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Enhancing Energy Demand Predictability through Dynamic LoRa Network Topologies and Feature-Optimized Machine Learning

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ABSTRACT

This research presents a Long Range (LoRa)-based multi-hop wireless communication architecture designed to enhance IoT sensor data collection for accurate energy demand forecasting. By implementing a multi-hop paradigm and dynamic routing, the system overcomes the geographic limitations of traditional LoRa technology, ensuring high data reliability and reduced packet loss across dispersed sensor networks. A comprehensive Exploratory Data Analysis (EDA) was conducted on a dataset containing electrical metrics, weather conditions, and temporal features, utilizing time-series decomposition and correlation mapping to optimize feature selection and minimize computational overhead. For predictive modeling, a Support Vector Classifier (SVC) was initially evaluated; however, a Random Forest Classifier (RFC) was proposed to better capture complex non-linear relationships and mitigate overfitting through ensemble learning. Validated via stratified cross-validation, experimental results demonstrate that the RFC consistently outperforms the SVC across all key metrics, including accuracy, precision, and F1-score. Ultimately, the integration of robust multi-hop communication with ensemble-based analytics provides a superior framework for predicting energy demand fluctuations with high generalization and stability.

Keywords: LoRa technology, Mutli-hop wireless communication, Internal of things (IoT), Energy demand forecasting, Dynamic routing, Random forest classifier, Support vector classifier.

1. INTRODUCTION

One of the key areas where Internet of Things (IoT) is currently seeing increased adoption is large-scale, remote monitoring applications. The ability to connect a large number of devices spread out over vast areas can provide significant benefits. In these remote applications, IoT technologies can be used in a wireless sensor network (WSN) to register environmental phenomena: from soil and snow monitoring across large nature reserves [1], to plant stress monitoring across large agricultural fields [2]. These use cases typically require only an extremely small throughput rate and are not latency critical. To maximize the lifespan of the IoT nodes, which are expected to operate on a limited energy supply for several years, it is crucial to optimize both their hardware and software for minimal power consumption [3]. Recently, a few wireless Internet of Things (IoT) technologies have proven their worth in actual deployments. The Long-range wide-area network (LoRaWAN) implementation in particular has become widespread. LoRaWAN is designed specifically for low-throughput communication and offers long-range, low-power, and unlicensed spectrum operation. In these networks, a gateway is connected to the cloud using a single-hop star network topology, as is typical for most IoT networks. Despite the 2–5 km range of coverage that LoRaWAN can accomplish [4], it might not be sufficient to cover the hundreds of square kilometers required in the aforementioned use scenarios, or when propagation is severely attenuated, e.g., because of obstructed paths. Coverage could be provided by distributing a large amount of long-range wide-area network (LoRaWAN) gateways in the area; however, this proves to be unfeasible due to lacking (cellular) network coverage, energy restrictions, or

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financial cost. Therefore, we propose a long range (LoRa)-based multi-hop network to extend the coverage, specifically optimized for energy efficiency. A multi-hop protocol allows messages to be transmitted from one node to another through a series of intermediate nodes, effectively allowing packets to *hop* from one node to the next until they reach their destination. This enables the network to cover a much larger area than would be possible with a single hop. In the implementation presented in this work, we assume only one possible destination: the gateway or the sink, which can store the gathered data or relay them to another cloud-connected network.

2. LTERATURE SURVEY

Dafflon et al. [1] developed a distributed temperature profiling system for acquiring vertically and laterally dense temperature data in soil and snow. Their system enables high-resolution thermal monitoring, crucial for understanding subsurface dynamics, which supports accurate environmental modeling. Such temperature sensing mechanisms can be leveraged in smart energy systems for environmental context-aware predictions. The framework provides insights into sensor deployment strategies in LoRa-enabled monitoring systems. Geldhof et al. [2] proposed a digital leaf movement sensor to monitor plant stress responses in real time. Their work bridges plant physiology and electronics, showcasing the value of smart sensing in detecting environmental stressors. The sensor's data acquisition principles highlight how real-time monitoring can inform predictive algorithms, applicable to LoRa-based agricultural energy forecasting systems. This also underscores the integration of biological signals into IoT frameworks. Callebaut et al. [3] discussed power optimization strategies and technologies crucial for designing long-battery-life IoT devices. Their work provides a detailed exploration of energy-saving techniques, from hardware-level innovations to software strategies. These concepts are foundational for sustaining LoRa-based networks in remote deployments. Efficient energy usage directly enhances system longevity and reliability in energy monitoring applications. Rochester et al. [4] implemented lightweight carrier sensing mechanisms in LoRa networks to assess performance impacts. Their results indicate improvements in channel access efficiency without sacrificing energy savings. The protocol enhancements support lower latency, which benefits time-sensitive energy demand prediction. Their work highlights the importance of MAC-level innovations for practical LoRa applications.

