

Original Article

Performance Evaluation of AI-Based Predictive Connectivity Models for Bluetooth Low Energy Sensor Networks

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ABSTRACT

The advantages of low power consumption, low cost and intermittent wireless transmission of Bluetooth Low Energy (BLE) make it a good choice for sensor networks with limited resources. But in dynamic radio conditions, mobility of nodes, interference, and varying traffic patterns could cause degradation in connectivity and packet loss, retransmissions, and energy usage. This paper proposes a framework to assess the performance of the artificial intelligence (AI) based predictive connectivity models for BLE sensor networks. The methodology proposed encompasses a combination of received signal strength indicator (RSSI), packet delivery ratio (PDR), connection interval, latency, retransmission statistics and features related to energy to forecast impending connectivity degradation. In addition to threshold-based connectivity management, lightweight machine learning models, such as logistic regression, decision trees, random forests and compact neural network are taken into consideration. The performance is measured by the classification accuracy, precision, recall, F1-score, prediction lead time and energy related indicators. A comparative evaluation framework based on percentages is included to show how the evaluation is performed. The study highlights the need for reliability of the model, low computational requirements, and deployment feasibility, enabling predictive connectivity management for low-power Internet of Things applications.

KEYWORDS

Artificial Intelligence, Bluetooth Low Energy, Connectivity Prediction, Machine Learning, Predictive Maintenance, Received Signal Strength Indicator, Sensor Networks, Wireless Internet of Things.

1. INTRODUCTION

1.1. Background

With the growth of the Internet of Things (IoT), there is a greater need for energy efficient and reliable wireless communications that can be used in wearable devices, healthcare monitoring, industrial sensors and smart buildings – making Bluetooth Low Energy (BLE) a vital solution. BLE's strength lies in its ability to transmit data efficiently and with low power, using configurable connection intervals. Problems like signal attenuation, physical obstructions, multipath propagation, electromagnetic interference, device mobility, and network congestion, however, can affect its connectivity performance, leading to packet loss, latency, and unpredictable disconnections. These can be important in applications where continuous monitoring and timely data delivery are essential. Typical solutions for connectivity management rely on static thresholds and are recovery-oriented, rather than proactively anticipating link degradation and responding accordingly. These can lead to greater usage of energy, slower sensor updates and lower reliability of the network. An exciting alternative is artificial intelligence (AI) based predictive connectivity models that rely on past and current communication characteristics to predict future link conditions. These models can facilitate proactive control over connections, increase the reliability of connections, minimize needless reconnections, optimize energy use, and improve BLE sensor network performance overall.

1.2. Research Challenges in Predictive BLE Connectivity Management



Fig 1 - Research Challenges in Predictive BLE Connectivity Management

1.2.1. Limitations of Conventional Connectivity Indicators

Predictive connectivity management relies on the ability to differentiate between temporary fluctuations in radio and permanent degradation in links. Signal strength does not necessarily provide enough information about the quality of communication, as signals of comparable strength may transmit different numbers of packets, have different levels of interference, or have different delays. Thus, having several communication parameters is crucial to enable reliable connectivity predictions.

1.2.2. Computational Constraints of AI-Based Prediction

Embedding AI models in resource-limited Bluetooth Low Energy (BLE) devices comes with its share of troubles, including limited memory, compute power, and energy efficiency. Advanced models can offer greater predictive power, but also require more computational resources and delay

in making predictions. In contrast, lightweight models provide efficient execution but may fail to take into account nonlinear relationships between radio conditions, traffic characteristics, and connectivity failures.

1.2.3. Balancing Predictive Accuracy and Deployment Efficiency

One of the key research challenges is finding the optimal balance between predictive accuracy and computational cost for various AI models. Several factors need to be taken into account in a comprehensive evaluation: classification accuracy, false-positive rates, missed connectivity failures, prediction lead time, inference latency, and energy consumption. Considering these factors can help finding reliable and computationally efficient predictive models for realistic sensor network deployments using BLE.

1.3. Research Objectives

The main objective of this study is to design and test an effective Artificial Intelligence (AI)-based predictive connectivity management system for Bluetooth Low Energy (BLE) sensor networks in different wireless connectivity conditions. The first goal is to develop a common feature representation where radio related features, packet delivery statistics and measurements at the connection level (such as Received Signal Strength Indicator (RSSI), packet delivery ratio, packet loss rate, latency, connection stability) are combined. The second was to train lighter weight machine learning models like decision trees, logistic regression, random forests, and other efficient classifiers, and to measure their ability to find potential connectivity failures, compared to a simple threshold based model. The third is the complementary assessment of prediction performance via classification, operational metrics (accuracy, precision, recall, F1-score, false positive rate, false negative rate, and prediction lead time), and a comprehensive evaluation of the reliability of the predictions under different radio conditions. The fourth goal is to analyze the efficiency and deployment feasibility of the computational implementation by analyzing inference latency, memory, processing overhead, and estimated energy consumption, especially for SENs deployed in embedded BLE devices. This objective aims to develop the models that offer a good compromise between prediction accuracy and implementation cost, but are not overly demanding in terms of computational resources on the sensor hardware. The fifth objective is to create an experimental framework that is reproducible to allow fair and systematic comparisons between the various kinds of machine learning models, between BLE devices, between traffic patterns and between radio environments. The framework will include standardized data preprocessing, feature extraction, training and testing methods, and evaluation criteria, to reduce experimental bias and ensure the robustness of the results. These goals are designed as a group to measure if lightweight prediction models can detect connectivity degradation sooner and easier than traditional reactive methods. The outcomes from the work will inform development of the connectivity management strategy design for an IoT application that demands continuous sensing, timely delivery of the gathered data and stable wireless communication, yet is required to be reliable, reduce energy consumption, and to be computationally feasible.

