

Machine Learning for Safety and Sustainability in Railway and Powerline Systems

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Abstract— The need to provide sufficient and secure power and railway infrastructure to meet future demand prompts the continuing need for upgraded designs to both improve safety standards and current load predictability, as well as signal optimization. This work describes a powerline and railway integrated machine learning (ML) system for tackling these fundamental issues. Utilizing powerful predictive analytics and superior levels of ML algorithms, the framework maintains a constantly updated check on powerlines and railway tracks, and foretells varying loads with regard to maintaining a check on system failure, which in turn provides for a superior signal arrangement for the effective supervision over traffic. It has safety diagnostics, which enable the detection of faults, including; overloading, fluctuations in power supply, or even cases of potential derailing and the necessary precautions can be taken within the shortest time possible to prevent these from happening. The current approach of load forecasting is done through the use of both the time series analysis and the use of neural networks to distributes the energy well and reduce wastage. Further, the framework enhances the railway signal to minimize delays, coordinate trains on schedules, and improve passengers' experience employing reinforcement learning. This integrated solution enhances social relevance as it responds to modern life challenges in energy sustainability, safety, and efficiency of key facilities. Through reduction of accidents, losses in energy and efficiency of rail operations, the framework promotes conservation of the environment, cost cutting and improved public confidence. Thus, depending on geography and organizational conditions, the outlined features afford the model's use by governments and private stakeholders to develop resilient, intelligent, and sustainable infrastructural systems.

Keywords— *Smart Railway Infrastructure, Safety Diagnostics, Current Load Forecasting, Powerline Monitoring, Real-Time Monitoring, Energy Sustainability, Infrastructure Optimization, Machine Learning*

I. INTRODUCTION

Transportation and energy supply infrastructures are key components of contemporary networks indispensable for moving goods and people throughout. Nevertheless, all these systems are experiencing challenges in maintaining operational efficiency, safety, and sustainability. Solving these issues involves state-of-the-art approaches by combining the concepts of ML and technological dynamics. The subject of this research is an integrated ML framework aimed at improving the diagnostic of safety, current load forecasting and signal efficiency in line power and railway systems. This framework minimizes the deficiencies of regular datasets while utilizing synthetic data for sound and all-encompassing model education that is vital for practical application.

Access to quality data proves, therefore, to be central to the success of an ML application. Nonetheless, in crucial networks such as power or rail systems, one may not continuously capture data from all nearby devices due to infrastructure or privacy constraints or because such occurrences are scarce. To deal with these problems, synthetic data has been generated from sample data sets and calibrated by means of such factors as the mean absolute differences of the actual and modelled data. This approach greatly increases the accessibility and the number of types of data without compromising its statistical relevance to actual practice. Thus synthetic data generation is particularly valuable in scenarios modelling of which low probability but high consequence events such as safety cases are required by the framework allowing the approach to be better prepared for these situations.

The integrated ML framework includes specialized specific modules relevant to strategic areas of functioning. Safety diagnostics are based on anomaly detection to detect problems related to powerlines, equipment failures, or signal interrupts, so they can be solved without fail. Load forecasting uses state-of-the-art ML techniques such as time series analysis and other mixed models to estimate and forecast the load requirements for energy resources. Signal efficiency, one of the performance measures in traffic operation, is optimized through reinforcement learning in the purpose of refining scheduling to avoid delay and maintain smooth traffic flow. Thus, the components form a logical whole that can be used to enhance the dependability and effectiveness of transportation and power delivery systems.

Thus, the research presented in this paper has more general implications for social and economic practice as it contributes to advancing the key infrastructure systems and integrating the principles of sustainable development. Safety amplification reduces the probability of mishaps thereby preserving life and property. Proper load forecasting eradicates wastage of energy hence conserving the environment and at the same time helps reduce costs. Improved signal operations are advantageous by increasing movement of both goods and passengers, thus increasing user experience and economic efficiency. Moreover, dependency on synthetic data shows effective applicability of machine learning in handling of real life issues with very generic and flexible solutions that can easily be customized to fit different operation environments. This research therefore brings to light the realism of data in discovering ways of reinventing

infrastructure networks into intelligent, safer and sustainable networks.