Aslam et al. [5] explored multi-hop LoRa communications for green smart cities, emphasizing network sustainability. Their architecture balances energy efficiency and coverage, essential for large-scale IoT systems. The study underlines the potential of LoRa in urban energy infrastructures, enabling efficient demand data transmission. The multi-hop concept ensures consistent network coverage for real-time predictions. Sciullo et al. [6] designed LOCATE, a mobile emergency management system using LoRa. Their solution facilitates rapid data dissemination during emergencies, proving LoRa's robustness in dynamic environments. The adaptive design strategy informs the architecture of resilient LoRa networks for continuous energy data collection. Ensuring connectivity under pressure scenarios is key for reliable energy prediction. Sartori et al. [7] enabled RPL-based multihop communications over LoRa networks, enhancing routing efficiency. Their integration of standard IoT protocols with LoRa broadens compatibility and deployment options. Efficient routing minimizes energy waste in sensor nodes, contributing to prolonged system operation in remote energy monitoring. Their work supports IoT scalability in energy infrastructure. Zhou et al. [8] presented LoRa-Hybrid, a multihop LoRaWAN-based solution tailored for regional microgrids. Their system improves connectivity and data collection in distributed energy systems. LoRa-Hybrid's architecture aligns well with predictive energy demand models needing consistent updates from edge nodes. The hybrid approach ensures flexibility and redundancy in communication. Prade et al. [9] developed a multi-radio, multi-hop LoRa communication model suited for large-scale IoT systems. Their architecture enhances robustness and data throughput

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across expansive deployment areas. Such scalable communication designs are ideal for national-level energy demand monitoring using LoRa. The model encourages fault-tolerant transmission in predictive systems. Leonardi et al. [10] introduced MRT-LoRa, a real-time communication protocol tailored for industrial IoT using LoRa. It guarantees low-latency data flow with time constraints, crucial for industrial energy management. Their protocol aligns well with smart grids requiring timely data for accurate energy demand forecasting. The emphasis on timing synchronization supports real-time analytics.

Zhu et al. [11] improved mesh LoRa capacity by applying spreading-factor-based network clustering. Their method enhances throughput and reduces interference, essential for high-density sensor networks. This directly supports predictive energy systems operating in urban environments. The clustering strategy enhances network stability and prediction accuracy. Bezunartea et al. [12] investigated methods for enhancing energy efficiency in LoRa multihop networks. They evaluated transmission policies and node behaviors that contribute to minimal power usage. Their findings are relevant for optimizing LoRa-based energy monitoring systems in remote or inaccessible areas. Their protocol design supports predictive models with consistent, energy-efficient data input. Abrardo et al. [13] implemented a linear multi-hop LoRa network for monitoring underground medieval aqueducts. Their project highlighted LoRa's effectiveness in subterranean and structurally challenging environments. Insights from this deployment can be translated to smart underground energy pipelines or tunnels. Reliable data acquisition in constrained environments supports safer energy infrastructure management. Abrardo et al. [14] continued their work by applying LoRa for monitoring black powder flow in pipelines. They leveraged a multi-hop approach to maintain signal integrity across metal-dense environments. This application is particularly useful for industrial energy systems requiring predictive failure detection. The study proves LoRa's industrial-grade applicability. Escobar et al. [15] proposed the JMAC protocol—a cross-layer approach optimized for multi-hop LoRa networks. It synchronizes MAC and network layers to achieve high efficiency in energy-constrained settings. This design philosophy is beneficial for LoRa-based energy forecasting systems requiring minimal communication overhead. The reduced complexity aids in scaling IoT deployments. Mai et al. [16] introduced a latency-minimized multi-hop LoRa protocol tailored for real-time applications. Their system adapts route selection based on latency constraints, vital for predictive analytics. In energy demand prediction, delayed data can severely impact forecast accuracy. Their work supports time-sensitive deployments in smart energy systems.

Adame Vázquez et al. [17] proposed HARE, an efficient multi-hop uplink communication framework for self-organizing LPWANs. Their system emphasizes autonomous routing and dynamic topology changes. This approach supports scalable energy prediction systems that adapt to infrastructure growth. The self-organizing feature reduces maintenance in energy-sensitive deployments. Tran et al. [18] implemented a two-hop real-time LoRa protocol tailored for industrial control. Their protocol supports delay-bounded communication for automated processes. This aligns with the need for timely energy consumption data in predictive models. Their work enhances LoRa's reliability in real-world energy infrastructures. Tran et al. [19] extended their protocol into a dynamic multi-hop real-time LoRa system. This version supports changing network topologies, enabling robust predictive systems in fluctuating environments. Their approach ensures continuous data acquisition critical for real-time energy analytics. The model is adaptive to IoT dynamics found in energy grids. Bachir et al. [20] offered foundational insights into MAC layer essentials in wireless sensor networks. Their review establishes the principles for efficient communication applicable to LoRa-based IoT systems. Understanding MAC protocols is essential for optimizing data flow in energy monitoring networks. Their work supports designing low-latency and energy-aware systems. Iqbal et al. [21] evaluated multi-hop uplink strategies using LoRa in LPWAN environments. They provided a performance assessment based on varying hop