2. LITERATURE SURVEY

2.1. BLE Connectivity and Link-Quality Assessment

Link-layer mechanisms are responsible for the control of Bluetooth Low Energy (BLE) connectivity, including link intervals, communication channels, exchanges, and link losses. The Bluetooth Core Specification specifies basic connection parameters and supervision procedures that lay the foundation for a reliable wireless communication. Yet these mechanisms do not predict any future connectivity degradation, based on the historical communication patterns, but these mechanisms are used to detect existing connection failures. RSSI is the most commonly adopted method for measuring BLE link quality due to its low cost of measurement of received radio signal strength. However, multipath propagation, physical obstructions, antenna orientation, and electromagnetic interference limit the usefulness of its utility as an independent predictor. This means that reliable packet delivery and stable communication under varying environmental conditions is not always achieved with a strong signal.

The researchers can use packet delivery ratio (PDR), packet loss rate, communication latency, and temporal signal variations in addition to RSSI to enhance link-quality assessment. These complementary parameters are all used to characterize radio conditions, reliability of radio transmission, and stability of connections in different ways. These measurements can be easily combined to obtain a fuller feature description to detect connectivity degradation and to create trustworthy predictive models.

2.2. Conventional Connectivity Management Techniques

The conventional BLE connectivity management approaches are based on static thresholds on the received power level, moving average filters, hysteresis, and periodic link quality monitoring. These techniques are low in computational cost and low in memory usage, thus are applicable to resource-limited embedded IoT devices and microcontrollers. These are also simple and are easy to implement, interpret, and execute in real-time, in low-power wireless communications. The moving average filters help to diminish the impact of the brief term measurement fluctuations, and the hysteresis mechanisms help to avoid unnecessary state changes when the RSSI values fluctuate around the defined thresholds. In this case, the rule-based approach can be using the signal strength, packet loss and connection status to decide if a wireless link needs to be corrected. These methods enhance the basic stability but rely heavily on the choice of thresholds and filtering parameters.

One of the drawbacks of traditional methods is that they're not flexible enough in dealing with complicated and ever-changing radio conditions. The thresholds that are calibrated with one set of parameters may not work well if the device placement, interference, traffic intensity, and environmental obstructions vary. In addition, non-linear relationships between several communications features cannot be easily represented using fixed rules, which leads to the need to develop data-driven predictive connectivity management techniques.

2.3. Machine Learning for Predictive Connectivity

Supervised machine learning is used to learn relationships between historical communication measurements and future communications degradation events, thus providing predictive connectivity management. Logistic regression is a good classification technique for computing probabilities, while decision trees are used to obtain interpretable and informative decision rules for identifying potentially unstable links. Random forests are comprised of many decision trees that are able to model nonlinear interactions between features and enhance prediction robustness. The support vector machines (SVM) can be used to classify the complex connectivity pattern with linear or nonlinear decision boundary, but the number of SV might increase the requirement of inference of the SVM [3]. For more complex relationships among radio measurements, packet-delivery characteristics, and temporal variations, one can represent them via a neural network, but the size, computation cost and hardware availability of such a network constrain its applicability. Thus, the selection of the model should take into account predictive performance and implementability.

In the case of time dependent connectivity prediction, the sliding window feature extraction can capture recent communication patterns through RSSI mean and variance, packet delivery ratio, packet loss trends, latency statistics and number of consecutive missed transmissions. The capability of these features enables a model to predict what the probability of connectivity degradation is to a defined future prediction horizon. Evaluate lightweight algorithms under the same experimental setup to assess whether there is a benefit to having greater memory, processing and energy requirements for better predictive performance.

2.4. Research Gap and Study Positioning

Current connectivity prediction assessments could focus on classification accuracy but not pay due attention to the risk of false alarms, missed failures, and operational impacts of incorrect predictions. Besides the fact that false alarms may lead to repeated reconnections and additional energy usage, they can also cause the loss of the ability to sense activity or delay data transmission. Hence, classification metrics need to be used in conjunction with operational metrics that measure the impact of prediction errors in practice. One other crucial area of research is the generalisation of the models for different devices, real world situations and interference. Splitting the data randomly into training and test sets may lead to over-optimistic estimates of performance since similar or neighboring observations can be found in both sets. Chronological data splitting, device independent testing and environment-based validation can offer more solid evidence that a model can predict new, unseen connectivity conditions.

