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Explainable Artificial Intelligence-Based Prediction of Power System Loading Conditions Under Diverse Operating Scenarios

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Abstract: - Accurate prediction of power system loading conditions is essential for ensuring reliable operation and effective decision-making in modern power networks. This study presents an explainable artificial intelligence (XAI)-based approach for predicting power system loading conditions under diverse operating scenarios using real operational data collected from the Egbin Power Station. The dataset was preprocessed through data cleaning and feature standardization to enhance data quality and model performance. Three machine learning models, namely Support Vector Machine (SVM), Gradient Boosting (GB), and Deep Neural Network (DNN), were developed to classify the loading conditions of four distribution feeders. The models were evaluated using accuracy, precision, recall, and Matthews correlation coefficient (MCC). The results show that the SVM model achieved high predictive performance with accuracies of 0.9963, 0.9863, 0.9838, and 0.985 for Feeders 4, 3, 2, and 1, respectively. However, the Gradient Boosting and Deep Neural Network models demonstrated superior performance, achieving perfect classification results with accuracy, precision, recall, and MCC values of 1 across all feeders. Furthermore, model interpretation techniques were applied to the Gradient Boosting and Deep Neural Network models to enhance transparency and explainability of the predictions. The results indicate that explainable ensemble and deep learning approaches can effectively capture complex nonlinear patterns in power system data while providing interpretable insights for operational decision-making. The proposed framework contributes to the development of reliable, transparent AI-driven tools for the intelligent monitoring and management of power system loading conditions.

Keywords: Explainable Artificial Intelligence, Loading condition, Support vector machine, Gradient boosting, Deep neural network

I. INTRODUCTION

The electric power system is one of the most critical infrastructures supporting modern societies, economic development, and industrial growth [1, 2]. With the rapid increase in electricity demand, power system operations have become significantly more complex due to the integration of distributed energy resources, dynamic load behavior, and the increasing variability of renewable energy generation [3 -5]. Traditionally, power system operators rely on deterministic analytical models and historical operational knowledge to monitor and manage system loading conditions [4, 6-7]. However, the growing complexity of modern power networks requires more advanced, intelligent techniques capable of accurately predicting system behavior across diverse operating scenarios. Accurate prediction of power system loading conditions is essential for maintaining grid stability, preventing equipment overloading, and ensuring a reliable electricity supply [8]. In many developing countries, including Nigeria, the power grid faces several operational challenges, such as limited infrastructure capacity, inadequate monitoring systems, aging equipment, and high levels of demand uncertainty [9, 10]. These challenges make it difficult for system operators to effectively anticipate loading conditions across substations and transmission networks. As a result, unexpected overload conditions may occur, which can lead to voltage instability, equipment failure, forced outages, or even widespread blackouts [10, 11].

The Nigerian power system, which serves millions of consumers across the country, is particularly vulnerable to these operational uncertainties due to the imbalance between generation capacity and rapidly growing electricity demand. Among the key nodes in the Nigerian transmission network is the Egbin substation, which plays a crucial role in the transmission of electrical power generated from the Egbin Power Station, one of the largest thermal power plants in the country [12, 13]. The operational reliability of the Egbin substation is vital for maintaining power flow stability across the southwestern region of Nigeria and for supporting the national grid. Due to its strategic importance, the substation frequently operates under varying loading conditions influenced by fluctuating demand patterns, generation availability, transmission constraints, and unexpected disturbances.

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Therefore, developing intelligent systems capable of predicting power system loading conditions at this critical node can significantly enhance operational planning, preventive maintenance, and real-time decision-making.

Predicting loading conditions in power systems is traditionally performed using statistical forecasting techniques [6, 14] and deterministic power flow analysis [15-17]. While these approaches have been widely used, they often struggle to capture nonlinear relationships between system variables and may not effectively handle large-scale operational datasets generated by modern power systems. Furthermore, conventional methods often rely on simplifying assumptions that may not accurately reflect real-world grid behavior, especially under uncertain and dynamic operating conditions. As power systems become increasingly complex and data-rich, there is a growing need for advanced predictive tools that can learn complex patterns from operational data. Artificial intelligence (AI) and machine learning techniques have recently emerged as powerful tools for modeling and predicting complex behaviors in power systems [6]. AI-based methods can automatically learn hidden patterns from historical operational data and use these patterns to predict future system conditions with high accuracy. These techniques can analyze large volumes of operational data collected from substations, transmission networks, and monitoring devices to identify critical relationships between system variables and loading conditions. Despite the significant predictive capabilities of machine learning models, one of the major limitations associated with many AI-based approaches is the lack of transparency and interpretability in their decision-making processes. Many advanced machine learning algorithms are often treated as "black-box" models, meaning that while they may produce accurate predictions, it can be difficult for system operators to understand how these predictions are generated. In critical infrastructures such as power systems, interpretability is essential because operators must be able to trust and validate the decisions generated by automated systems. Without sufficient transparency, AI models may face resistance from power industry practitioners who require clear explanations for operational recommendations. To avoid this problem this research adopts Explainable Artificial Intelligence (XAI) in predicting the loading conditions.

XAI has emerged as a promising solution to this challenge by providing techniques that allow machine learning models to explain their predictions in a transparent and interpretable manner [18, 19]. XAI methods enable researchers and system operators to understand the influence of different input variables on model predictions and identify key factors contributing to system loading conditions. By providing interpretable insights into the behavior of machine learning models, XAI enhances trust, accountability, and practical usability of AI-based solutions in real-world engineering applications [20, 21]. The application of explainable AI in power system analysis offers several important benefits. It enables system operators to identify the most influential factors affecting power system loading conditions, which can improve operational planning and preventive control strategies. More so, it helps validate the reliability of machine learning models by providing insights into their decision-making processes. Explainability supports regulatory and operational transparency, which is critical for the adoption of AI technologies in energy infrastructure management. Therefore, integrating explainable AI with machine learning models provides a powerful framework for developing intelligent decision-support systems for modern power grids.