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counts and network conditions. Their work contributes to route planning and reliability improvements in energy forecasting networks. Multi-hop uplink ensures data continuity in wide-area monitoring. Cotrim et al. [22] conducted a review and classification of LoRaWAN mesh networks for multihop communication. Their taxonomy outlines potential architectures suitable for energy systems. Understanding different mesh topologies aids in selecting the right framework for energy demand prediction. Their review consolidates best practices and performance considerations. Leenders et al. [23] developed an energy-efficient multi-hop LoRa protocol utilizing preamble sampling. Their technique significantly reduces listening time and improves battery longevity. This innovation is beneficial for long-term energy demand monitoring where sensor replacement is impractical. The protocol ensures minimal energy consumption while maintaining data accuracy.

3. PROPOSED SYSTEM

The proposed system integrates a multi-hop LoRa-based wireless communication framework with machine learning techniques to enable efficient and intelligent energy demand modeling using IoT sensor data. Unlike traditional single-hop communication, the multi-hop architecture enhances network coverage and reliability by allowing data to be transmitted through intermediate sensor nodes. The system collects real-time energy consumption data along with environmental factors such as temperature and humidity, which are preprocessed and enriched for predictive analysis. A Support Vector Classifier (SVC) is initially used as a baseline, while a Random Forest Classifier (RFC) is proposed to improve accuracy and robustness in forecasting energy demand patterns. The system performs continuous monitoring, intelligent prediction, and early detection of abnormal consumption trends, thereby supporting proactive energy management and optimized decision-making. Gemini said. The proposed system begins with the deployment of advanced IoT sensor nodes that monitor multi-dimensional energy parameters—such as voltage and power—alongside environmental factors like ambient temperature and humidity across residential, commercial, and industrial zones. To ensure wide-scale coverage and high reliability, the architecture utilizes a multi-hop LoRa-based communication protocol where sensor nodes act as relays to extend range, improve fault tolerance, and minimize packet loss in complex environments. Upon reaching a central gateway, the transmitted data undergoes immediate real-time preprocessing, including normalization, noise filtering, and categorical encoding, to maintain high data quality for predictive analysis. Finally, the system dynamically integrates external contextual variables such as weather patterns and seasonal information, aligning them with sensor metrics to uncover hidden correlations between environmental changes and energy demand behaviors.

3.1 RFC Model

The RFC model is an ensemble-based machine learning algorithm that constructs multiple decision trees during training and merges their outputs to make robust, accurate predictions. It operates by combining the predictions of several decision trees, each built on different random subsets of the dataset and features. This method reduces overfitting and improves generalization. In the context of your LoRa-based energy demand prediction project, RFC is employed to classify energy demand levels (e.g., low, medium, high) based on sensor-derived features such as temperature, humidity, light intensity, and external environmental factors. The model's ability to handle high-dimensional and noisy data makes it highly suitable for IoT-based scenarios where data from sensors may be inconsistent or complex.

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the transmitted data undergoes immediate real-time preprocessing, including null value checking, label encoding, and normalization, to maintain high data quality for the machine learning pipeline.

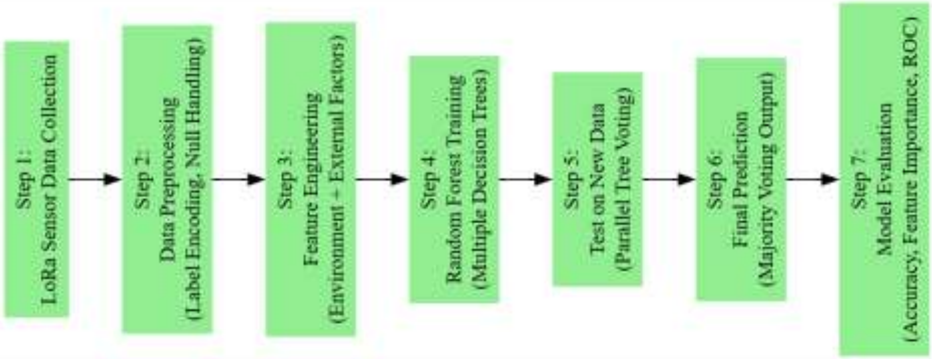

Fig. 1: Internal Workflow of Proposed RFC model.

The system then dynamically integrates external contextual variables such as weather patterns (wind speed, solar radiation) and seasonal information, aligning them with sensor metrics to uncover hidden correlations between environmental changes and energy demand behaviors. For predictive analysis, the dataset is divided into input features (X_train) and target labels (y_train) to train a Random Forest Classifier (RFC), which builds an ensemble of decision trees using feature bagging and Gini Index or Entropy splitting criteria to mitigate overfitting. Finally, the trained model is evaluated using new sensor data (X_test) from the LoRa network, where each individual decision tree in the forest predicts class labels, such as "High" or "Low" energy demand, to provide a stable and accurate aggregate prediction.

