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On the Accuracy and Efficiency of Received Signal Strength Modelling for a Forest Environment

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***Abstract*—Within telecommunications, the accuracy and efficiency of machine learning models (ML) define their utility, and consequently, the choice of ML mechanisms assumes paramount importance. This study focuses on the exploration and comparison of diverse ML and ensemble learning techniques, with a specific emphasis on their significance in crafting precise and extensive models. To this end, the quality of the received signal and the optimization and functioning of wireless communication networks rely heavily on accurately predicting the received signal strength indicator (RSSI) and path loss (PL). The studied environment, which is highly complex, spans 2000 km2 of the intricate landscapes of the American River Hydrologic Observatory (ARHO) networks and is characterized by a diverse blend of terrain features and vegetation distributions. Notable independent variables under consideration include path distance, canopy coverage, terrain variability, and path angle. The proposed ensemble ML approaches demonstrate remarkable accuracy and efficiency when it comes to modeling and predicting the RSSI values in forested environments.**

***Index Terms*—Machine learning, ensemble learning, internet of things, radio propagation.**

I. Introduction

The Internet of Things (IoT) is increasingly utilized to manage a wide range of essential processes and infrastructures in modern societies. This trend is attributed to its remarkable flexibility, adaptability, and cost-effectiveness. However, due to the crucial nature of the assets being controlled, and the services to be delivered, it is imperative to thoroughly comprehend the deployment environment from a radio propagation standpoint [1]. This understanding underscores the significance of radio characterization, which seeks to forecast and enhance the utilization of the radio spectrum in wireless networks. This becomes particularly critical in the context of future IoT implementations, where substantial proliferation of devices is anticipated, leading to a rapid surge in interference. Such interference can have a detrimental impact on network performance [2].

The emergence of the fifth generation (5G) of mobile networks has introduced the adoption of a wider spectrum encompassing higher-frequency millimeter-wave (mm-wave) bands. These bands hold the promise of achieving remarkably high data rates. However, realizing the full potential of microwave communications is dependent on the development of precise channel models and accurate predictions of the received signal strength indicator (RSSI) and path loss (PL). These predictions play a pivotal role in tasks such as determining cell coverage, strategically placing base stations (BS), and fine-tuning network performance [3]. However, the utilization of higher frequency bands presents challenges due to increased losses from factors such as open space, scattering, and diffraction that arise from the propagation environment. In particular, within complex environments such as forested areas, diverse variables such as path distance, canopy coverage, terrain variability, and path angle can exert a notable impact on RSSI compared to lower frequency bands characterized by longer wavelengths. Although it is essential to have dependable and efficient models for PL estimation in network planning and optimization, comprehending their applicability in mm-wave frequencies across diverse propagation scenarios remains an ongoing pursuit, especially in complex environments [4].

RSSI estimation, which encompasses both the signal's transmission and its attenuation during propagation, is regarded as a fundamental factor for evaluating the performance of wireless communication. This assessment is particularly crucial during the phases of network planning and optimization [5].The RSSI estimation and its related counterpart, radio propagation modeling, primarily concentrate on predicting PL within the realm of wireless communication and can be framed as a

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supervised regression task. ML techniques can achieve high precision and effectiveness, with respect to computational complexity and prediction time, as well as strong suitability for various applications in wireless networks [6].

The authors in [7] apply a probabilistic neural network (PNN) to predict a sliding-window pattern of RSSI signals, in a factory setting, while artificial neural network (ANN) is utilized in [8] for RSSI estimation in an indoor environment.

In this paper, our objective is to evaluate the utility of the various ensemble ML methods in creating RSSI prediction models of complex forested environments for cellular communications. The models are evaluated in terms of their accuracy and efficiency. Different ensemble ML methods result in models of different levels of accuracy and efficiency. The rest of this paper is structured as follows. Section II describes the data collection campaign and modeling details. In Section III, the ensemble ML techniques utilized are explained. Section IV presents the simulation metrics and outcomes, and Section V concludes with remarks about the importance of ML in the derivation of models with high accuracy.