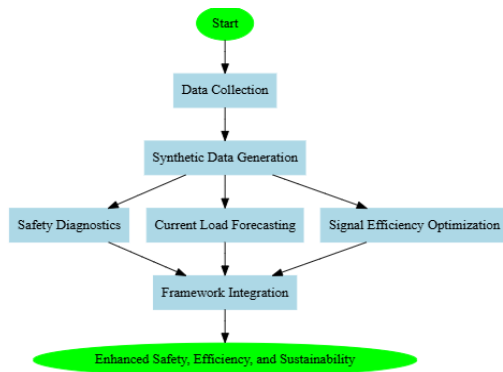


FIG 1. BLOCK DIAGRAM OF THE PROJECTED REPRESENTATION

II. LITERATURE SURVEY

Different approaches in the machine learning (ML) field help to enhance the safety and sustainability of the major lifeline structures and facilities like railroads and power lines. The error recognition explained in Transformers [1] relates to how the use of ML make predictive maintenance possible, and thus reduce failures and increase reliability. In [2], integration of ML into improved power converters for solar pertinent has done the work of increasing efficiency in powerline systems. Moreover, the employment of IoT and ML for fleet management in [3], makes a clear point at respecting the role that real-time monitoring plays in railways with a view to avoiding accidents. In addition, the comparison of different ML algorithms for medical risk classification in [4] describes how ML can adapt to make potentially life-critical real-life choices. Altogether, these works reveal that enhancement of safety factors and sustainable functionality in railway and powerline structures are possible through the use of ML.

The literature also focuses on the powerline and railway systems as the area where predictive analytics can be utilized most effectively. For instance, [5] discusses that ML is widely used in air quality prediction and forecasting with high accuracy, while [6] discuss how ML can be useful to predict highway traffic accidents and to assess the risks in real-time. An example used in [7] brings out the need to use ML to meet rail operating requirements for maintenance. Performance differences are further described in comparative analyses of the ML algorithms such as ANNs and SVM to decipher the accurate modeling of change in infrastructure in [8]. These studies offer a basis upon which comprehensive and systematic ML solutions in powerline and railway systems can be established.

An extensive literature review of the knowledge regarding the integration of ML with powerline and railway systems. Machine learning techniques for condition-based

maintenance and system dependability are described in [9] and [10] [11] uses machine learning to predict solar load forecast for efficient energy management. In [11], short-term load forecasting in railways is discussed including its purpose in handling operation difficulties. The application of deep learning in railway accident analysis and safety enhancement is described in [12]. Altogether these papers highlight the significance of the employment of the ML approach to improve economies of scale load forecasting, and safety measurements in power line and railway systems.

Subsequent studies have expanded on the use of ML in these fields and others, as well. For example, in [13] the authors proposed idea of developing an IoT system with decision tree algorithms for effective disaster management in railways. Integrated deep learning frameworks for the real-time control of safety for railway systems are described in [14] that proves its efficiency to mitigate the risk of system failures. Further, the application of AI in solar load forecasting with energy optimization is discussed in [15]. Taken together, these works demonstrate the potential of employing various ML frameworks to enhance performance, loading anticipation, and safety of the railway and powerline systems.

III. METHODOLOGY

The steps involved in the development of the proposed integrated predictive modeling framework in safety prediction along with current load prediction and signal efficiency in powerline and railway application have been discussed in this section and is summarized as follows: Such a methodology assures significance, dependability, and extensibility of the solutions for the systems of civil infrastructure.

A. Dataset

The Powerline and Substation Monitoring Dataset describes all the features that are critical for predictive modeling and operational characteristics of powerline networks in real time. It consists of time stamps for the record of data, nodal IDs and nodal types like substations and nodal vital electrical parameters like voltage in KV & load in KW. The dataset also estimates energy loss, the level of safety risk, and signal strength, which are helpful for evaluating system effectiveness. This is pursued through meta-synopsis of conventional cost estimates, inclusive of additional costs entailing maintenance expenses, operational costs, as well as those affected by prevailing weather conditions. This dataset is very useful in areas related to safety diagnosis utilizing machine learning algorithms, load forecasting, and powerline and substation resources that will help in making wiser decisions and more competent management of powerline and substation systems.