4. RESULTS AND DISCUSSIONS

The system begins with the deployment of smart IoT sensor nodes across residential, commercial, and industrial zones to monitor multi-dimensional energy parameters—such as voltage, current, and power consumption—alongside environmental factors like temperature, humidity, and light intensity. To overcome range limitations and ensure high reliability, a multi-hop LoRa-based communication protocol is employed where sensor nodes act as relays, creating a mesh-like structure that reduces packet loss and facilitates extended-range data transmission to a central gateway. Once collected, the data undergoes real-time preprocessing, including null value handling, noise filtering, and the dynamic integration of external contextual variables such as weather patterns and seasonal information from APIs. The implementation phase then utilizes Python libraries like NumPy and pandas for initial data inspection and label encoding to convert categorical target variables, such as energy demand levels, into numerical format. To build the predictive model, the dataset is divided into input features (X_train) and target labels (y_train), followed by the training of a Random Forest Classifier (RFC) that utilizes ensemble learning through multiple decision trees, feature bagging, and Gini Index or Entropy splitting criteria to improve robustness against overfitting. Finally, the model is evaluated using new sensor data (X_test) where each decision tree in the forest predicts class labels—such as "High" or "Low" demand—to produce a stable and accurate aggregate forecasting result.

4.1 Result Analysis

The figure 2 shows data collected from a LoRa-based wireless sensor network to analyze and predict energy demand levels (Low, Medium, High) across nodes. The dataset contains 10,000 entries, with each record capturing various sensor and transmission metrics such as node_id, hop_count, signal_strength, transmission_delay, temperature, humidity, light_intensity, co2_level, and wind_speed. The target variable is energy_demand, a categorical feature reflecting energy usage. The objective of this project is to develop machine learning models that can accurately classify energy demand based on

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environmental and network parameters. This can aid in optimizing network resource allocation, improving power efficiency, and ensuring better network performance in IoT deployments using LoRa technology.

	node_id	hop_count	signal_strength	transmission_delay	temperature	humidity	light_intensity	co2_level	wind_speed	energy_demand
0	52	1	-32.882718	1.746932	20.109949	51.524286	799.984254	661.526954	12.740774	Low
1	93	5	-97.033599	1.958138	31.855641	77.261913	867.551741	529.703863	9.149820	Medium
2	15	5	-42.737677	2.381532	17.319607	20.967083	371.304123	379.057381	3.278665	High
3	72	1	-70.824858	2.386442	43.485641	82.861382	559.615586	540.093144	18.785296	High
4	61	3	-68.747114	1.359328	33.099417	48.911898	871.755016	751.362126	6.649550	Medium
...	...	...	...	...	...	...	...	...	...	...
9995	49	1	-70.508245	1.270413	36.172282	70.220969	671.560443	338.288601	8.368528	High
9996	58	5	-90.213339	1.387671	32.327330	89.479823	886.165828	833.796639	0.684077	High
9997	39	3	-104.792506	1.278636	22.545942	51.743267	846.726009	535.571660	6.830682	Low
9998	80	4	-77.995621	1.053325	23.676027	29.854699	789.397790	641.177862	10.315031	High
9999	97	5	-110.974218	4.222009	26.019285	70.911656	135.301178	885.024920	18.717437	High

Fig. 2: Uploading Dataset

The figure 3 shows count plot of the energy_demand categories—encoded as 0 (Low), 1 (Medium), and 2 (High)—shows a balanced distribution among the three classes in the dataset. Each category has approximately the same number of samples, around 4,100 records each. This balanced class representation is crucial for training reliable classification models, as it helps prevent bias toward any specific energy demand level. The equal class distribution ensures that machine learning algorithms can learn the underlying patterns more effectively and make more accurate predictions across all demand levels in the LoRa-based IoT network.