II. Data collection

The training and validation process for all the ML techniques involved utilized real-world data from an extensive measurement campaign conducted in the California Sierra Nevada. Measurements were carried out within the American River Hydrologic Observatory (ARHO) networks [9]. Various sensors, interconnected through 14 separate low-power wireless mesh networks, are utilized to measure snow depth, air temperature, air relative humidity, soil temperature, soil moisture, and solar radiation. These networks are deployed within the American River basin, spanning an area of 2,000 km^2, and 2,218 wireless links were utilized. RSSI measurements were carried out using 2.4 GHz radios, annotated with several characteristics, including:

- Path ground distance: This numeric value, measured in meters, signifies the span between the two radios engaged in communication. It is derived from their respective GPS positions and elevations.
- Mean percentage of tree canopy cover: Indicating a value ranging from 0% to 100%, this metric is the average derived from the National Land Cover Database (NLCD) vegetation map. It illustrates the typical extent of vegetation along the line of sight connecting the two nodes.
- Terrain complexity: Referring to the diversity of elevation values along the line-of-sight path, it is quantified by calculating the standard deviation of raster values from the Digital Elevation Model (DEM).
- Vegetation variability: This aspect is determined by computing the standard deviation of NLCD vegetation map values along the communication path.
- Path angle: This angle is the inclination between the line-of-sight path and the horizontal plane.
- Canopy coverage at the source: It involves bilinearly interpolating the NLCD vegetation map values at both the source and the receiver locations, resulting in a value between 0% and 100%.
- Canopy coverage at the receiver: Similarly to the "Source canopy coverage" feature, it estimates the vegetation cover at the receiver's node using the NLCD map values.

It is worth mentioning that in the given dataset the initial transmission signal strength is not included. In our work, the attenuation-related parameters are adequate to estimate the RSSI values, without the need for the transmission signal strength as an input parameter. The latter serves as a reference signal and remains fixed. Thus, including a fixed parameter would not contribute to the model's performance and the absence from the dataset does not effect the prediction accuracy. For further details, see [9].

III. Machine Learning Models

Over the past years, ML techniques have been proposed for channel modeling in order to address the challenges posed by site-specific and complex requirements of deterministic methods, as well as the limitations arising from the inaccuracies of stochastic approaches [10]. The ensemble method represents an ML approach in which multiple models, typically diverse in nature and often referred to as "weak learners," are trained and their results are merged to enhance the overall prediction. A prevalent category involves bagging and boosting learners, where different versions of the same learner (e.g., decision trees) are combined simultaneously or sequentially [11].

A. Extreme gradient boosting (XGBoost)

XGBoost stands as a distributed and scalable machine learning framework centered on gradient-boosted decision trees (GBDT). The concept of gradient boosting involves the amalgamation of predictions from multiple simpler models to effectively predict a target variable in a supervised learning context. XGBoost occupies a prominent position among machine learning libraries, catering to regression, and classification tasks. It provides the capability of parallel tree boosting and functions as a distributed gradient-boosting library designed for high effectiveness, adaptability, and portability [12].

B. Gradient Boosting Decision Tree (GBDT)

GBDT is a boosting ensemble technique that consists of a collection of individual decision trees. GBDT training occurs sequentially, and the combined output of all trees contributes to the final prediction using the gradient boosting methodology. The residual error from the preceding decision tree serves as input for the subsequent decision tree. This subsequent tree is trained by following the direction of the negative gradient of the previous decision tree. GBDT has gained popularity for addressing various challenges in wireless networks due to its precision, efficiency, and strong interpretability [13].

C. Categorical boosting (Catboost)

CatBoost builds on the principles of gradient boosting and decision trees. At its core, boosting involves the sequential integration of multiple weaker models. Through gradient boosting, decision trees are sequentially fitted, enabling them to learn from the errors of preceding trees and mitigate those errors. This iterative process continues until the chosen loss function is no longer being minimized, resulting in the continual inclusion of new functions alongside existing ones. Catboost can effectively address the issue of prediction bias, leading to improved accuracy, reduced prediction times, and notable efficiency, especially in low-latency settings [12].