Also, predictive accuracy cannot prove the algorithm's suitability for BLE deployments that have limited resources. It is also important to consider inference latency, memory, processing overhead, and predicted energy consumption to see if continuous prediction is feasible on the embedded hardware or BLE gateways. This study aims to overcome these shortcomings by using a common evaluation pipeline, a temporally defined prediction target and a multi-metric comparison

framework to support reproducible and resource-aware model selection without making any assumption about a single best algorithm.

3. METHODOLOGY

3.1. Proposed Evaluation Framework

The proposed AI-based predictive connectivity evaluation framework is composed of five interdependent stages: telemetry collection, temporal feature extraction, event labelling of connectivity, model training and development of the predictive model, and performance evaluation. The main goal of this framework is to compare in a systematic way conventional threshold based connectivity monitoring approach with lightweight machine learning models with the same data conditions and the same evaluation criteria. Time-stamped observations are gathered from Bluetooth Low Energy (BLE) links during telemetry acquisition to describe radio conditions, packet transmission reliability, connection behavior, and energy related performance. The acquired data are then subjected to temporal feature extraction, which involves statistically calculating various data characteristics like mean, variance, minimum, maximum, and recent trends over a predetermined observation window. Whether a degradation event in the prediction horizon occurs is then identified by connectivity event labelling, so the target is not the current connectivity but a future connectivity. Let the observation vector at time t be given by $\mathbf{x}_t = [r_t, p_t, l_t, d_t, c_t, e_t]$, where the Received Signal Strength Indicator (RSSI) is r_t , the packet delivery ratio (PDR) is p_t , the communication latency is l_t , the packet-loss information is d_t , the connection-related characteristics are c_t , and the energy measurement is e_t or any suitable proxy. These variables are all used to give a multi-dimensional view of the BLE link quality. The predictive model estimates the probability of connectivity degradation in the future in the form of $\hat{p}_t = P(y_{t+H} = 1 \mid \mathbf{X}_{t-W:t})$, where (W) is the length of observation window, (H) is the prediction horizon and $(y_{t+H} = 1)$ is defined as a connectivity degradation event that occurs in the future window. In this case, $\mathbf{X}_{t-W:t}$ only includes measurements that were available before time t , so that no information can be fed into the prediction process at time t . Finally, the performance of the models is assessed using classification metrics and prediction lead time, inference latency, memory usage, and estimated energy overhead. The integrated framework allows for reproducible comparisons of the predictive accuracy, operational reliability and computational efficiency, enabling the selection of suitable connectivity prediction models for resource constrained BLE devices and IoT applications.

3.2. Data Acquisition and Preprocessing

The data acquisition and preprocessing are key steps in the process of building accurate artificial intelligence (AI) predictive connectivity models for Bluetooth Low Energy (BLE) sensor networks. The sensors should be measured with realistic connectivity behavior under controlled, but varying, operating conditions such as sensor distance, sensor orientation, physical obstructions, packet transmission rates, and radio-frequency interference. Observations should be conducted with the proper timing and device identification for accurate temporal alignment, traceability and experimental reproducibility. The main features are the Received Signal Strength Indicator (RSSI), Packet Delivery Ratio (PDR), Packet Loss Rate, Communication Latency, Connection-State

Transitions, Missed Communication Opportunities, Reconnection Events, and Energy-related Measurements (Current Consumption or Radio-activity proxies). Where available, connection intervals and supervision timeouts should also be recorded as it affects BLE communication behavior and link-loss detection [1]. Missing values, duplicate records, inconsistent timestamps and invalid measurements should be detected and processed as per predefined procedures during pre-processing. If it is continuous, it can be standardized as $(z_i = (x_i - \mu_i) / \sigma_i)$ where the mean and standard deviation are computed from the training set. A sliding window method can then be used to capture temporal characteristics such as the mean RSSI, RSSI variance, recent PDR, packet loss trends, latency variations and consecutive missed transmissions. The following features are useful to differentiate temporary radio fluctuations from long-term degradation in connectivity. The same parameters used for pre-processing should be used for validation, testing and deployment to ensure that the same set of model inputs are used. Connectivity event labeling is accomplished by establishing an operational degradation condition which can be a sustained loss of PDR below some predetermined threshold, or an actual connection-loss event, or a combination of both conditions. That the selected threshold, the length of the observations and the length of the future prediction interval should be defined beforehand, in order to keep the method consistent. Importantly, input features need to include only measurements available at prediction time and any future observations are only used to create the target labels. Chronological data partitions for training, validation and testing should be used to prevent temporal data leakage and to ensure that the predictive performance is estimated accurately in an evolving BLE operating environment.