In the context of the Nigerian power system, limited research has focused on the application of explainable AI for predicting loading conditions in critical substations. Most existing studies focus primarily on load forecasting or fault detection, while relatively few works address the problem of interpretable prediction of operational loading states under diverse operating scenarios. Furthermore, the variability associated with demand fluctuations, transmission constraints, and generation uncertainties necessitates the development of robust predictive models capable of handling multiple operating conditions. Addressing this research gap can significantly improve situational awareness and operational reliability in the Nigerian grid network. Motivated by these challenges, this study proposes an Explainable Artificial Intelligence–based framework for predicting power system loading conditions across diverse operating scenarios, using operational data from the Egbin substation in the Nigerian grid network. The proposed approach integrates advanced machine learning techniques with explainability tools to provide both accurate predictions and interpretable insights into system behavior. The study evaluates the performance of three widely used machine learning algorithms: Support Vector Machine (SVM), and Gradient Boosting (GB) and Deep Neural Network (DNN). These models are trained using operational features associated with power system conditions, and their predictive performance is compared across different loading scenarios. Beyond prediction accuracy, the research emphasizes interpretability by incorporating explainable AI techniques that reveal the importance of different system variables influencing loading conditions. By combining predictive performance with model interpretability, the proposed framework aims to support power system operators in making informed operational decisions and improving grid stability under uncertain operating environments. The insights from explainable models can also help engineers identify critical system parameters that influence power flow patterns and potential overload conditions. This research contribute to the development of intelligent decision-support systems for power system operation in Nigeria and other developing power networks facing similar operational challenges. By leveraging data-driven approaches and explainable AI methods, the proposed framework can enhance situational awareness, support proactive operational planning, and reduce the risk of system instability caused by unexpected loading conditions.

The major technical contributions of this research are summarized as follows:

1. This study developed a framework that integrates machine learning algorithms with explainable artificial intelligence techniques to predict and interpret power system loading conditions under diverse operating scenarios.
2. The proposed approach incorporates explainable AI methods to analyze feature importance and provide interpretable insights into the factors influencing power system loading conditions, enabling better understanding and trust in AI-based predictions.
3. The study applies the proposed predictive framework to real operational conditions associated with the Egbin substation, providing practical insights that can support grid operators in improving operational reliability, preventing overload conditions, and enhancing decision-making in power system management.

II. RESEARCH METHOD

The step-by-step approach adopted for this research is presented in Figure 1.

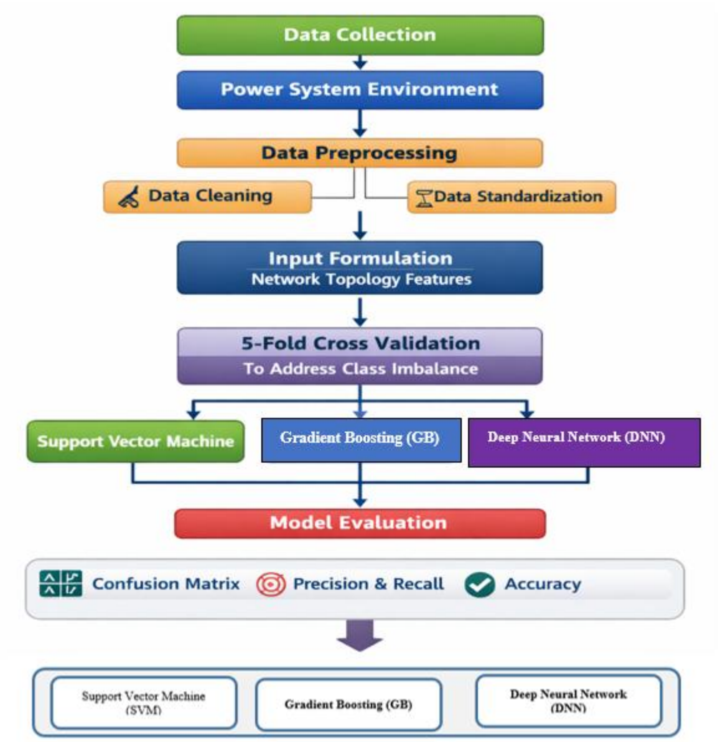


Figure 1. The research framework

The operational data of the power system network used in this study were collected from the substation environment, focusing on the Egbin substation within the Nigerian grid network. The dataset includes important operational parameters such as the network topology characteristics, the loading conditions of each feeder, and the equipment ratings of the station. These parameters are essential for understanding the operational behavior of the power system and for accurately classifying the loading conditions under different operating scenarios based on equation (1).

$$Lc = \begin{cases} Normal\ Loading & L(t) < FR \\ High\ Loading & L(t) = FR \\ Overloading & L(t) > FR \end{cases} \quad (1)$$

Where L(t) is the load on the feeder at time t, FR is the feeder rating.

Before applying machine learning techniques, the collected data were subjected to data preprocessing procedures to ensure the quality and reliability of the dataset. In practical power system datasets, issues such as missing values, noisy measurements, and inconsistent data entries often occur due to sensor faults, communication failures, or recording errors. Therefore, data cleaning and treatment techniques were implemented to remove noise and handle missing values. This process ensures that the dataset used for model training and testing is accurate, consistent, and suitable for machine learning analysis. Furthermore, since the dataset represents energy-related operational measurements, feature scaling is necessary to ensure that all variables contribute equally to the learning process. In this study, the Min–Max normalization approach [6] was employed to standardize the dataset. The Min–Max method scales each feature within a defined range, typically between 0 and 1, which helps prevent features with larger numerical values from dominating those with smaller values during model training. This normalization process improves model convergence and enhances predictive performance. Following preprocessing, input feature formulation was performed using the network topology behavior of the power system, which is mathematically represented in Equation (2). The topology-based representation captures the structural and operational relationships among different components of the power network, including buses, feeders, and transmission lines. By incorporating these topology-based features, the machine learning models can effectively learn patterns associated with various loading conditions in the network.

$$Lc_i = F(L_i, L_j) \quad (2)$$

Where is the loading condition to be predicted at bus *i*, L_i and L_j is the load at bus *i* and *j* respectively.