D. Light Gradient Boosting Machine (LGBM)

LightGBM represents a form of gradient boosting methodology, which originated as a successor to its precursor, XGBoost. LGBM is engineered to excel in training larger datasets within a significantly reduced timeframe while achieving similar levels of accuracy compared to XGBoost. This efficiency is enabled through a technique called Gradient-based one-sided sampling (GOSS), which strategically extracts the most valuable information by intentionally excluding samples with lesser information (small gradients) within the dataset. Additionally, LightGBM introduces an innovation known as exclusive feature bundling (EFB) to curtail model complexity. This is achieved by merging akin features in a nearly lossless manner. LGBM boasts enhanced accuracy, increased computational speed, and reduced utilization of system memory, compared to many other gradient boosting frameworks [14].

IV. Machine Learning Model Evaluation

A. Evaluation metrics

Regression models can be evaluated based on their (i) accuracy, (ii) efficiency, and (iii) coverage or extension. Accuracy measures how close the model's predictions are to the actual values based on error metrics, while efficiency concerns computational resources required to train and use the model, and is essential because regression models are often used in real-time or resource-constrained applications. Finally, coverage addresses the prediction uncertainty through prediction intervals. It is typically expressed as prediction intervals, which capture the uncertainty associated with the model's predictions.

The most extensive criterion for regression models is their accuracy, which, as defined earlier, refers to how well the model's predictions match the actual numerical values in the data set. This assessment of predictive performance is numerically quantified using metrics such as the mean absolute error (MAE), the mean absolute percentage error (MAPE), the Mean Squared Error (MSE), and the Root Mean Squared Error (RMSE). These metrics measure the accuracy of the model's predictions in terms of the magnitude of the errors and are mathematically defined in the subsequent equations.

[15]:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|RSSI_i - \overline{RSSI}_i| \tag{1}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(RSSI_i - \overline{RSSI}_i)^2 \tag{2}$$

$$RMSE = \sqrt{(\frac{1}{N})\sum_{i=1}^{N}(RSSI_i - \overline{RSSI}_i)^2} \tag{3}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}|\frac{RSSI_i - \overline{RSSI}_i}{RSSI_i}| \times 100\% \tag{4}$$

where N denotes the test set number of input records, $RSSI$ represents the actual RSSI value, and $\overline{RSSI}$ the predicted one for the i-th sample.

The MAE represents the mean of the absolute discrepancies between the actual and predicted values. On the contrary, the RMSE places greater emphasis on significant errors by squaring the differences before extracting the square root. A reduced RMSE signifies increased predictive accuracy, reflecting closer alignment between predicted and actual values. The MSE is frequently employed to gauge the efficacy of regression models, determining the average squared divergence between observed and projected outcomes. Meanwhile, MAPE, expressed as a percentage, facilitates comparisons of predictive accuracy across various models or methods for estimating RSSI values. Lower values of MAE, RMSE, or MAPE indicate higher accuracy.

Among the metrics, MAPE is the perfect candidate to measure the precision and possibly coverage of RSSI prediction models in forest environments for several reasons. First, it quantifies the relative error between the predicted and actual RSSI values as a percentage. In forest environments, where the absolute RSSI values can vary significantly due to factors like tree density, terrain, and interference, using a relative measure like MAPE can provide a clearer picture of the prediction accuracy. Second, unlike MAE or RMSE, which focus solely on the magnitude, MAPE displays both the magnitude and tendency of errors. This is valuable in scenarios where both overestimations and underestimations of RSSI can have similar operational implications. While MAPE primarily measures prediction accuracy, it indirectly provides insights into prediction coverage. If MAPE is consistently high across different parts of the dataset, it can suggest that the model is struggling to accurately predict RSSI values across a range of scenarios or conditions, indicating potential limitations in its coverage. In a complementary analysis, coverage is typically expressed in terms of confidence intervals of a prediction, as, for example, depicted in residual box plots. However, despite its advantages, it is vital to recognize that the MAPE has certain limitations, such as sensitivity to extreme values and its potential undefined status when actual values are zero. Therefore, it is commonly paired with other metrics to provide a comprehensive assessment of prediction performance [14].

