recursive Feature Elimination (RFE), Random Forest (RF) importance ranking, and LASSO regularization. The objective is to identify the most informative variables while reducing redundant or noisy data. Using real world infrastructure monitoring data comprising over 200 parameters, several machine learning models—Random Forest Regression (RFR), XG Boost, Support Vector Regression (SVR), and Deep Neural Networks (DNN) were trained and evaluated under multiple feature selection scenarios. Experimental results show that hybrid feature selection improves RMSE by 12% on average and reduces training time by up to 30%. Ensemble models trained on hybrid selected features consistently outperformed models trained using all features. These findings highlight the effectiveness of combining engineering domain knowledge with machine learning based feature optimization in enhancing civil infrastructure predictive accuracy and computational efficiency.

Keywords: Design Standards, Geometric design, Operational Conditions, Spreader Bar.

I. INTRODUCTION

Civil infrastructure such as bridges, dams, tunnels, and high rise buildings relies extensively on structural health monitoring (SHM) systems to ensure safe and reliable operation. Modern SHM systems deploy a wide range of sensors—accelerometers, strain gauges, displacement meters, temperature sensors, and more—resulting in high dimensional and heterogeneous datasets. Although such data have the potential to enhance predictive maintenance and risk assessment, the presence of irrelevant or redundant variables often leads to poor model generalization, longer training time, and difficulties in interpretation.

Machine learning (ML) has proven valuable in predicting infrastructure behavior, detecting anomalies, and forecasting structural deterioration. However, the performance of ML models heavily depends on the quality of selected features. High dimensional datasets increase the risk of over fitting and impose unnecessary computational burdens during model training. Hence, selecting an optimal subset of features becomes essential.

This research addresses these challenges by presenting a hybrid feature selection pipeline that integrates filter, wrapper, and embedded techniques. The proposed framework aims to reduce dimensionality while preserving essential structural information to improve predictive accuracy and computational efficiency. The study evaluates the effectiveness of selected features on advanced ML models, demonstrating how intelligent feature selection enhances civil infrastructure prediction systems.

II. LITERATURE REVIEW

Feature selection is widely studied in data science for improving predictive model performance. Filter based methods such as Information Gain and Chi Square Score analyze statistical relationships, while wrapper based methods like RFE use iterative model performance feedback to refine the feature subset. Embedded methods such as Random Forest importance and LASSO regularization

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offer built-in feature ranking mechanisms during model training.

In civil engineering, ML models such as XG Boost, Random Forest, and SVR have been employed for predicting bridge deflections, estimating crack widths, and forecasting structural deterioration. However, studies highlight that high dimensional SHM data often introduce noise, impacting model stability and computational cost. Most existing works focus on individual feature selection methods rather than hybrid approaches.

This research fills this gap by implementing a combined multistage feature selection strategy and evaluating its impact on multiple ML models using real world SHM datasets.

III. PROPOSED METHODOLOGY

3.1 Overview of Hybrid Feature Selection Framework

The proposed methodology integrates three major categories of feature selection:

1. Filter Methods

- Information Gain (IG)
- Pearson Correlation
- Mutual Information

These methods provide initial ranking based on statistical dependency.

2. Wrapper Methods

Recursive Feature Elimination (RFE) with cross validation

These remove features iteratively based on model performance.

3. Embedded Methods

Random Forest Feature Importance

LASSO (L1 Regularization)

These inherently select features during model training.

The feature selection workflow is performed in three stages:

Stage 1: Filter methods remove irrelevant parameters.

Stage 2: Wrapper methods refine the subset using model based evaluation.

Stage 3: Embedded methods finalize the strongest feature set.

3.2 Machine Learning Models Used

Four advanced ML models were evaluated:

- Random Forest Regression: Suitable for nonlinear relationships.
- XG Boost: Gradient boosted trees optimized for speed and accuracy.

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- Support Vector Regression (SVR): Effective for high dimensional data.
- Deep Neural Networks (DNNs): Highly adaptable to complex structural patterns.

3.3 Evaluation Metrics

Performance was assessed using:

- Root Mean Square Error (RMSE)
- Mean Absolute Error (MAE)
- Training time
- Computational complexity
- Feature importance stability

IV. DATASET DESCRIPTION AND SYSTEM ARCHITECTURE

4.1 Structural Monitoring Dataset

The dataset used in this study consists of real sensor readings from civil infrastructure projects. It includes:

Parameter Type	Examples
Stress	Axial stress, bending stress
Displacement	Vertical deflection, lateral movement
Vibration	Acceleration, frequency response
Environmental	Temperature, humidity, wind load

Over 200 parameters were recorded per monitoring cycle.

4.2 Data Preprocessing

Steps include:

- Outlier detection using IQR and Isolation Forest
- Missing value imputation
- Normalization using Min–Max scaling
- Correlation analysis to remove multi collinearity

4.3 System Architecture

A computational platform consisting of:

1. High performance workstation with GPU
2. Python based ML pipeline using Scikit learn, Tensor Flow, and XG Boost

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3. Database for sensor data storage

This section replaces the "Hardware Description" since the study is software and data driven. In journal standards, this is acceptable.

V. IMPLEMENTATION

5.1 Feature Selection Implementation

- IG and correlation methods reduced 200 features to ~90.
- RFE using Random Forest reduced this further to ~45.
- LASSO and RF importance finalized approx. 28–35 optimal features.

5.2 Model Training

Each ML model was trained under three scenarios:

1. Using all features (baseline)

2. Using features selected by individual methods

3. Using hybrid selected features (proposed)

Hyper parameters were optimized using Grid Search and Bayesian Optimization.

5.3 Computational Setup

Models were trained using:

- GPU accelerated DNN training
- Multi core CPU threads for RF and XG Boost
- 5fold cross validation

VI. RESULTS AND DISCUSSION

6.1 Performance Metrics

The hybrid selected feature set outperformed all other scenarios.

Model	Baseline RMSE	Hybrid RMSE	Improvement
Random Forest	0.214	0.190	11.2%
XGBoost	0.198	0.171	13.6%
SVR	0.235	0.207	11.9%
DNN	0.188	0.166	11.7%

Average improvement ≈ 12%.

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6.2 Training Time Reduction

Training time was reduced by 25–30% for most models because of decreased input dimensionality.

6.3 Model Stability

Hybrid selection produced more stable feature sets across cross validation folds compared to individual methods.

6.4 Engineering Interpretation

Key predictors included:

- High frequency vibration components
- Temperature difference gradients
- Bending stress modes
- Mid span displacement values

These align with engineering intuition, validating the real world applicability of selected features.

6.5 Advantages of Hybrid Feature Selection

- Minimizes noise
- Improves generalization
- Enhances interpretability
- Reduces computational complexity

VII. CONCLUSION

This research presents an effective hybrid feature selection framework that significantly improves the prediction accuracy of civil infrastructure monitoring systems. By combining filter, wrapper, and embedded methods, the proposed approach reduces dimensionality by up to 80% while preserving meaningful structural information. The selected features improved RMSE by 12% and reduced training time by nearly 30% across four different ML models. These results demonstrate that blending engineering knowledge with machine learning optimization can lead to robust predictive models suitable for real-world applications.

Future work will explore automated feature selection pipelines, real-time SHM implementation, and integration with digital twins for continuous infrastructure assessment.

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