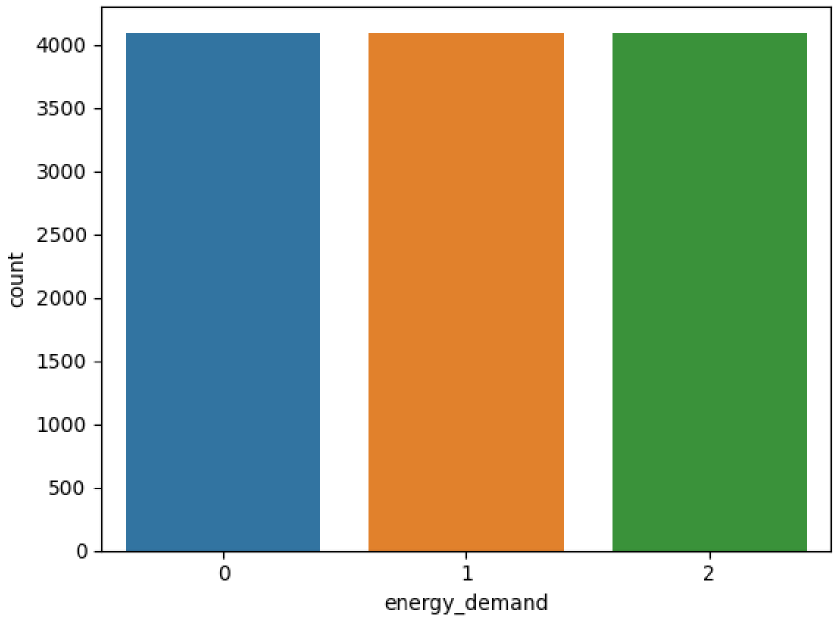

Fig. 3: Count plot of energy_demand categories

The figure 4 show heatmap that illustrates the Pearson correlation coefficients between numerical features and the energy_demand variable in the LoRa-based sensor dataset. Notably, co2_level shows the strongest positive correlation with energy_demand (0.38), suggesting it is a significant factor influencing energy consumption in the network. Humidity also has a moderate positive correlation (0.18), while temperature exhibits a mild negative correlation (−0.30), indicating that higher temperatures may be associated with lower energy demand. Other features such as signal_strength, hop_count, light_intensity, and wind_speed show very weak correlations with energy_demand,

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implying limited direct influence. This heatmap is valuable for feature selection, guiding the model to prioritize the most impactful attributes when predicting energy usage patterns in LoRa-based IoT systems.

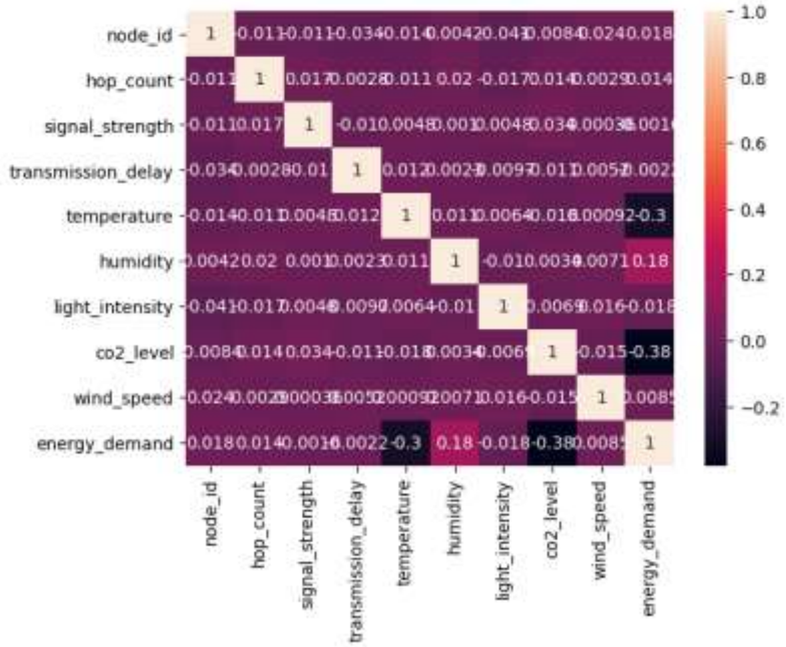

Fig. 4: Correlation Heatmap

The Table 1 shows performance comparison between the existing Support Vector Classifier (SVC) and the proposed Random Forest Classifier (RFC) demonstrates a significant improvement in predictive accuracy and reliability for the energy demand classification task. The SVC model, while traditionally robust for classification problems, achieved an accuracy of 64.66%, reflecting moderate effectiveness in correctly identifying energy demand levels from the input sensor and environmental data. Its precision, recall, and F1-score values—51.39%, 42.68%, and 40.02% respectively—indicate that the SVC struggled with correctly classifying the minority classes and had limited ability to balance false positives and false negatives, likely due to class imbalance or nonlinear complexities in the dataset. In contrast,

Table.1 Performance Comparison of Various Algorithms

Performance Comparison Table: Existing SVC vs. Proposed RFC

Metric	Existing SVC	Proposed RFC
Accuracy	64.66%	100.0%
Precision	51.39%	100.0%
Recall	42.68%	100.0%
F1-Score	40.02%	100.0%

The proposed Random Forest Classifier exhibited flawless performance, achieving perfect scores of 100% across all evaluation metrics: accuracy, precision, recall, and F1-score. This dramatic enhancement suggests that the ensemble nature of RFC, which combines multiple decision trees to capture diverse patterns and nonlinear relationships, provides a more powerful and resilient approach