B. Numerical Results

For the RSSI estimation in complex forested environments, a dataset comprising 4,157,324 measurements collected from 2,218 wireless connections within the ARHO networks, is utilized [11]. The complete set of RSSI values, accompanied by their corresponding feature sets, was randomly split into two groups: 80% of the data was employed for training,

TABLE I
ERROR MEASUREMENT METRICS FOR PATH LOSS PREDICTION

ML Model	MAE (dBm)	MSE (dBm)	RMSE (dBm)	MAPE (%)
XGBoost	2.884	20.006	4.472	3.738
LGBM	3.03	20.463	4.523	3.915
CatBoost	3.139	21.492	4.635	4.062
GBDT	4.075	29.888	5.467	5.267

while the remaining 20% was designated for testing. The 80/20 division is a commonly applied empirical guideline in various scenarios. To assess our models, we employ the Scikit-Learn open-source ML library, which is implemented using the Python programming language. The parameters of each model were tuned using the Optuna framework, as described in [16], to exhibit their optimal performance, and were evaluated based on the metrics related in Section III-D. For our experiments, we exploit the capabilities of an NVIDIA GeForce RTX 3080 GPU with 8704 cores and 10GB of memory. The experiments are executed in a workstation with a 12th Gen Intel(R) Core(TM) i9-12900K CPU and 32 GB RAM.

The error evaluation performance of the suggested ensemble ML models is depicted in Table I. XGBoost demonstrates superior performance compared to the other algorithms concerning the accuracy of RSSI predictions. It has consistently outperformed all other methods in the performance metrics mentioned earlier. XGBoost achieved an MAE of 2.884 dBm, an MSE of 20.006 dBm, an RMSE of 4.472 dBm, and a MAPE of 3.738%. Both LGBM and CatBoost models closely approach the XGBoost performance, with MAPE values of 3.915% and 4.0621%, respectively. This suggests that LGBM and CatBoost could serve as viable alternatives for the RSSI prediction task, yet GBDT yields the least favorable outcome with a MAPE value of 5.267%. On the basis of the metrics, boosting ensemble methods seem to accurately estimate the RSSI values even in a complex forested environment. In general, the ensemble ML algorithms in this study are proven superior in terms of accuracy in RSSI estimation, scoring better results than most of the methods studied in [9]. The evidence of this statement is shown in the comparison, in terms of MAE, with the methods used in [9], that utilize the same dataset, and is presented in Table II.

Fig. 1 is a scatter plot that illustrates the relationship

TABLE II
MAE COMPARISON

ML Model	Contributing study	MAE (dBm)
XGBoost	[This study]	**2.884**
LGBM	[This study]	**3.030**
CatBoost	[This study]	**3.139**
GBDT	[This study]	4.075
Random Forest	[9]	3.720
k-nearest neighbors	[9]	5.100
Neural Network	[9]	5.150
Adaptive Boosting	[9]	5.550

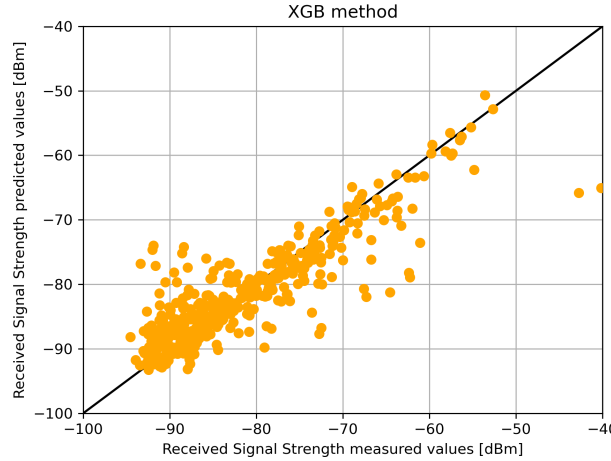

Fig. 1. Estimated versus real measurement values.

between the recorded values where the black line corresponds to the optimal prediction scenario) and the predicted values generated by the best-performing ML technique, namely XGBoost (shown as orange dots). The effectiveness of the prediction model is reflected in the proximity of the prediction dots to the line representing the actual measured test values. The correlation visually indicates a minimal disparity between the actual and forecast values, owing to the low MAPE values in estimating RSSI.

Fig. 2 displays the comparative results of all techniques in predicting RSSI values in a forested environment. As illustrated, XGBoost outperforms the other methods, while the worst performance is measured for the GBDT learner. The suggested ensemble ML methods exhibit high precision characteristics with respect to computation time.