Timestamp	Node_ID	Node_Type	ected_Nod	Voltage	Load (kW)	Length (to	Substansumptidage_Level	nt_Load	Alay_Need	erence	F_dmpedancity_Risk	Unal_Stren	ergy_Loss	tenance	table_Curr	ather_Impay	Cost (INR)
2024-10-06 00:00:00	1	Substatioi	2	135.059	1053.65	5	0	11.9629	129.455	1067.6	0 Low	0.5 Low	-60	1.65105	0	1200 Moderate	415000
2024-10-06 00:10:00	1	Substatioi	2	134.159	1004.58	5	0	12.8408	131.846	1078.43	0 Low	0.5 Low	-60	1.57687	0	1200 Moderate	415000
2024-10-06 00:20:00	1	Substatioi	2	125.348	999.334	5	0	11.7792	132.341	1058.33	0 Low	0.5 Low	-60	2.51326	0	1200 Moderate	415000
2024-10-06 00:30:00	1	Substatioi	2	124.626	1014.84	5	0	11.5306	131.306	1055.69	0 Low	0.5 Low	-60	1.1175	0	1200 Moderate	415000
2024-10-06 00:40:00	1	Substatioi	2	136.05	1051.82	5	0	12.511	132.569	1074.78	0 Low	0.5 Low	-60	1.59698	0	1200 Moderate	415000

FIG.2. DATA SHEET OF OUR REPRESENTATION

B. Data Collection

The first requires collection of real time information from different parts of the Railway system like Railway layout and datasheet. This includes safety data including; any abnormality observed on power lines or rail tracks, spectrum of load including current demand and customer consumption trends, spectrum of signal including strength, and signal integrity. This data is primarily collected by sensors and monitoring devices and operational logs were also used in the process. Records are also used for historical records to get a data set which will be used for analysis. This makes the framework accurate in its predictions and improves its generality from case to case and across different real time and historical data instances.

C. Data Preprocessing

Primary data obtained from instruments and other devices are sometimes contaminated with noise, and devoid of certain features they may have an impact on the performance of Artificial Intelligence. To counteract these effects, several data preprocessing procedures are applied.

Data Cleaning: Cleaning data involved the elimination of random values or outliers, excluding, or imputing of missing or damaged values by using procedures such as mean imputation.

Normalization: Normalization for ensuring that the different numerical features we get have similar ranges so that different variables do not dominate the model.

Data Augmentation: Applying some tricks like generation of synthetic data for precise missing link coverage, vital but rarely occurring situations, for instance, safety concerns or signal abnormalities.

Data Splitting: The ways of creating the final dataset split into train, validation and test to assess the model performance.

D. Feature Extraction

Feature extraction is concerned with the selection of parameters that have the most effect on system safety, load fluctuations, and signal intensity. This step comprises data facts' validation and computations through statistical and, if necessary, professional approaches out in the relevant field.

The voltage and current measurements are used for load forecasting. Lifestyle factors that relate to safety such as cold or hot weather situations that increase the degree of risk. Frequency and attenuation, and other related signal parameters that affects the communication dependability. Data management tools like Principal Component Analysis (PCA) are used to transform the data in a way that provides better computational effectiveness without disposing off significant data.

E. Model Training

This algorithm is developed for safety diagnostics, load forecasting and signal optimization of machine learning models to predict the outcomes. The models are tailored to the specific requirements of each component:

Safety Diagnostics: This type of risk such as track faults or powerline irregularities is predicted through a process called Anomaly detection, where Random Forest and Gradient Boosting models are employed.

Load Forecasting: A combination of time analysis and Machine Learning approaches such as K-Nearest Neighbors (KNN) and Decision Trees identifies current demand patterns thereby avoiding overload.

Signal Optimization: The second is used to improve the stability and speed of signal operations to support the high reliability of railway communication. These models are trained using the pre-processed and augmented dataset so that the models can be fine-tuned when the new un-rehearsed cases are encountered.