One of the major challenges in classification-based machine learning tasks is the presence of class imbalance, where certain classes appear more frequently than others. If not properly addressed, class imbalance can lead to biased models that favor the majority class while poorly predicting minority classes. To mitigate this challenge, a 5-fold cross-validation technique was employed during model training and testing. The dataset was partitioned into five subsets, where four subsets were used for training and one subset for testing in each iteration, resulting in a 4:1 training-to-testing ratio. This approach ensures that every data sample is used for both training and testing at different stages, thereby improving model robustness and ensuring that all classes are represented during the training process. According to the No-Free-Lunch theorem, no single machine learning model performs optimally across all possible problems [22]. Therefore, evaluating multiple models is necessary to identify the most suitable algorithm for a particular task. In this research, three widely used machine learning algorithms were implemented, namely Support Vector Machine (SVM), Gradient Boosting (GB) and Deep neural network. These models were trained and tested using the prepared dataset to predict power system loading conditions under varying network operating scenarios.

Since the problem is formulated as a classification task, the performance of the trained models was evaluated using several confusion-matrix-based performance metrics. These metrics include precision, recall, and accuracy, which are defined in Equations (3)–(6) [22, 23].

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (5)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

Where TP and TN are true positive and true negative, FP and FN are false positive and false negative respectively.

Precision measures the proportion of correctly predicted positive observations among all predicted positives, while recall evaluates the ability of the model to correctly identify actual positive cases. Accuracy provides an overall measure of the model's correct predictions across all classes. However, in situations involving class imbalance, accuracy alone may not provide a reliable performance assessment. Therefore, the Matthews Correlation Coefficient (MCC) was also used as an additional evaluation metric, as expressed in Equation (7) [23]. MCC provides a balanced evaluation by considering true positives, true negatives, false positives, and false negatives simultaneously, making it particularly effective for imbalanced classification problems.

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (7)$$

Although machine learning models can provide accurate predictions, many of these models operate as black-box systems, meaning that the internal decision-making processes are not easily interpretable by human users. In critical infrastructures such as power systems, it is essential for engineers and operators to understand how predictive decisions are made in order to build trust in automated systems. To address this challenge, an Explainable Artificial Intelligence (XAI) approach based on SHapley Additive exPlanations (SHAP) was incorporated into the framework. SHAP provides a unified method for interpreting machine learning models by quantifying the contribution of each input feature to the final prediction. Through this approach, the most influential system variables affecting loading condition predictions can be identified and analyzed. The SHAP-based explanation model used in this study is mathematically described in Equation (8) [24].

$$\emptyset_i = \sum_{S \subseteq F\{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!}[f(S \cup \{i\}) - f(S)] \qquad (8)$$

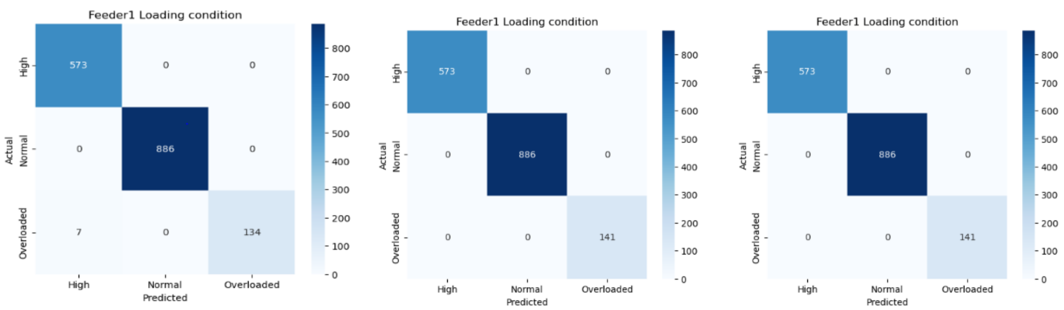
$\emptyset_i$ SHAP value of feature i, F set of all features, S subset of features excluding i, F(s) model prediction using features in subset S, F(SU{i}) prediction when feature i is added. This explainability component enhances transparency, allowing power system engineers to better understand the relationship between network topology behavior and predicted loading conditions. The simulation of the training and testing of the data was carried out in python environment.

III. RESULTS AND DISCUSSION

The results of this section are presented in this section, under four sub sessions

A. Loading Condition Predictions of the Feeders 1

The confusion matrices for the SVM, GB, and DNN models, predicting the loading conditions on each feeder 1 in the network, is presented in Figure 2 and the performance metrics of the model is presented in Table 1.