To conclude on the coverage of the accuracy of our predictions we further compare our proposed models by means

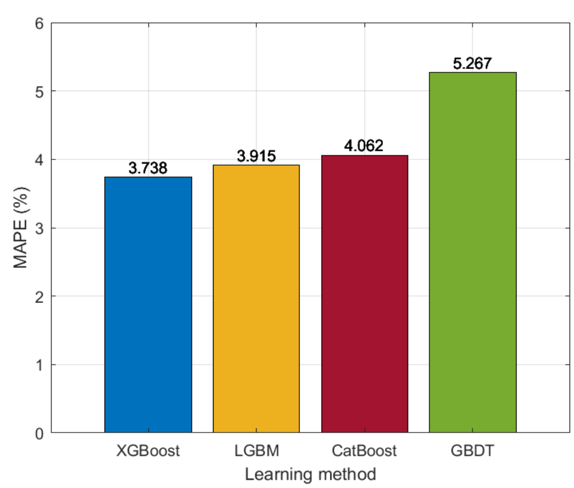

Fig. 2. Comparative results of MAPE (%).

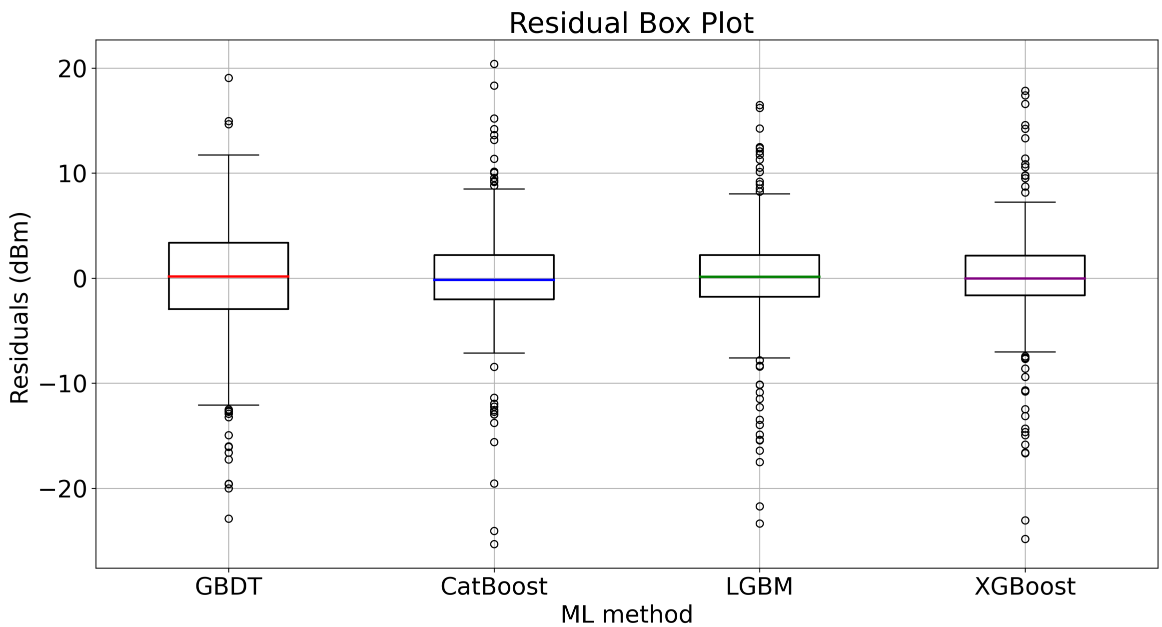

Fig. 3. Box plot for predictions and true values residuals

of a residual box plot for the predicted and measured values in Fig. 3. As expected, both biases and variances of XGBoost are smaller than all other methods, suggesting that the residual between true and predicted values is smaller, achieving greater accuracy results. All the residual values are near zero when compared to the magnitude of the response variable with the number of outliers in all approaches being rather small.

RSSI is one crucial metric that is essential for various processes and functionalities in mobile communication networks. RSSI is used to determine the strength of signals from neighboring base stations and make informed decisions regarding which base station to connect to and when to initiate a handover between cells as the user moves. Furthermore, Radio Resource Management (RRM) algorithms use RSSI to manage radio resources efficiently, including user scheduling algorithms. Such algorithms operate at millisecond timescales on a per-user basis to ensure that each user receives an adequate signal strength for reliable communication while optimizing spectrum utilization. To this end, the efficiency of an ML method is a critical consideration, particularly in real-time resource-constrained deployments.