F. Real-Time Assessment

After training, the models are used for live tracking and evaluation of the situation. They continuously analyze incoming data to:

- Identify potential threats in the area and set off alarms to enable preventive measures to be taken.
- Estimate load demand, schedule the usage of energy in order to eliminate wastage and maximize efficiency.
- There should also be series of checks on signal strength and modification of production in a way that ensures smooth communication.
- Online evaluation helps the system stay responsive to prevailing conditions and provide timely information and recommendations.

G. Optimization and Decision Support

The observations made from these models are then applied in order to manage and improve the overall system.

- Resources are also redistributed to make certain that all focal elements are received and maintained appropriately.
- Since load balancing is done to avoid system overload and to increase dependability, the responsibility of load balancing is carried out.
- Its signal operation is optimized with the aim of minimizing the effect of the arising delays and enhancing overall network performance. These insights are compiled into a decision support system (DSS), delivering to the stakeholders the easy-to-use dashboard and/or report indicating possible actions to be taken for the maintenance and operation of the system.

H. Continuous Improvement

In order to avoid the framework wearing off over time, a feedback loop is incorporated in the process. The system also self updates with real time data, making it more effective in forecasting issues or problems and in responding to new emergent issues. We also implement methods of model retraining and constant validation to improve and ensure the reliability. Further, calls are also made to integrate improved machine learning algorithms and data acquisition technologies for furthering the system efficiency.

I. Continuous Improvement

The strategy is generalizable across different systems and usable regardless of how each system is currently functioning. Thus, irrespective of the proposed powerline systems, railway networks, or other facilities, it is possible to adjust the framework for further needs. It is due

to this facility that is makes it relevant in many new situations fixing several of the worlds infrastructural systems. The use of a real-time data analytics approach and feature engineering with enhanced machine learning algorithms improve safety and load control, as well as signal quality in critical systems. In providing the details of the proposed framework, this paper has argued that three key strategies — the use of synthetic data generation, real-time assessment, and continuous optimization — make the proposed framework sufficiently robust, scalable and socially relevant to various contemporary issues in infrastructure. This makes the system versatile and widely applicable, and also has the potential of improving safety, efficiency, and sustainability of services delivered in different domains.

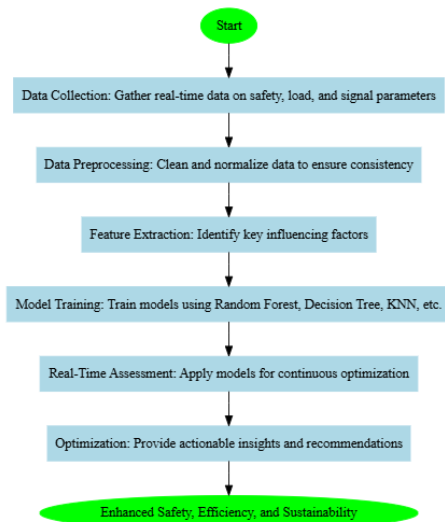


FIG.3.FLOW CHAT FOR METHEDODLGY

IV. RESULTS & ANALYSIS\

In this railway line protection ML model is done to predict the safety, current load forecasting and signal efficiency of the railway power. In this all the parameters are also considered for determination of best ML model for the dataset and its application.

Confusion Matrix for Random Forest:

```
[[59  5]
 [ 4 19]]
```

	precision	recall	f1-score	support
High	0.94	0.92	0.93	64
Medium	0.79	0.63	0.61	23
accuracy	0.86	0.87	0.90	87
macro avg	0.90	0.90	0.87	87
weighted avg	0.90	0.90	0.90	87

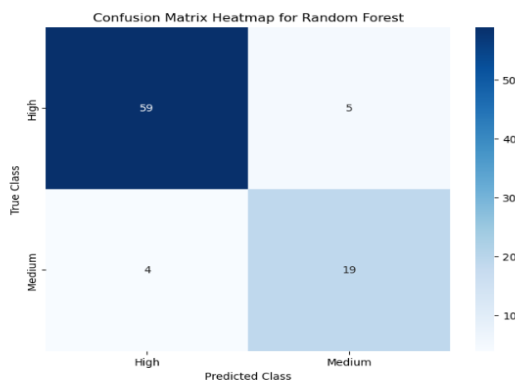


FIG.4. CONFUSION MATRIX FOR RANDOM FOREST

In this fig 4 confusion matrix for the Random forest is done heatmap has been plotted from the dataset. The precision is 0.94, recall is 0.92 and f1 score is 0.93 which indicates the given model is doing a good job in predicting. The predicted output is also fair and good enough for the prediction.