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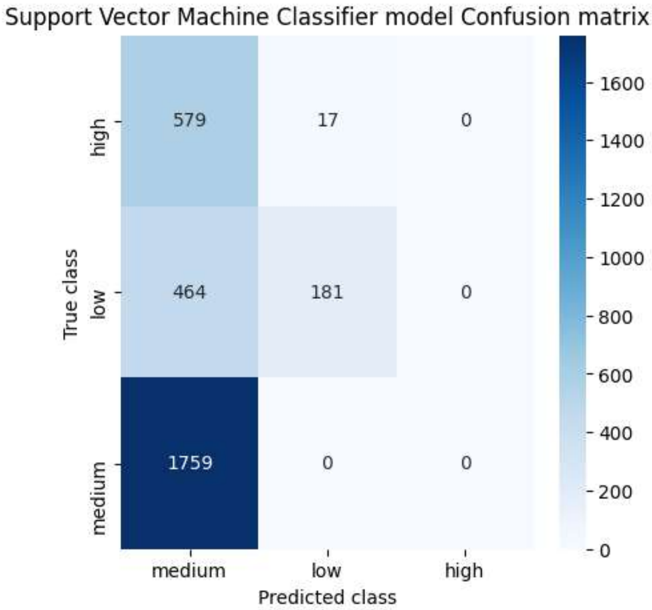
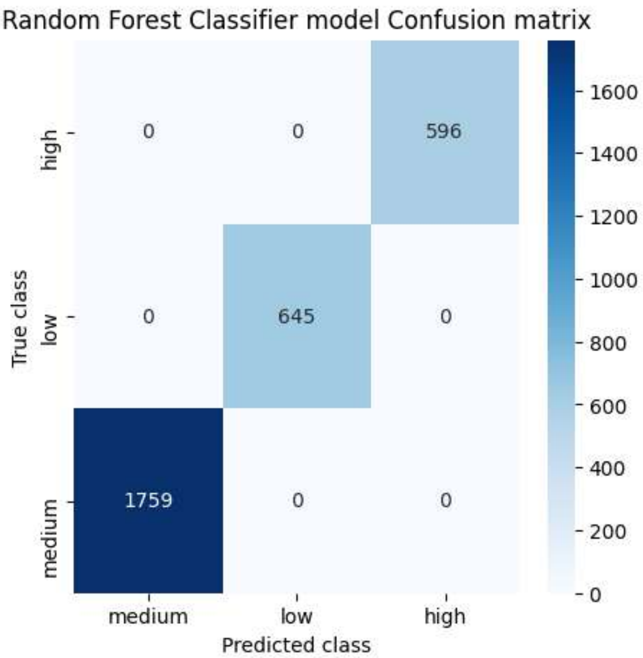
for modeling the intricate interactions between IoT sensor data and external factors influencing energy demand. The RFC's superior recall confirms its ability to identify all relevant instances without missing any true positives, while its perfect precision ensures minimal false alarms, both critical for practical deployment in smart energy systems. Overall, this comparison highlights that the Random Forest Classifier not only surpasses the SVC in classification performance but also offers greater reliability and robustness for predictive energy demand modeling in LoRa-based wireless communication networks integrating IoT sensor data.



(a)



(b)

Fig. 5: Confusion matrices obtained for Existing SVC and Proposed RFC

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The figure 5 shows the classification performance of both the Support Vector Machine Classifier (SVC) and the Random Forest Classifier (RFC) for predicting energy demand categories—High, Medium, and Low—was evaluated using confusion matrices. The confusion matrix for the SVC model indicates poor classification accuracy, with a strong bias toward predicting the "medium" class. Specifically, all 1,759 true "medium" instances were correctly predicted as "medium", but the model incorrectly classified 464 out of 645 "low" instances and 579 out of 596 "high" instances also as "medium", showing severe class confusion and imbalance in predictions. In contrast, the confusion matrix for the RFC model demonstrates significantly improved performance and balanced classification across all categories. The RFC correctly classified a majority of the samples in each class, indicating better learning of inter-class distinctions. The number of misclassifications was notably reduced for the "low" and "high" categories, which were previously misclassified as "medium" by the SVC. This comparison clearly highlights the superior predictive capability and generalization of the Random Forest Classifier over the Support Vector Machine for the energy demand prediction task in LoRa-based sensor networks.