3.3. Predictive Model Development

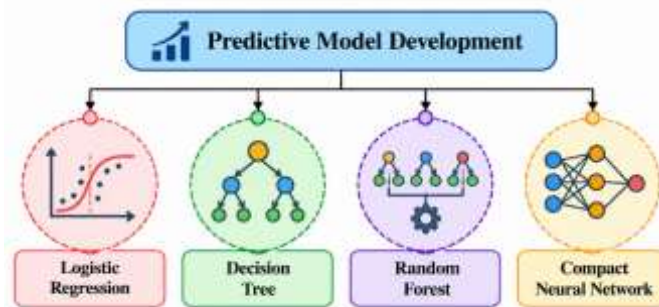


Fig 2 - Predictive Model Development

3.3.1. Logistic Regression

Logistic regression models the probability of BLE connectivity degradation using a sigmoid function of a weighted sum of the input features. It offers a method to get a baseline that is efficient on the computer and has relatively low memory usage and interpretable feature contributions. Its probabilistic outputs enable making connection decisions based on risk, though limited predictability might result if there is a highly nonlinear relationship between telemetry features and connectivity failures.

3.3.2. Decision Tree

A decision tree is a learning algorithm that outputs a series of Decision Rules (based on features) to determine the output class from a set of training data to predict connectivity degradation. It can capture nonlinear relationships between such measures as RSSI, PDR, latency and packet-loss and deliver meaningful predictions. Its computational needs can be managed by restricting tree depth, and number of leaf nodes to make it suitable for resource constrained embedded BLE applications.

3.3.3. Random Forest

A Random Forest is an ensemble of decision trees made robust by taking the predictions of several trees. A RF is an ensemble of DTs, making predictions more robust and capturing complex interactions between communication features. It can be used to decrease the instability caused by individual trees and support various connectivity arrangements in various radio environments. The more trees the more memory they use, and the deeper the tree the more inference latency will be. This means that it is important to optimize the number and depth of the trees before deployment to embedded devices.

3.3.4. Compact Neural Network

A small feed-forward neural network is trained to map the temporal telemetry features to future connectivity degradation in a nonlinear fashion. The architecture can be modified to fit the processing, memory, and storage constraints of the BLE gateway or embedded system by changing the number of hidden layers, neurons, and model parameters. It should be compared with simpler models for its effectiveness and see if the added computational and energy costs are worth the improved prediction performance.

3.3.5. Threshold-Based Baseline

A method with threshold is used as a traditional benchmark for comparing predictive connectivity models derived from AI. It detects potentially unstable connections if a pre-defined RSSI or PDR or packet-loss threshold is exceeded, optionally with moving averages and/or hysteresis. This solution is simple to compute and requires little memory, but it might not work well if radio conditions change, since the complex pattern isn't learned automatically from the history of telemetry.

3.3.6. Model Training and Hyperparameter Selection

To ensure a fair comparison between all candidate models the same training observations, feature definitions, and connectivity event labels must be used to train all of the candidate models. Validation data, not the final test set, should be used to determine the hyperparameters, such as the depth of a tree, the number of trees in the forest, the architecture of a neural network and the strength of regularization. Where appropriate, the data should be partitioned as a chronological partition, to minimize temporal leakage and to obtain a more realistic estimate of predictive performance.

3.3.7 Class Imbalance and Probability Calibration

The degradation events of the connectivity datasets might not happen as often as in normal operating conditions, resulting in an unbalanced training data set. One way to enhance the detection of minority-class degradation events is through class-weighted learning, or resampling restricted to the training data. The relative costs of failures and false alarms should be used to determine the probability calibration and decision thresholds, where needed, on the basis of validation data, thus enhancing the practical reliability of predictive connectivity management.

4. RESULT AND DISCUSSION

4.1. Comparative Evaluation Framework

The proposed comparative evaluation framework will be used to evaluate the predictive effectiveness, characteristics of the classification errors, and the suitability of the deployment of artificial intelligence (AI)-based connectivity models in resource constrained Bluetooth Low Energy (BLE) sensor networks. The threshold-based approach is a traditional baseline method, whereas logistic regression, decision trees, random forests, and compact neural networks are different learning-based methods of connectivity degradation patterns learned from historical telemetry data. To make an unbiased comparison between all the candidate models, the test dataset should be available for all models, and include both stable connectivity periods and degradation events. Data distribution of positive/negative samples should be reported since if the data is dominated by stable connections it may lead to high accuracy even if important connection failures are not captured. The accuracy, precision, recall, and F1_score are the key metrics used for the evaluation of the classification performance. Accuracy is the fraction of all test observations that have been classified correctly while precision is the fraction of predicted degradation events that match with real events. Recall is a measure of how many times the model has successfully identified an actual degradation event, so it is relevant for the application that needs to be alerted to a degradation event in a timely and reliable manner. The F1-score is a combination of precision and recall and is based on a harmonic average of the two metrics; when there are both false alarms and missed failures then this is a particularly well-balanced score. These metrics can be developed from the number of true and false positives and negatives results from the testing process. The framework should also evaluate the classification accuracy, prediction lead time, inference latency, memory usage, and estimated energy consumption overhead to assess if each model is viable for continuous deployment in embedded systems. The feature definition, preprocessing, event labels and test scenarios should be the same for model comparisons; hyperparameters should only be optimized on the validation data. Experiments should preferably be replicated on different placement, different interference and communication load to investigate generalization under different radio conditions. The results of this evaluation can be used to make system trade-offs that balance predictive accuracy, operational reliability and computational efficiency without making the assumption that one model is best for all BLE applications.