SVM GB DNN

Figure 2. Prediction of loading conditions of feeder 1

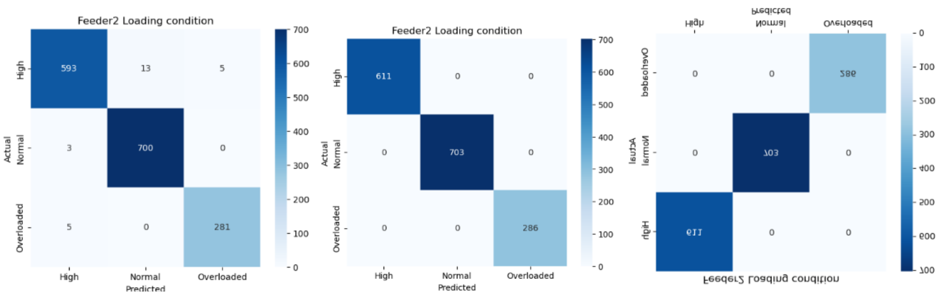
Table 1: Models Evaluation for Feeder 1

Model	Class High			Class normal			Class Overloaded		
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
SVM	0.98	0.98	0.98	0.99	1.00	0.99	0.96	0.94	0.95
GB	1	1	1	1	1	1	1	1	1
DNN	1	1	1	1	1	1	1	1	1

The results presented in Table 1, evaluate the performance of three machine learning models Support Vector Machine (SVM), Gradient Boosting (GB), and Deep Neural Network (DNN) for predicting feeder load conditions categorized as High, Normal, and Overloaded. The evaluation metrics include precision, recall, and F1-score for each class. The results indicate that both the Gradient Boosting and Deep Neural Network models achieved perfect classification performance across all load condition classes, with precision, recall, and F1-score values equal to 1. This implies that the models correctly identified all instances of high, normal, and overloaded feeder conditions without any false positives or false negatives. Such performance demonstrates the strong capability of these models to capture the complex nonlinear relationships between the input features and feeder load states. In particular, Gradient Boosting benefits from its sequential learning mechanism, where multiple weak learners are combined to iteratively reduce prediction errors, thereby improving classification accuracy. Similarly, the Deep Neural Network effectively models nonlinear interactions among variables through multiple hidden layers and activation functions. In contrast, the Support Vector Machine exhibited slightly lower performance, although its results remain highly competitive. For the high load condition, the SVM achieved precision, recall, and F1-score values of 0.98, indicating a small number of misclassified instances. The model performed very well for the normal load class, achieving perfect recall (1.00) and a high F1-score of 0.99. However, the most noticeable misclassification occurred in the overloaded class, where the precision, recall, and F1-score were 0.96, 0.94, and 0.95, respectively. This suggests that some overloaded cases were incorrectly classified as either high or normal load conditions. Such misclassification may occur because SVM relies on defining optimal hyperplanes for class separation, which may struggle when class boundaries are highly nonlinear or overlapping. From a power system operation perspective, accurate identification of feeder load conditions is critical for preventing equipment overloading and ensuring system reliability. The perfect classification performance observed for Gradient Boosting and Deep Neural Network models suggests that these approaches are highly suitable for real-time feeder monitoring and predictive load condition analysis. The results demonstrate that advanced machine learning approaches, particularly Gradient Boosting and Deep Neural Networks, can significantly enhance the accuracy of load condition prediction in distribution feeders, thereby supporting intelligent monitoring and decision-making in modern power systems.

B. Loading Condition Predictions of the Feeders 2

The confusion matrices for the SVM, GB, and DNN models, predicting the loading conditions on each feeder 1 in the network, is presented in Figure 3 and the performance metrics of the model is presented in Table 2.



SVM GB DNN

Figure 3. Prediction of loading conditions of feeder 2

Table 2: Models Evaluation for Feeder 2

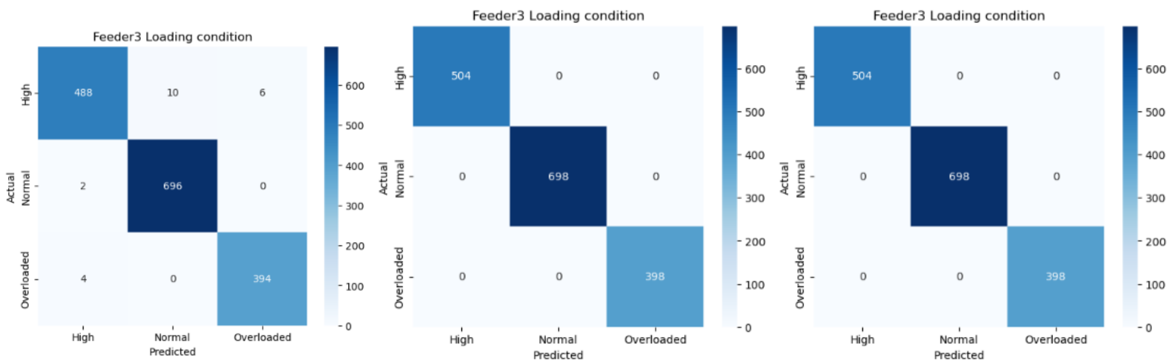
Models	Class High			Class normal			Class Overloaded		
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
SVM	0.99	0.97	0.98	0.98	1.00	0.99	0.98	0.98	0.98
GB	1	1	1	1	1	1	1	1	1
DNN	1	1	1	1	1	1	1	1	1

Result in Table 2 presents the performance evaluation of three machine learning models Support Vector Machine (SVM), Gradient Boosting (GB), and Deep Neural Network (DNN) for predicting the load conditions of Feeder 2, which are categorized into High, Normal, and Overloaded states. The performance of each model is evaluated using precision, recall, and F1-score metrics. The results indicate that both the Gradient Boosting and Deep Neural Network models achieved perfect classification performance for all load condition categories. Each class recorded precision, recall, and F1-score values of 1, demonstrating that all instances were correctly classified without any false positives or false negatives. This consistent performance further confirms the robustness of these models in capturing complex nonlinear relationships among the system variables. In particular, Gradient Boosting effectively improves prediction accuracy by sequentially combining multiple decision trees to correct errors made by previous learners, while the Deep Neural Network captures nonlinear interactions between input variables through multiple hidden layers and nonlinear activation functions. The perfect classification achieved by these two models indicates their strong capability for accurate feeder load condition monitoring. In contrast, the Support Vector Machine model also demonstrated strong predictive capability but exhibited minor misclassifications compared to the other models. For the High load condition, the SVM achieved precision, recall, and F1-score