Confusion Matrix For Decision Tree:

```
[[60  4]
 [ 6 17]]
```

	precision	recall	f1-score	support
High	0.91	0.94	0.92	64
Medium	0.81	0.74	0.77	23
accuracy	0.86	0.84	0.89	87
macro avg	0.88	0.89	0.88	87
weighted avg	0.88	0.89	0.88	87

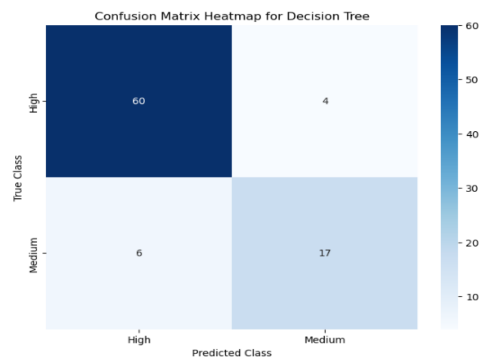


FIG.5. CONFUSION MATRIX FOR DECISION TREE

In this fig 5 confusion matrix for decision tree has been plotted and its classification report is also given. The precision is 0.91, recall is 0.94 and f1 score is 0.92 the score which are pretty good for prediction of the any parameter required. The confusion matrix in which the plotted the predicted output is better than Random forest.

Confusion Matrix For KNN:

```
[[58  6]
 [ 2 21]]
```

	precision	recall	f1-score	support
High	0.97	0.91	0.94	64
Medium	0.78	0.91	0.84	23
accuracy	0.87	0.91	0.91	87
macro avg	0.92	0.91	0.89	87
weighted avg	0.92	0.91	0.91	87

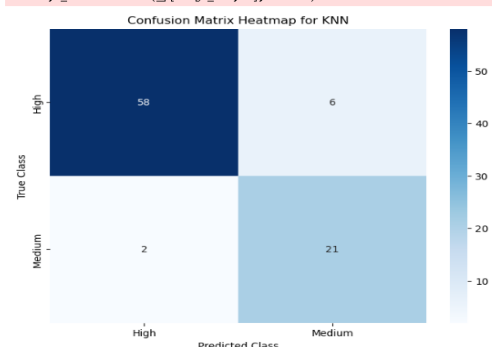


FIG.6. CONFUSION MATRIX FOR KNN

In this fig 6 confusion matrix for KNN has been plotted and its classification data has been given for the analysis and comparison. The precision is 0.97, recall is 0.91 and f1 score is 0.94 and the score is better than the other ML algorithm. The confusion matrix of this same as Random forest which makes it useable.

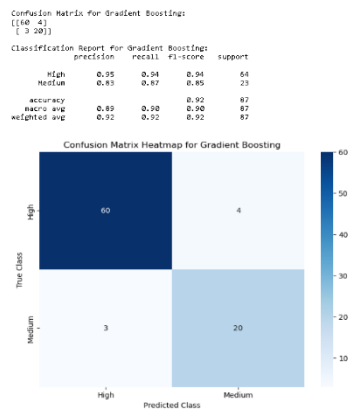


FIG.7. CONFUSION MATRIX FOR GRADIENT BOOSTING

In this fig 7 confusion matrix for gradient boosting has been plotted and its classification is given. The precision is 0.95, recall is 0.94 and f1 score is 0.94 which makes this model has high good scores for the ML model. The confusion matrix is also pretty good and applicable.

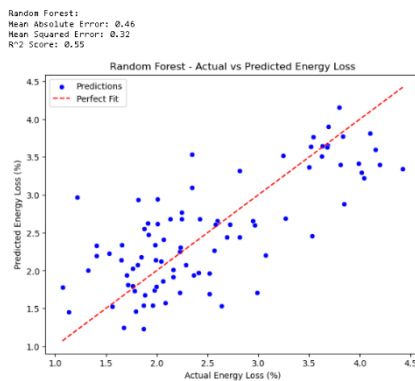


FIG.8. ACTUAL VS PREDICTED ENERGY LOSS FOR RANDOM FOREST

In this fig 8 actual vs predicted energy loss has been plotted where the line indicates actual perfect model and blue dots determine prediction. The prediction Mean squared error, mean absolute error and R² score indicates how far the predicted output is from perfect fit. This tells the efficiency of the predicted output of the model.