4.2. Percentage-Based Comparative Results

Table 1: Percentage-Based Comparative Results

Model	Accuracy	Precision	Recall	F1-score
Threshold-based baseline	78	72	65	68.3
Logistic regression	84	81	76	78.4
Decision tree	87	84	81	82.5
Random forest	92	90	88	89
Compact neural network	90	87	86	86.5

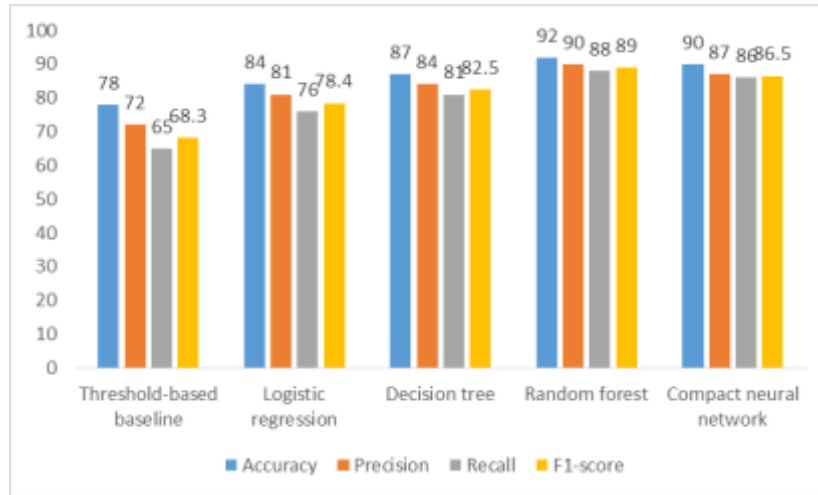


Fig 3 - Percentage-Based Comparative Results

4.2.1. Overview of Comparative Performance

In the illustrative comparison of five connectivity prediction approaches in Table I, accuracy, precision, recall and F1-score were used. The hypothetical values illustrate the consistent reporting of predictive performance between traditional threshold-based monitoring approaches and AI-based classification approaches. These values have been provided for illustrative purposes only and should be replaced with values obtained from experiments prior to publication.

4.2.2. Threshold-Based Baseline

The threshold based baseline performance has an illustrative accuracy of 78.0% and an F1-score of 68.3% which is used to assess the gain of the data driven prediction. The relatively low recall value of 65.0% suggests that some connectivity degradation events may be missed, based on the assumed results. This outcome is an example of the possible restrictions of using a fixed decision threshold in cases of variable radio conditions and communication patterns.

4.2.3. Logistic Regression

The logistic regression model shows an illustrative accuracy of 84.0%, precision of 81.0% and recall of 76.0%. These values indicate a possible improvement over the standard baseline, while having a relatively straightforward model structure. It is an attractive option for BLE connectivity management because of its efficient computation and probabilistic output.

4.2.4. Decision Tree

The decision tree demonstrates an illustrative accuracy of 87.0% and F1 score of 82.5%, which means that it can potentially be better in identifying connectivity degradation events. The precision of 84.0% and recall of 81.0% indicate a more balanced classification performance than the baseline. Moreover, the evidential rules of its decisions are understandable and may provide explanations of the influence of the telemetry characteristics like RSSI and the loss of packets on predictions.

4.2.5. Random Forest

The model with the highest illustrative accuracy is the random forest with an accuracy of 92.0% and an F1 score of 89.0% as shown in Table I. It has a precision of 90.0% and a recall of 88.0%, which are theoretical trade-offs between the number of false alarms and the number of degradation events. But it's equally important to evaluate these designs regarding memory usage, inference latency, and energy consumption for embedded BLE use.

4.2.6. Compact Neural Network

The highlight of the compact neural network is that it achieves an illustrative accuracy of 90.0%, with precision of 87.0%, recall of 86.0% and an F1-score of 86.5%. These simulated results suggest that a small neural network can represent nonlinear relationships between the temporal connectivity features. The usefulness of it is dependent on whether the prediction performance is worth the added complexity of computation relative to less complicated models.