values of 0.99, 0.97, and 0.98, respectively. The slightly lower recall value indicates that a small proportion of high load instances were incorrectly classified as another class. For the Normal load condition, the model achieved precision and recall values of 0.98 and 1.00, respectively, resulting in an F1-score of 0.99. This indicates that all actual normal load conditions were correctly detected, although a few instances from other classes may have been incorrectly labeled as normal. For the Overloaded condition, the model achieved balanced performance with precision, recall, and F1-score values of 0.98, indicating only a very small number of misclassifications. The slight reduction in performance observed in the SVM model may be attributed to the nature of its classification mechanism, which relies on constructing optimal separating hyperplanes between classes. In cases where the relationships among features are highly nonlinear or where class boundaries overlap, SVM may experience difficulty achieving perfect separation. In contrast, ensemble-based approaches such as Gradient Boosting and nonlinear architectures like Deep Neural Networks are better suited to capture complex patterns within the data. From an operational perspective, accurate identification of feeder load conditions is essential for preventing feeder overloading, maintaining system reliability, and supporting proactive load management strategies. The results obtained for Feeder 2 demonstrate that Gradient Boosting and Deep Neural Network models provide highly reliable predictions and can serve as effective tools for intelligent monitoring of distribution feeder conditions.
Overall, the findings from Feeder 2 are consistent with those obtained for Feeder 1, where Gradient Boosting and Deep Neural Network models also achieved perfect classification performance. This consistency across multiple feeders further strengthens the potential of advanced machine learning techniques for predictive monitoring and control in modern power distribution systems.

C. Loading Condition Predictions of the Feeders 3

The confusion matrices for the SVM, GB, and DNN models, predicting the loading conditions on each feeder 1 in the network, is presented in Figure 4 and the performance metrics of the model is presented in Table 3.



SVM GB DNN

Figure 4.Prediction of loading conditions of feeder 3

Table 3: Models Evaluation for Feeder 3

Models	**Class High**			**Class normal**			**Class Overloaded**		
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
SVM	0.99	0.97	0.98	0.99	1.00	0.99	0.98	0.99	0.99
GB	1	1	1	1	1	1	1	1	1
DNN	1	1	1	1	1	1	1	1	1

Table 3 presents the performance evaluation of three machine learning models—Support Vector Machine (SVM), Gradient Boosting (GB), and Deep Neural Network (DNN)—for predicting the operational load conditions of Feeder 3, categorized as High, Normal, and Overloaded. The performance metrics considered include precision, recall, and F1-score, which collectively provide a comprehensive assessment of classification accuracy and reliability.

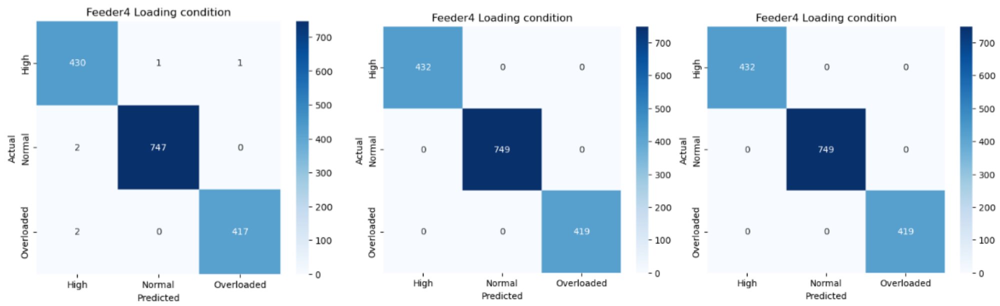
The results show that both the Gradient Boosting and Deep Neural Network models achieved perfect classification performance across all load conditions. Each class recorded precision, recall, and F1-score values of 1, indicating that the models correctly identified all instances of high, normal, and overloaded feeder conditions without any misclassification. This outcome highlights the strong capability of these models to capture complex nonlinear relationships among the input variables associated with feeder load behavior. Gradient Boosting achieves this performance through its ensemble learning mechanism, which sequentially combines multiple decision trees to minimize classification errors. Similarly, the Deep Neural Network effectively models nonlinear feature interactions using multiple hidden layers and nonlinear activation functions, enabling it to learn intricate patterns within the dataset.

In contrast, the Support Vector Machine model demonstrated slightly lower performance compared to GB and DNN, although the results remain highly accurate overall. For the High load condition, SVM achieved precision, recall, and F1-score values of 0.99, 0.97, and 0.98, respectively, indicating that a small proportion of high load instances were misclassified. For the Normal load condition, the model performed strongly with precision, recall, and F1-score values of 0.99, 1.00, and 0.99, respectively, meaning that all actual normal load cases were correctly identified. For the Overloaded condition, the model achieved balanced performance with precision and recall values of 0.98 and 0.99, resulting in an F1-score of 0.99.

These results suggest that while SVM performs effectively, ensemble-based and deep learning models such as Gradient Boosting and Deep Neural Networks provide superior predictive capability for feeder load condition classification due to their ability to model complex nonlinear relationships within the dataset

D. Loading Condition Predictions of the Feeders 4

The confusion matrices for the SVM, GB, and DNN models, predicting the loading conditions on each feeder 1 in the network, is presented in Figure 4 and the performance metrics of the model is presented in Table 3.