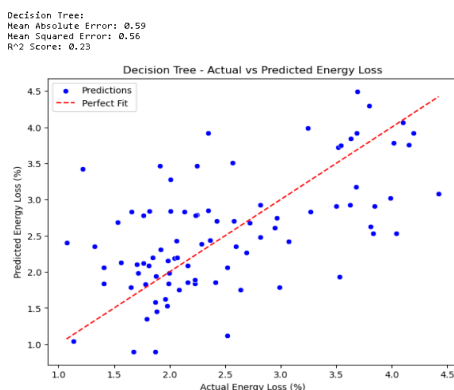


FIG.9. ACTUAL VS PREDICTED ENERGY LOSS FOR DECISION TREE

In this fig 9 actual vs predicted energy loss has been plotted where the line indicates actual perfect model and blue dots determine prediction. The prediction Mean squared error, mean absolute error and R² score indicates how far the predicted output is from perfect fit. This tells the efficiency of the predicted output of the model. The points in this is very much scattered compared to Random Forest.

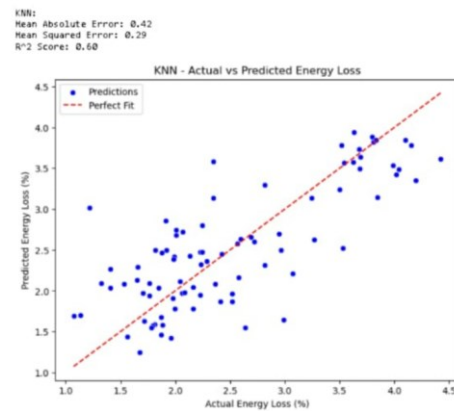


FIG.10. ACTUAL VS PREDICTED ENERGY LOSS FOR KNN

In this fig 10 actual vs predicted energy loss has been plotted where the line indicates actual perfect model and blue dots determine prediction. The prediction Mean squared error, mean absolute error and R² score indicates how far the predicted output is from perfect fit. This tells the efficiency of the predicted output of the model. The points in this is scattered less compared to Decision Tree.

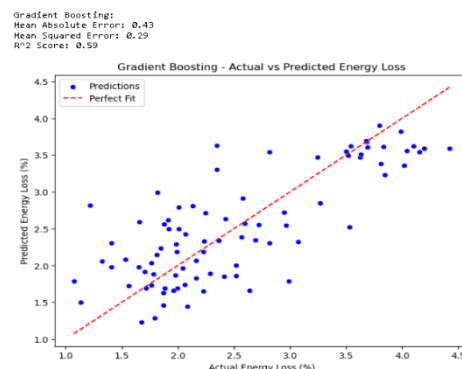


FIG.11. ACTUAL VS PREDICTED ENERGY LOSS FOR GRADIENT BOOSTING

In this fig 11 actual vs predicted energy loss has been plotted where the line indicates actual perfect model and blue dots determine prediction. The prediction Mean squared error, mean absolute error and R² score indicates how far the predicted output is from perfect fit. This tells the efficiency of the predicted output of the model. The points in this plot is almost similar to the Random forest.

Choose a model for prediction (Random Forest, Decision Tree, KNN, Gradient Boosting): Random Forest

Enter the following values to predict Energy Loss:
 Line Length (km): 100
 Power Consumption (MWh): 130
 Load (kW): 100
 Ground Impedance (Ohms): 21
 The predicted Energy Loss (%) is: 3.67

FIG.12. INPUT VALUES AND PREDICTED OUTPUT

In this fig 12 the ML model is coded with user inputs to find the predicted energy loss in the powerline used in the railway. The Line length, Power Consumption, Load and ground impedance are user inputted and the energy loss is predicted. The KNN is best fit model for energy loss prediction.