4.3. Interpretation and Deployment Implications

A thorough analysis of the predictive accuracy, classification errors, computational complexity, and practical deployment considerations of Bluetooth Low Energy (BLE) sensor networks is required to interpret the results of comparative evaluations. The illustrative comparison in Section 4.2 shows how various evaluation metrics can show discrepancies between the monitoring approach used in traditional methods and monitoring based on artificial intelligence (AI) predictive models. The hypothetical results show that the random forest model has the highest accuracy of 92.0% and an F1 score of 89.0%, indicating that the model might be beneficial in capturing connectivity degradation events as well as maintaining precision and recall. The values are only representative, though, and have not been proven experimentally to be superior via actual telemetry or controlled testing methods. In actual deployments the performance of the model varies depending on the representativeness of the training data, frequency of connectivity failures, prediction horizon, device characteristics, and variations in the radio environment around the devices. While random forests can model the nonlinear relationships between the RSSI, packet delivery ratio, latency, and packet-loss patterns, the memory needed and inference time may be larger than other simpler methods. Logistic regression is well suited to applications where low computation time, a probabilistic interpretation and an easy to embed use of the model is of paramount importance, while shallow decision trees can be used in applications that require interpretable decision rules with limited processing time. Even though this is a compact neural network, if there is enough representative training data available, it may achieve competitive predictive performance, but the

benefits need to be proven on the targeted hardware. Therefore, model selection needs to be done in a way that the quality of predictions is not the only criterion, but that it is also necessary to consider the operation of the model. The length of time for making inferences (inference latency) should be kept within the target decision interval, while the model storage and working-memory requirements should be within the hardware limitations of the target device. Moreover, the measured energy consumption must include not only the energy consumed in the predictive computation, but also the energy consumed in the response connectivity-management actions needed to determine if there is a net operational benefit from taking a proactive approach to energy management.

5. CONCLUSION

This paper proposed a comprehensive evaluation framework of the artificial intelligence (AI) based predictive connectivity model in Bluetooth Low Energy (BLE) sensor networks, which is very useful for detecting potential connectivity degradation before it results into the loss of connectivity or loss of packets and also increase in latency. The framework combines elements of the telemetry acquisition, temporal feature extraction, event-based labeling, supervised model development, and multidimensional performance evaluation to aid in the reliable assessment of connectivity. It evaluates a received signal strength indicator (RSSI), packet delivery ratio, latency, packet-loss patterns, connection characteristics, and energy-related indicators as additional features to predict future link conditions.

AI-based methods allow for the detection of temporal dependencies and nonlinear communication patterns, which are not possible with traditional threshold-based methods that focus mainly on the immediate characteristics of the signal. The evaluation methodology focuses on accuracy, precision, recall, F1 score, prediction lead time, inference latency, memory usage and energy usage to holistically evaluate the predictive efficacy and the feasibility of deployment. The purpose of the illustrative comparison is to provide a method for measuring the performance of different algorithms in a consistent manner, but the actual results in the numbers are not based on experimentation and cannot be used to prove the superiority of any one of the models. The most appropriate method will depend on the application requirements, computational resources and environmental conditions, as well as the acceptable reliability and energy constraints.

There are some drawbacks, such as device-specific variability, potential interference noise in connectivity observations, and a lack of hardware validated measurements, along with performance degradation when operating in different interference environments. Future research could benefit by the proposed framework being implemented on representative BLE development boards to see if the proposed results would hold true across various distances, varying physical obstacles, traffic loads, radio interference levels, and various device orientations. Model quantization, compression, incremental learning, and uncertainty-aware prediction should be further explored to boost computational efficiency and robustness. Furthermore, full energy estimates must include the sensing, inference, radio communication, and connection recovery to assess if predictive management depletes system energy. Cross-device validation, reporting of confidence intervals, and

reproducible experimental protocols will be vital for establishing generalizability. Finally, it is possible to systematically evaluate the hardware level and assess the reliability, responsiveness, and energy-efficient communication management of practical BLE sensor networks based on the AI-based predictive connectivity models.