To understand the impact of the ensemble ML methods on the computational performance, we evaluate efficiency based on the average inference times recorded during testing. From the results, which are depicted in Fig. 4, one can realize that all models achieve relatively small inference times. Nonetheless, the inference times exhibit a notable disparity among the ensemble ML methods. XGBoost demonstrates the highest inference time of , signifying a comparatively (more than twenty times up) longer time for prediction tasks. On the the other hand, LightGBM, CatBoost, and GBDT exhibit significantly lower inference times, with CatBoost and LGBM registering the shortest average inference time at 1.4 ms and 1.7 ms respectively. The results highlight that LightGBM and CatBoost are the most efficient methods in terms of inference times, followed closely by GBDT. XGBoost, while a powerful ML method, exhibits comparatively higher inference times, suggesting a potential trade-off between model complexity and computational efficiency. The results also demonstrate the close relation between accuracy and complexity.

Normalizing ML performance metrics like MAPE by inference time can provide valuable insights into the trade-off

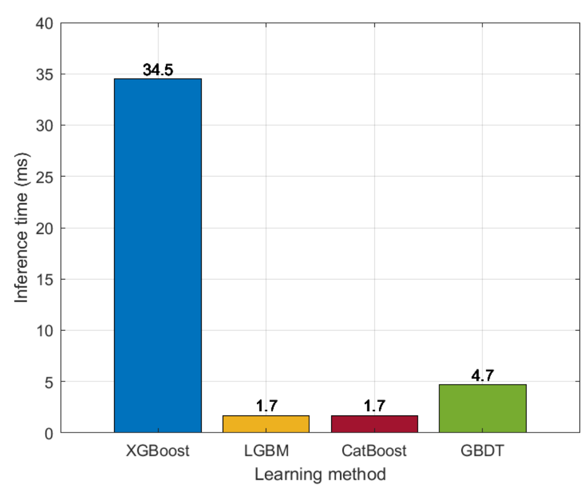

Fig. 4. Average inference time comparison results.

TABLE III
PREDICTION AND ACCURACY NORMALIZATION

ML Model	Prediction normalization (%/ms)	Accuracy normalization (ms/%)
XGBoost	0.1083	9.2295
LGBM	2.3029	0.4342
CatBoost	2.3894	0.4185
GBDT	1.1206	0.8923

between prediction accuracy and computational efficiency.

For illustrative purposes, Table III presents the trade-offs for each algorithm in two columns: A prediction normalization (PN) column, where the relative error distance per millisecond is calculated, and an accuracy normalization column, where the inference time in milliseconds per percentage of relative error is given. Higher PN values suggest better efficiency, while higher AN values offer better accuracy for the computational resources used. CatBoost and LGBM exhibit the highest PN value and stand out as the most efficient in this aspect. While GBDT has relatively lower PN value, suggesting a slower prediction error per unit of time, XGBoost is by far the most inefficient. However, while CatBoost has the highest PN value, it has the next lowest AN value. This implies that while it is computationally efficient, it may sacrifice a bit of accuracy compared to XGBoost and LGBM. XGBoost has the highest AN value, which clearly indicates that it offers better accuracy albeit at the expense of longer inference times.

V. CONCLUSION

In this study, we have introduced an ensemble-based procedure for ML modeling to estimate RSSI values within intricate forested surroundings. We compared the effectiveness of predicting RSSI using four distinct methods: GBDT, XGBoost, LGBM, and Catboost. The results were promising, showing that all the boosting ensemble methods achieved substantial accuracy in estimation, exceeding the less effective GBDT learner. In particular, XGBoost emerged as the superior performer among the methods. This indicates that ensemble ML techniques hold promise for addressing RSSI prediction challenges and aiding future wireless network planning endeavors. In addition, results also show the computational efficiency of the four methods in predicting RSSI values. Shorter inference times, as demonstrated by LGBM and CatBoost, enhance the suitability of these methods for applications where low-latency predictions are essential. There remain potential future tasks, such as extending and validating this framework across various data frequencies, developing efficient feature selection approaches, exploring different Deep Learning (DL) techniques, and evaluating the framework's performance in diverse intricate environments.

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