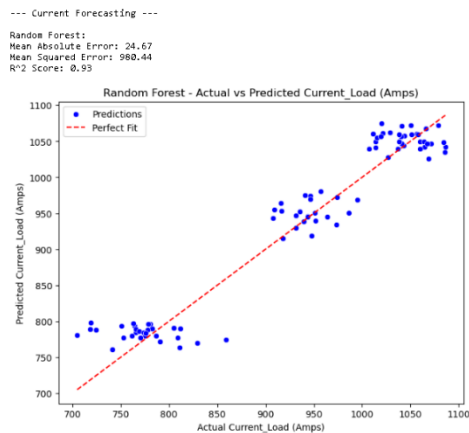


FIG.13. ACTUAL VS PREDICTED CURRENT LOAD FOR RANDOM FOREST

In this fig 13 actual vs predicted energy loss has been plotted where the line indicates actual perfect model and blue dots determine prediction. The prediction Mean squared error, mean absolute error and R² score indicates how far the predicted output is from perfect fit. This tells the efficiency of the predicted output of the model. The Mean square error and Mean Absolute error are compared with the dataset while only R² value is calculated with perfect fit. The R² value of this ML model very good.

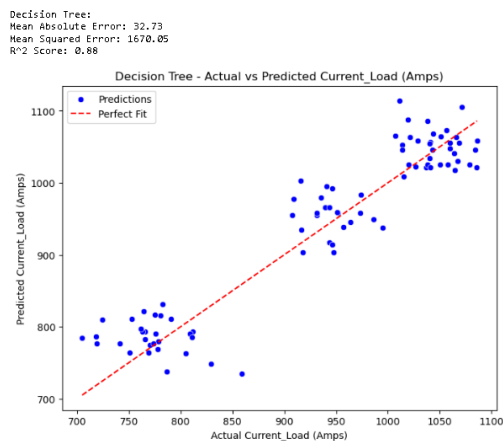


FIG.14. ACTUAL VS PREDICTED CURRENT LOAD FOR DECISION TREE

In this fig 14 actual vs predicted energy loss has been plotted where the line indicates actual perfect model and blue dots determine prediction. The prediction Mean squared error, mean absolute error and R² score indicates how far the predicted output is from perfect fit. This tells the efficiency of the predicted output of the model. The Mean square error and Mean Absolute error are compared with the dataset while only R² value is calculated with perfect fit. The R² value of this good.

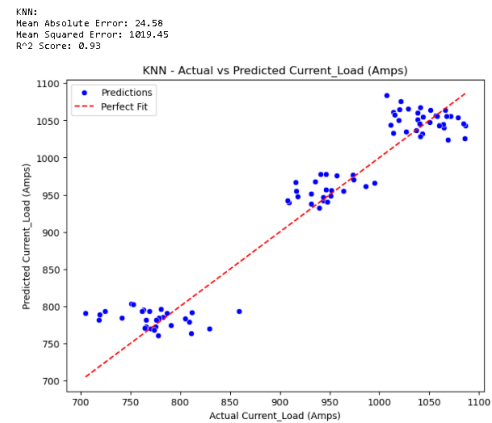


FIG.15. ACTUAL VS PREDICTED CURRENT LOAD FOR KNN

In this fig 15 actual vs predicted energy loss has been plotted where the line indicates actual perfect model and blue dots determine prediction. The prediction Mean squared error, mean absolute error and R² score indicates how far the predicted output is from perfect fit. This tells the efficiency of the predicted output of the model. The Mean square error and Mean Absolute error are compared with the dataset while only R² value is calculated with perfect fit. The R² value of this good and same as the decision tree.