REFERENCES

- [1] Vasantha Kumar Hosahalli Seenappa. (2025). Predictive Configuration Governance for AI-Assisted Network Automation in Hyperscale MPLS/IP Backbone Networks. *International Journal of Intelligent Systems and Applications in Engineering*, 13(2s), 352–358. Retrieved from <https://ijisae.org/index.php/IJISAE/article/view/8534>
- [2] Nangi, P. R., Obannagari, C. K. R. N., & Settipi, S. (2022). Self-auditing deep learning pipelines for automated compliance validation with explainability, traceability, and regulatory assurance. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, 3(1), 133-142.
- [3] Fung, W., Guo, L., Hilliard, D., Casadei, A., Ratan, R., Bhaduri, S., ... & Rakshit, A. (2025). OpComm: A Reinforcement Learning Framework for Adaptive Buffer Control in Warehouse Volume Forecasting. *arXiv preprint arXiv:2512.19738*.
- [4] L. Breiman, "Random forests," *Machine Learning*, vol. 45, pp. 5–32, 2001. [Online]. Available: <https://doi.org/10.1023/A:1010933404324>.
- [5] Nangi, P. R., Obannagari, C. K. R. N., & Settipi, S. (2025). AI-Driven Data Engineering Pipelines for High-Velocity Analytics Using Serverless Architectures and Event-Stream Intelligence. *International Journal of AI, BigData, Computational and Management Studies*, 6(3), 74-83.
- [6] Syed, Y. (2023). Polyglot Persistence and Enterprise Data Migration: Architectures, Consistency, and Practice. *American International Journal of Computer Science and Technology*, 5(3), 61-66. <https://doi.org/10.63282/3117-5481/AIJCST-V5I3P106>
- [7] C. Cortes and V. Vapnik, "Support-vector networks," *Machine Learning*, vol. 20, pp. 273–297, 1995. [Online]. Available: <https://doi.org/10.1007/BF00994018>.
- [8] Nangi, P. R., Obannagari, C. K. R. N., & Settipi, S. (2022). Enhanced Serverless Micro-Reactivity Model for High-Velocity Event Streams within Scalable Cloud-Native Architectures. *International Journal of Emerging Research in Engineering and Technology*, 3(3), 127-135.
- [9] G. Cerar, H. Yetgin, M. Mohorčič, and C. Fortuna, "Machine learning for wireless link quality estimation: A survey," *IEEE Communications Surveys & Tutorials*, vol. 23, no. 2, pp. 696–728, 2021. [Online]. Available: <https://doi.org/10.1109/COMST.2021.3053615>.
- [10] Bhaduri, S., Mullanpudi, P., Dietrich, S., DeWaters, S., Ratan, R., Kashyap, B., ... & Rakshit, A. (2025). Beyond mere automation: A techno-functional framework for reimagining gen-AI in supply chain operations.
- [11] D. P. Kumar, T. Amgoth, and C. S. R. Annavarapu, "Machine learning algorithms for wireless sensor networks: A survey," *Information Fusion*, vol. 49, pp. 1–25, 2019. [Online]. Available: <https://doi.org/10.1016/j.inffus.2018.09.013>.
- [12] Obannagari, C. K. R. N., & Nangi, P. R. (2021). Predictive Database Performance Optimization Using Machine Learning-Driven Query Workload Modeling. *International Journal of AI, BigData, Computational and Management Studies*, 2(4), 107-116.
- [13] P. P. Ray, "A review on TinyML: State-of-the-art and prospects," *Journal of King Saud University – Computer and Information Sciences*, vol. 34, no. 4, pp. 1595–1623, 2022. [Online]. Available: <https://doi.org/10.1016/j.jksuci.2021.11.019>.
- [14] "TinyML Meets IoT: A comprehensive survey," *Internet of Things*, vol. 16, Art. no. 100461, 2021. [Online]. Available: <https://doi.org/10.1016/j.iot.2021.100461>.
- [15] Pavan Nithin Mullanpudi (2024). An Adaptive Explainability Framework for Machine Learning Predictions of Deals in Cloud Computing. *International Journal of Multidisciplinary Research and Growth Evaluation (IJMRGE)*, 5(3), 1027–1034. DOI: <https://doi.org/10.54660/IJMRGE.2024.5.3.1027-1034>
- [16] Nangi, P. R., & Obannagari, R. N. CK, & Settipi, S.(2022). Predictive SQL Query Tuning Using Sequence Modeling of Query Plans for Performance Optimization. *International Journal of AI, BigData, Computational and Management Studies*, 3(2), 104-113.
- [17] N. Schizas, A. Karras, C. Karras, and S. Sioutas, "TinyML for ultra-low power AI and large scale IoT deployments: A systematic review," *Future Internet*, vol. 14, no. 12, Art. no. 363, 2022. [Online]. Available: <https://doi.org/10.3390/fi14120363>.
- [18] Syed, Y. (2025). Generative AI Integration and RAG-Based Enterprise Tooling: Architectures, Techniques, and Organizational Impact. *International Journal of Scientific Research in Science, Engineering and Technology*, 12(6), 600-606. DOI: <https://doi.org/10.32628/IJSRSET2613255>