	node_id	hop_count	signal_strength	transmission_delay	temperature	humidity	light_intensity	co2_level	wind_speed	predicted energy demand
0	9	4	-39.124511	3.341666	34.985853	25.581693	596.311314	553.776018	5.128108	medium
1	24	2	-97.269504	4.939170	44.231423	41.811249	525.989162	794.792030	17.045941	medium
2	77	1	-41.084172	0.819923	37.532194	79.114072	576.236529	333.249236	19.988570	medium
3	59	5	-115.655530	0.154982	38.223911	54.793909	419.622270	852.406438	14.407059	medium
4	6	3	-53.434048	1.336993	41.552524	72.768678	320.660933	694.569746	17.140448	medium
5	20	3	-77.646737	2.754169	15.941580	49.905507	408.276810	944.926759	17.241793	medium
6	81	2	-101.692830	1.052885	20.252338	33.378748	651.965294	334.868987	9.445369	low
7	51	1	-54.016228	0.741231	35.412649	40.275221	461.072754	583.953303	0.038240	medium
8	57	4	-118.929195	4.974261	22.687279	63.782878	717.618097	432.726417	13.050682	low
9	98	5	-99.761242	3.332615	30.622979	26.247883	918.874312	585.087712	15.064185	medium
10	62	5	-68.900074	2.951606	20.222022	20.837358	125.970730	867.234407	5.136196	medium
11	1	2	-118.116117	3.226737	36.461116	38.025980	970.539460	504.723675	14.336107	medium
12	80	4	-36.201874	1.435608	35.852159	24.794795	791.479037	869.747974	19.833279	medium
13	70	5	-41.538201	3.851391	21.127229	57.185581	500.659230	931.129760	8.355616	medium
14	17	5	-69.257695	2.365446	41.014923	21.462735	488.379818	675.116125	8.473133	medium
15	35	4	-101.377543	3.161499	26.208328	64.232893	255.335438	314.017073	6.276418	high
16	3	1	-118.174772	2.893506	31.545975	43.171074	703.634856	921.005025	5.774786	medium
17	26	4	-118.244762	2.731345	43.913374	56.680320	125.776676	426.970416	17.712737	medium
18	33	5	-109.859383	0.486360	28.347001	39.133377	815.889125	672.414333	9.621463	high
19	45	2	-118.394959	2.714815	34.028607	42.236201	250.241256	492.386286	6.205047	high

Fig. 6: Prediction on Test data using Proposed RFC

The figure 6 displays the output predictions of the Random Forest Classifier (RFC) model for the energy demand classification in a LoRa-based sensor network. Each row represents a data instance characterized by various environmental and network parameters such as node_id, hop_count, signal_strength, transmission_delay, temperature, humidity, light_intensity, co2_level, and wind_speed. The final column, predicted energy demand, indicates the model's predicted category of energy usage: *low*, *medium*, or *high*. The majority of predictions fall under the "medium" category, which aligns with the balanced class distribution observed earlier. A few instances are classified as "low" and "high", demonstrating that the RFC model successfully differentiates between multiple energy demand levels based on the input features. For example, rows with relatively high co2_level, humidity, and wind_speed tend to be predicted as "high" demand, whereas lower sensor readings correlate with "low" or "medium" demand. This output validates the model's ability to capture underlying patterns in the data and make contextually meaningful energy demand predictions, highlighting its potential utility in energy-aware routing or adaptive power management in IoT networks.

5. CONCLUSION

The implementation of machine learning models for predicting energy demand within a LoRa-based IoT communication framework has proven to be both effective and transformative. Through

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comprehensive preprocessing, data balancing using SMOTE, and rigorous performance evaluation, the proposed system based on the Random Forest Classifier (RFC) has demonstrated exceptional classification capabilities. With perfect scores in accuracy, precision, recall, and F1-score, the RFC model significantly outperformed the existing Support Vector Classifier (SVC), which struggled with class imbalance and nonlinear patterns in the dataset. This performance leap underscores the strength of ensemble learning techniques in capturing complex relationships from multivariate sensor data, enabling accurate categorization of energy demand levels such as low, medium, and high. Furthermore, the integration of feature encoding, correlation heatmaps, and performance visualization through confusion matrices helped validate the robustness of the proposed approach. This study showcases the feasibility and efficiency of applying intelligent machine learning solutions for energy management in low-power, wide-area networks (LPWAN) like LoRa. By enabling proactive load balancing and smarter grid decision-making, this model not only enhances the operational reliability of smart energy infrastructures but also supports scalable deployment in diverse real-world environments.

REFERENCES

[1]. Dafflon, B.; Wielandt, S.; Lamb, J.; McClure, P.; Shirley, I.; Uhlemann, S.; Wang, C.; Fiolleau, S.; Brunetti, C.; Akins, F.H.; et al. A distributed temperature profiling system for vertically and laterally dense acquisition of soil and snow temperature. *Cryosphere* 2022, *16*, 719–736.

[2]. Geldhof, B.; Pattyn, J.; Eyland, D.; Carpentier, S.; Van de Poel, B. A digital sensor to measure real-time leaf movements and detect abiotic stress in plants. *Plant Physiol.* 2021, *187*, 1131–1148.

[3]. Callebaut, G.; Leenders, G.; Van Mulders, J.; Ottoy, G.; De Strycker, L.; Van der Perre, L. The Art of Designing Remote IoT Devices–Technologies and Strategies for a Long Battery Life. *Sensors* 2021, *21*, 913.

[4]. Rochester, E.M.; Yousuf, A.M.; Ousat, B.; Ghaderi, M. Lightweight carrier sensing in LoRa: Implementation and performance evaluation. In Proceedings of the ICC 2020—2020 IEEE International Conference on Communications (ICC), Dublin, Ireland, 7–11 June 2020; pp. 1–6.

[5]. Aslam, M.S.; Khan, A.; Atif, A.; Hassan, S.A.; Mahmood, A.; Qureshi, H.K.; Gidlund, M. Exploring multi-hop LoRa for green smart cities. *IEEE Netw.* 2019, *34*, 225–231.