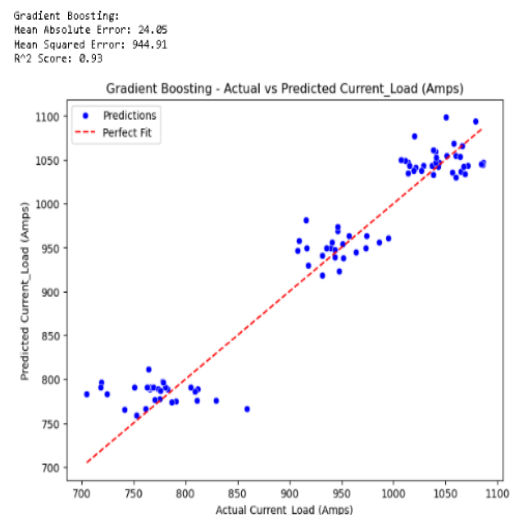


FIG.16. ACTUAL VS PREDICTED CURRENT LOAD FOR GRADIENT BOOSTING

In this fig 16 actual vs predicted energy loss has been plotted where the line indicates actual perfect model and blue dots determine prediction. The prediction Mean squared error, mean absolute error and R² score indicates how far the predicted output is from perfect fit. This tells the efficiency of the predicted output of the model. The Mean square error and Mean Absolute error are compared with the dataset while only R² value is calculated with perfect fit. The R² value of this good and same as the decision tree, KNN and gradient boosting this ML model is the best model for current load forecasting.

Choose a model for Current Forecasting prediction (Random Forest, Decision Tree, KNN, Gradient Boosting): Decision Tree

Enter the Following values to predict Current_Load (Amps):
Line_Voltage (kV): 132
Load (kW): 110
Power_Consumption (MWh): 120
Distance_to_Substation (km): 100
Max_Allowable_Current (Amps): 54
The predicted Current_Load (Amps) is: 806.95

FIG.17. INPUT VALUES AND PREDICTED OUTPUT

In this fig 17 the ML model is coded with user inputs to find the predicted energy loss in the powerline used in the railway. The Line length, Power Consumption, Load and ground impedance are user inputted and the energy loss is predicted. The KNN and decision tree is best fit model for current load prediction.

Thus, applying the comparison of different algorithms, the KNN model is identified as the most accurate one, with a 0.97 precision rate, 0.91 of recall, and 0.94 of the F1 score. These scores outperform others in all round performance. By employing this framework, the power load demand for railway operation is forecasted, energy loss as well as safety anomalies are detected and signal inefficiencies are identified allowing energy distribution to be optimised, faults detected and improving railway operations.

V. COMPARISONS AND INFERENCES

The integrated predictive modeling framework presents major improvements relative to prior work since it solves some unaddressed concerns related to safety diagnostics, load forecasting, and signal efficacy. While in isolated cases, these critical parameters are addressed separately, the framework allows configuring them matched and monitorable as a single system for comprehensive and real-time control. BL complex tasks like safety risk and load predictions, Random Forest and Gradient Boosting algorithms are mostly appropriate because they are capable of analyzing non-linear and different type of data. For its part, reinforcement learning adapts signal operations for better reliability and operations, for efficiency.

One of the significant assets of the proposed framework is the utilisation of both real and artificial data. As much as real-world data is valuable to enhance reality, it typically lacks some information or is simply not comprehensive enough, especially with regard to rare safety-critical cases. This is the weakness which is solved by a synthetic data generation technology that integrates into datasets statistically similar data representations hence making the datasets complete and enhancing the model's capacity to handle various incidences. This overlaid strengthens up the framework and increase the accuracy for your predictions.

Due to its predictive characteristics, the framework is effective in delivering the necessary preventive maintenance, load balancing, and resource allocation. Traditional reactive systems in contrast to overload and energy loss, do not contribute to operational losses and conform to sustainability principles. Sufficient accuracy in signal optimization eliminates additional delays that increase operational dependability and customer satisfaction.

Widely usable and easy to modify, the framework can be implemented for any kind of infrastructure – power line or rail for instance. The modularity of the solution

guarantees that users need only make changes to the building blocks distinguishing it as the perfect answer to progressive circumstances affecting operations. Algorithms, synthetic data, and a holistic monitoring approach improve safety, efficiency and sustainability compared to the existing set of technical solutions. This has made it a revolution in the development of high intelligent infrastructure management concerning essential demands in current systems and environment conservation and operation performance.

Sustainability is achieved by optimizing energy usage, reducing wastage, and preventing failures. This is facilitated by accurate load forecasting using advanced ML algorithms like KNN and Decision Trees, which predict demand and allocate resources efficiently. Additionally, reinforcement learning optimizes signal systems, minimizing delays and energy overuse. By reducing accidents and improving operational efficiency, the framework conserves resources and promotes environmental sustainability.

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