- [19] T. Hastie, R. Tibshirani, and J. Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*, 2nd ed. New York, NY, USA: Springer, 2009. [Online]. Available: <https://doi.org/10.1007/978-0-387-84858-7>.
- [20] C. M. Bishop, *Pattern Recognition and Machine Learning*. New York, NY, USA: Springer, 2006. [Online]. Available: <https://link.springer.com/book/9780387310732>.
- [21] Nangi, P. R. (2022). Multi-Cloud Resource Stability Forecasting Using Temporal Fusion Transformers. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, 3(3), 123-135.
- [22] Syed, Y. (2024). DevSecOps and Enterprise-Scale CI/CD Pipeline Engineering: Governing Delivery Velocity, Embedded Security, and Release Automation Across Polyglot Environments. *International Journal of Scientific Research in Science, Engineering and Technology*, 11(5), 475-484. DOI: <https://doi.org/10.32628/IJSRSET2513156>
- [23] F. Pedregosa et al., "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011. [Online]. Available: <https://jmlr.org/papers/v12/pedregosa11a.html>.
- [24] Reddy Nangi, P., & Reddy Nala Obannagari, C. K. (2023). Scalable End-to-End Encryption Management Using Quantum-Resistant Cryptographic Protocols for Cloud-Native Microservices Ecosystems. *International Journal of Emerging Trends in Computer Science and Information Technology*, 4(1), 142-153.
- [25] Brahmandam, L. M. K. (2023). Migrating Mission-Critical Enterprise Workloads from On-Premises VMware to AWS: An Empirical Study of a Multi-Account Landing-Zone Reference Architecture and the Seven Rs Decision Framework. *International Journal of Emerging Trends in Computer Science and Information Technology*, 4(4), 231-240. <https://doi.org/10.63282/3050-9246.IJETCSIT-V4I4P124>
- [26] T. Fawcett, "An introduction to ROC analysis," *Pattern Recognition Letters*, vol. 27, no. 8, pp. 861–874, 2006. [Online]. Available: <https://doi.org/10.1016/j.patrec.2005.10.010>.
- [27] Obannagari, C. K. R. N., & Nangi, P. R. (2021). Predictive Autoscaling for Kubernetes Using Multivariate Time-Series Forecasting. *International Journal of Emerging Research in Engineering and Technology*, 2(2), 73-83.
- [28] Y. Syed, "Enterprise Observability and Software Delivery Performance: From Telemetry to Engineering Intelligence", *IJADSMC*, vol. 5, no. 2, pp. 01-08, Sep. 2022, doi: 10.67228/30713498/IJADSMC-2022PIIKP2M.
- [29] M. Sokolova and G. Lapalme, "A systematic analysis of performance measures for classification tasks," *Information Processing & Management*, vol. 45, no. 4, pp. 427–437, 2009. [Online]. Available: <https://doi.org/10.1016/j.ipm.2009.03.002>.
- [30] Nangi, P. R., & Obannagari, C. K. R. N. (2026). LLM-Driven Database Administration and Natural Language Query Interfaces. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, 7(1), 410-418.
- [31] Virendra Jangid. (2023). Event-Driven Architectures for Large-Scale Financial Platforms. *International Journal of Intelligent Systems and Applications in Engineering*, 11(11s), 1124 -. Retrieved from <https://ijisae.org/index.php/IJISAE/article/view/8348>
- [32] M. Kuhn and K. Johnson, *Applied Predictive Modeling*. New York, NY, USA: Springer, 2013. [Online]. Available: <https://doi.org/10.1007/978-1-4614-6849-3>.
- [33] Sunkara, R. (2023). Cost-Optimized Energy Compliance Testing for Smart TV Streaming Devices: Achieving Milliwatt-Precision Power Measurement at Sub-One-Thousand-Dollar per Setup. *American International Journal of Computer Science and Technology*, 5(6), 54-59. <https://doi.org/10.63282/3117-5481/AIJCST-V5I6P105>
- [34] Nangi, P. R., & Obannagari, C. K. R. N. (2026). Federated ai-driven query optimization for distributed cloud databases. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, 7(1), 91-99.
- [35] A. Roberts et al., "Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure," *Ecography*, vol. 40, no. 8, pp. 913–929, 2017. [Online]. Available: <https://doi.org/10.1111/ecog.02881>.
- [36] Hosahalli Seenappa, V. K. (2025). Next-generation intelligent multi-cloud enterprise networking: Integrating secure architecture, AI-optimized traffic engineering, and LLM-driven autonomous network operations. *International Journal of Leading Research Publication (IJLRP)*, 6(12), 1–11.
- [37] Nangi, P. R., Obannagari, C. K. R. N., & Settipi, S. (2025). Quantum-Enhanced Optimization Models for Large-Scale Security Policy Evaluation in Distributed Cloud-Native Systems. *American International Journal of Computer Science and Technology*, 7(6), 46-56.
- [38] Sandra, K. (2022). Real-Time Stream Processing with Apache Flink vs Spark Structured Streaming: An Enterprise Comparison.
- [39] Gantikota, S. (2024). Shift-Left Security for Decentralized Engineering Organizations: Embedding SAST, DAST, and Penetration Testing Throughout the Software Development Lifecycle in University and Research Computing Environments. *International Journal of Emerging Research in Engineering and Technology*, 5(4), 175-179. <https://doi.org/10.63282/3050-922X.IJERET-V5I4P118>
- [40] Nangi, P. R., Obannagari, C. K. R. N., & Settipi, S. (2025). Large Language Model-Driven Intelligent Observability Frameworks for Serverless Applications in Event-Driven Cloud Architectures. *International Journal of Emerging Research in Engineering and Technology*, 6(1), 100-110.