SVM GB DNN

Figure 5.Prediction of loading conditions of feeder 4

Table 4: Models Evaluation for Feeder 4

Models	**Class High**			**Class normal**			**Class Overloaded**		
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
SVM	0.99	1	1	1	1.00	1	1	1	1
DNN	1	1	1	1	1	1	1	1	1
GB	1	1	1	1	1	1	1	1	1

Table 4 presents the classification performance of three machine learning models—Support Vector Machine (SVM), Deep Neural Network (DNN), and Gradient Boosting (GB)—for predicting the load conditions of Feeder 4**.** Similar to the previous feeders, the load states are categorized into High**,** Normal**,** and Overloaded**,** and the evaluation metrics include precision, recall, and F1-score. The results indicate that all three models achieved near-perfect classification performance for Feeder 4. Both the Deep Neural Network and Gradient Boosting models recorded perfect scores across all classes, with precision, recall, and F1-score values equal to 1. This implies that these models correctly classified every instance of the feeder load conditions without any errors. The consistent perfect performance of these models across multiple feeders highlights their strong ability to learn the underlying patterns and nonlinear relationships present in the power system load dataset. Ensemble learning methods such as Gradient Boosting are particularly effective because they iteratively reduce prediction errors by combining multiple weak learners, while Deep Neural Networks excel in capturing complex feature interactions through layered nonlinear transformations. The Support Vector Machine also demonstrated excellent performance for

Feeder 4. For the High load condition, the model achieved precision and recall values of 0.99 and 1.00, respectively, resulting in an F1-score of approximately 1. This indicates that nearly all high load instances were correctly identified, with only minimal classification uncertainty. For the Normal and Overloaded conditions, the model achieved perfect precision, recall, and F1-score values of 1, demonstrating flawless classification for these two classes. The improved SVM performance in Feeder 4 compared to other feeders may suggest that the data distribution in this feeder exhibits greater class separability, enabling the SVM hyperplane to effectively distinguish between different load conditions. Overall, the results confirm that advanced machine learning techniques can provide highly accurate predictions for feeder load condition monitoring, supporting proactive power system management and improved operational reliability.

E. Model comparison Metrics for the feeders

The comparative performance of three machine learning models—Support Vector Machine (SVM), Gradient Boosting (GB), and Deep Neural Network (DNN) across four feeders is illustrated in the figure 6.

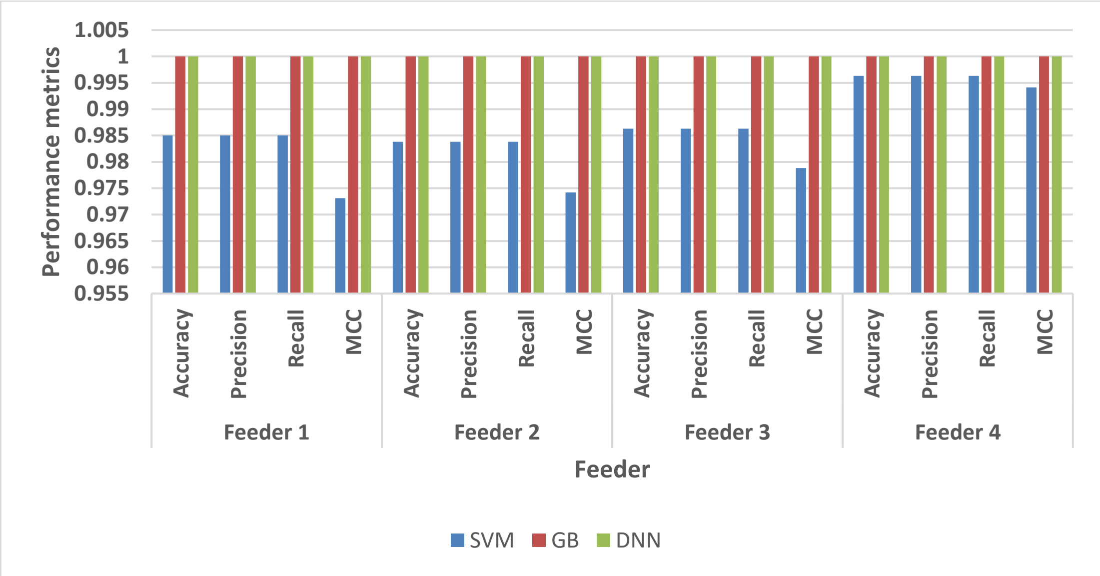


Figure 6. Comparison of model performance across the feeders

The evaluation metrics considered include accuracy, precision, recall, and Matthews Correlation Coefficient (MCC),
which together provide a comprehensive assessment of classification reliability and predictive consistency for load condition prediction. Overall, the results demonstrate that both the Gradient Boosting and Deep Neural Network models consistently achieved perfect or near-perfect performance across all feeders, whereas the Support Vector Machine exhibited slightly lower performance in some cases. This difference highlights the ability of ensemble learning and deep learning approaches to capture complex nonlinear relationships within the feeder load datasets.

For Feeder 1, the SVM model achieved accuracy, precision, and recall values of approximately 0.985, with an MCC of around 0.97. Although these values indicate strong classification performance, they are slightly lower than those achieved by the Gradient Boosting and Deep Neural Network models, which both reached perfect scores of 1.0 across all performance metrics. This indicates that the latter models correctly classified all load conditions without misclassification. A similar trend is observed for Feeder 2, where the SVM model demonstrated high but slightly reduced performance compared with the other models. The SVM accuracy and recall values remained close to 0.98, while the MCC value dropped to approximately 0.975, indicating minor classification inconsistencies. In contrast, both the Gradient Boosting and Deep Neural Network models maintained perfect predictive performance, suggesting that they were better able to capture the underlying data patterns associated with feeder load conditions.