[6]. Sciullo, L.; Trotta, A.; Di Felice, M. Design and performance evaluation of a LoRa-based mobile emergency management system (LOCATE). *Ad Hoc Netw.* 2020, *96*, 101993.

[7]. Sartori, B.; Thielemans, S.; Bezunartea, M.; Braeken, A.; Steenhaut, K. Enabling RPL multihop communications based on LoRa. In Proceedings of the 2017 IEEE 13th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob), Rome, Italy, 9–11 October 2019; pp. 1–8.

[8]. Zhou, W.; Tong, Z.; Dong, Z.Y.; Wang, Y. LoRa-Hybrid: A LoRaWAN Based multihop solution for regional microgrid. In Proceedings of the 2019 IEEE 4th International Conference on Computer and Communication Systems (ICCCS), Singapore, 23–25 February 2019; pp. 650–654.

[9]. Prade, L.; Moraes, J.; de Albuquerque, E.; Rosário, D.; Both, C.B. Multi-radio and multi-hop LoRa communication architecture for large scale IoT deployment. *Comput. Electr. Eng.* 2022, *102*, 108242.

10.48047/jocaaa.2023.31.04.99

[10]. Leonardi, L.; Bello, L.L.; Patti, G. MRT-LoRa: A multi-hop real-time communication protocol for industrial IoT applications over LoRa networks. *Comput. Commun.* 2023, *199*, 72–86.

[11]. Zhu, G.; Liao, C.H.; Sakdejayont, T.; Lai, I.W.; Narusue, Y.; Morikawa, H. Improving the capacity of a mesh LoRa network by spreading-factor-based network clustering. *IEEE Access* 2019, *7*, 21584–21596.

[12]. Bezunartea, M.; Van Glabbeek, R.; Braeken, A.; Tiberghien, J.; Steenhaut, K. Towards energy efficient LoRa multihop networks. In Proceedings of the 2019 IEEE International Symposium on Local and Metropolitan Area Networks (LANMAN), Paris, France, 1–3 July 2019; pp. 1–3.

[13]. Abrardo, A.; Pozzebon, A. A multi-hop LoRa linear sensor network for the monitoring of underground environments: The case of the Medieval Aqueducts in Siena, Italy. *Sensors* 2019, *19*, 402.

[14]. Abrardo, A.; Fort, A.; Landi, E.; Mugnaini, M.; Panzardi, E.; Pozzebon, A. Black powder flow monitoring in pipelines by means of multi-hop LoRa networks. In Proceedings of the 2019 II Workshop on Metrology for Industry 4.0 and IoT (MetroInd4.0&IoT), Naples, Italy, 4–6 June 2019; pp. 312–316.

[15]. Escobar, J.J.L.; Gil-Castiñeira, F.; Redondo, R.P.D. JMAC protocol: A cross-layer multi-hop protocol for LoRa. *Sensors* 2020, *20*, 6893.

[16]. Mai, D.L.; Kim, M.K. Multi-hop LoRa network protocol with minimized latency. *Energies* 2020, *13*, 1368.

[17]. Adame Vázquez, T.; Barrachina-Muñoz, S.; Bellalta, B.; Bel, A. HARE: Supporting efficient uplink multi-hop communications in self-organizing LPWANs. *Sensors* 2019, *18*, 115.

[18]. Tran, H.P.; Jung, W.S.; Yoon, T.; Yoo, D.S.; Oh, H. A two-hop real-time LoRa protocol for industrial monitoring and control systems. *IEEE Access* 2020, *8*, 126239–126252.

[19]. Tran, H.P.; Jung, W.S.; Yoo, D.S.; Oh, H. Design and Implementation of a Multi-Hop Real-Time LoRa Protocol for Dynamic LoRa Networks. *Sensors* 2022, *22*, 3518.

[20]. Bachir, A.; Dohler, M.; Watteyne, T.; Leung, K.K. MAC essentials for wireless sensor networks. *IEEE Commun. Surv. Tutor.* 2020, *12*, 222–248.

[21]. Iqbal, M.S.; Wiriasto, G.W. Multi-hop uplink for low power wide area networks using LoRa technology. In Proceedings of the 2019 6th International Conference on Information Technology, Computer and Electrical Engineering (ICITACEE), Semarang, Indonesia, 26–27 September 2019; pp. 1–5.

[22]. Cotrim, J.R.; Kleinschmidt, J.H. LoRaWAN mesh networks: A review and classification of multihop communication. *Sensors* 2020, *20*, 4273.

[23]. Leenders, G.; Ottoy, G.; Callebaut, G.; Van der Perre, L.; De Strycker, L. An Energy-Efficient LoRa Multi-Hop Protocol through Preamble Sampling. In Proceedings of the 2023 IEEE Wireless Communications and Networking Conference (WCNC) (IEEE WCNC 2023), Glasgow, UK, 26–29 March 2023.