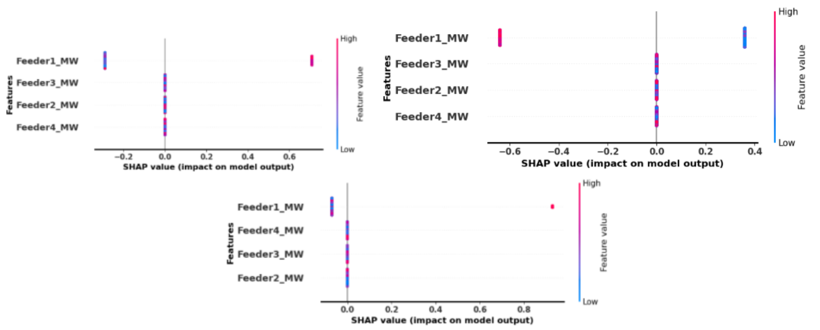
For Feeder 3, the SVM model again exhibited strong predictive capability, with accuracy values approaching 0.986 and MCC around 0.979. However, slight deviations from perfect classification still occurred, reflecting occasional misclassification between the load condition classes. Meanwhile, the Gradient Boosting and Deep

Neural Network models once again achieved perfect scores across all evaluation metrics, demonstrating consistent predictive robustness. The results for Feeder 4 reveal an improvement in the performance of the SVM model compared with the previous feeders. The accuracy, precision, and recall values for SVM increased to approximately 0.996, while the MCC value also improved significantly, approaching 0.995. This suggests that the data distribution for Feeder 4 may present clearer class boundaries, allowing the SVM hyperplane to separate the load condition classes more effectively. Nevertheless, the Gradient Boosting and Deep Neural Network models continued to achieve perfect performance across all metrics.

The consistently superior performance of Gradient Boosting can be attributed to its ensemble learning mechanism, where multiple decision trees are sequentially combined to minimize prediction errors. This approach enables the model to capture nonlinear interactions and subtle patterns within the dataset. Similarly, the Deep Neural Network model effectively learns complex feature relationships through multiple hidden layers and nonlinear activation functions, making it well suited for modeling complex power system data. In contrast, the Support Vector Machine relies on constructing optimal hyperplanes to separate classes. While SVM performs well in high-dimensional feature spaces, it may struggle when class boundaries are highly nonlinear or overlapping, leading to minor misclassification.
The comparative analysis shows that Gradient Boosting and Deep Neural Networks provide the most reliable and consistent performance for feeder load condition prediction across all feeders, achieving perfect classification results. Although the Support Vector Machine also demonstrates strong predictive capability, its slightly lower performance suggests that ensemble-based and deep learning approaches may be more suitable for complex load condition monitoring tasks in modern power distribution systems. Therefore GB and DNN can be applied in the network for load condition prediction. In order to enables the operators to determines the features that affects the loading conditons, the model interpretability is perform based on SHAP.

IV. MODEL INTERPRETABILITY

The model interpretations of GB and DNN, which can be deployed due to their high accuracy, are described in Figures 7 to 10.



High Normal Over loaded

Figure 7a GB Model Interpretability in Predicting the condition on Feeder 1

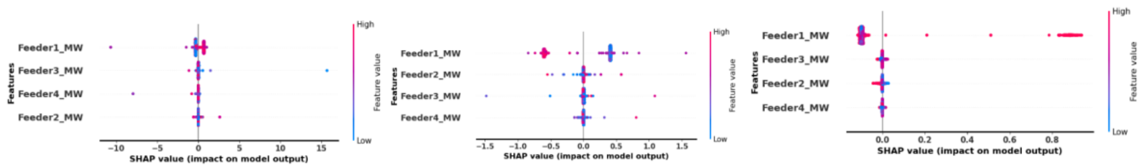


Figure 7b. DNN Model Interpretability in Predicting the condition on Feeder 1

In Figure 7a and 7b, indicates that the loads on feeder 1 has much influence in predicting the loading conditon on the feeders across all the loading classes. However the effects on each of the predicting classes differs under different load. This will enables the operators to know the actions to be intiated to avoid system contingency during any loading conditon. Likewise in Figure 8a and 8b, both the GB and DNN models, shows that the load on feeder two has the highest infleunce in predicting the feeder 2, loading conditions. However, the GB model in Figure 7a, shows that feeder 1, 3, and 4, has no influence in predicting the Feeder 2, model.

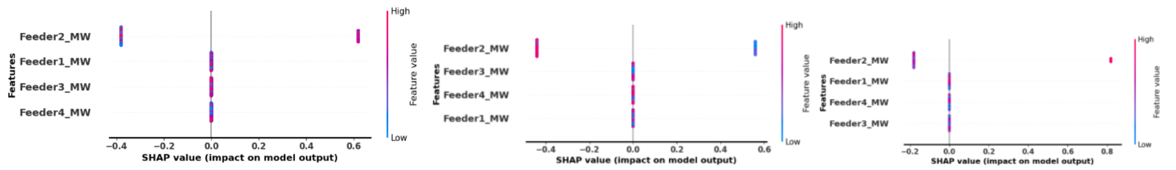


Figure8a.GB Model Interpretability in Predicting the condition on Feeder 2

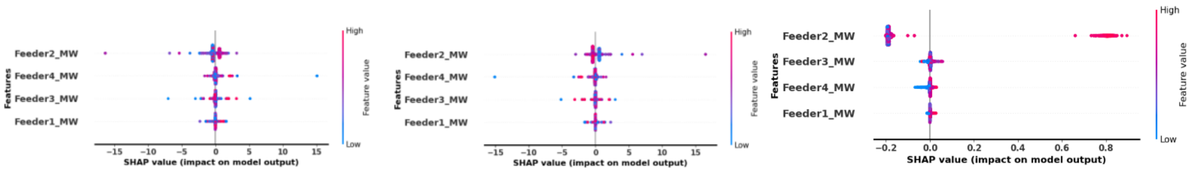


Figure8b. DNN Model Interpretability in Predicting the condition on Feeder 2

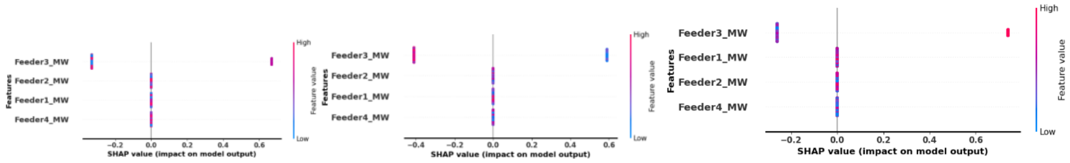


Figure9a. GB Model Interpretability in Predicting the condition on Feeder 3

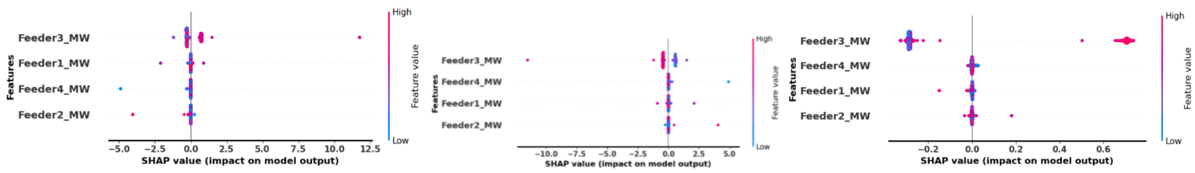


Figure9b. DNN Model Interpretability in Predicting the condition on Feeder 3

Furthermore, in Figure 9a and 9b, the GB and DNN models shows that the load on feeder 3, has the highest impact in predciting the loading conditon on the feeder, DNN models shows that other feeders has low impact, however, GB indicates that other feeders has no impact in predicting the loading conditons, with SHAP values of zero. Likewise, in Figure 10a and 10b, the GB and DNN indicates that load on feeder four has more significant effect in predictibg the loading conditon on the feeder. DNN indicates that other feeder has less impact while GB shows that other feeder as low impact with a SHAP values of zero. The SHAP values results enables system operators to determine the actions to be intaited when the system is operating under contingency that can caused failure.

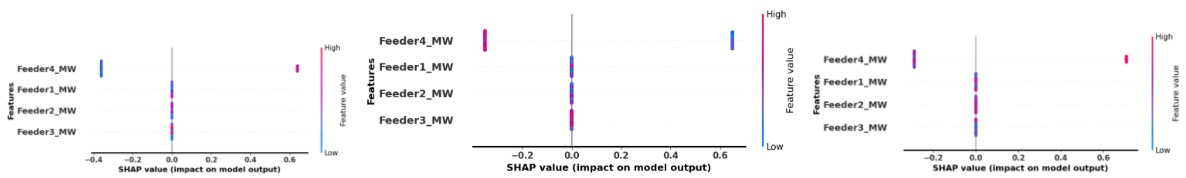


Figure10a. GB Model Interpretability in Predicting the Condition on Feeder 4

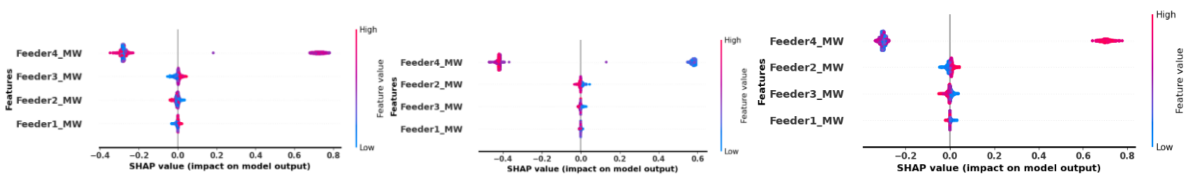


Figure 10b. DNN Model Interpretability in Predicting the Condition on Feeder 4.

V. CONCLUSION

This study presented an explainable artificial intelligence (XAI)-based framework for predicting power system loading conditions under diverse operating scenarios using real operational data obtained from the Egbin Power

Station. Accurate prediction of loading conditions is essential for maintaining the stability, reliability, and operational efficiency of modern power systems, especially in networks experiencing varying demand and operational uncertainties. In this research, the dataset was carefully preprocessed through data cleaning and feature standardization to ensure data quality and improve the learning capability of the developed models. Three machine learning models were implemented and evaluated, including the Support Vector Machine, Gradient Boosting, and Deep Neural Network. The models were trained to classify the loading conditions of four feeders under different operational scenarios. The performance evaluation was conducted using accuracy, precision, recall, and Matthews correlation coefficient (MCC). The results demonstrated that all models achieved high predictive performance. The SVM model produced strong results with accuracies of 0.9963, 0.9863, 0.9838, and 0.985 for Feeders 4, 3, 2, and 1, respectively, indicating its capability in capturing the underlying patterns of the dataset. However, the Gradient Boosting and Deep Neural Network models outperformed SVM, achieving perfect classification performance across all feeders with accuracy, precision, recall, and MCC values equal to 1. In addition to predictive modeling, explainability techniques were applied to the Gradient Boosting and Deep Neural Network models to interpret their decision-making processes. This aspect enhances transparency and enables power system operators to understand the influence of different features on loading condition predictions, thereby increasing trust in AI-based decision-support tools. The key technical contributions of this study include the development of an XAI-based predictive framework for power system loading condition classification, a comprehensive comparison of multiple machine learning approaches using real operational data, and the integration of model interpretation techniques for improved transparency. The findings demonstrate that explainable ensemble and deep learning models provide reliable and interpretable solutions for intelligent monitoring and management of power system loading conditions in practical power network environments. Further reach should considered the uncertainties in the integration of distributed energy resources.

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