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Non-contact power system fault diagnosis: a machine learning approach with electromagnetic current sensing

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ABSTRACT

Modern power system protection schemes incorporate artificial intelligence (AI) techniques. However, in a conventional way, most of these schemes rely on the data of current and voltage collected from current transformer (CT) and potential transformer (PT) respectively. CTs suffer from the drawback of core saturation and impact the accuracy and effectiveness of intelligent methods. Also, it has the constraints of size, safety, and economy. The research here explores the effectiveness of magnetic sensors in advanced power system protection schemes as an alternative to traditional current sensing. In the presented work, a novel dataset is prepared by transforming transmission line currents into magnetic field components. Several supervised as well as unsupervised machine learning algorithms have been applied to this data instead of traditional currents and voltage for fault prediction. The paper discusses the comparative evaluation of these algorithms based on various performance metrices which reveals that Gaussian Naïve Bayes (GNB), K-nearest neighbor (KNN), random forest (RF), and extreme gradient boost (XGB) algorithms excel in fault detection, while multilayer perceptron (MLP) and KNN performs better fault classification. The findings promise the potential for developing compact, safe, and cost-effective protection schemes utilizing magnetic field sensors.

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1. INTRODUCTION

Traditional power systems are rapidly evolving into complex, interconnected smart grids, enhancing efficiency, reliability, and sustainability through advanced monitoring and control technologies [1]. However, this transition poses challenges in achieving faster and more accurate fault prediction, crucial for maintaining grid stability and resilience [2], necessitating the intelligent technique based diagnostic actions [3]. Conventionally, fault protection in substations relies on current transformers (CTs) and potential transformers (PTs), which can be economically inefficient and prone to errors during fault transients [4]. CT saturation can lead to measurement inaccuracies and relay misoperations [5]. To overcome these limitations, electromagnetic sensing may offer a viable alternative, providing real-time, contactless monitoring for improved fault detection reliability and accuracy [6]. Over the years, the researchers have been effectively using supervised and unsupervised ML techniques, neural networks, ensemble methods to develop robust fault analysis framework due to their capacity to analyze large datasets and ability of extracting meaningful patterns and insights [7]. Nevertheless, inherent complexities of smart grid environments demand more and more research.

Ukwuoma *et al.* [8] proposed multiscale attention network (MSA) for fault diagnosis outperformed the XGBoost, multilayer perceptron (MLP), and conventional graph neural networks. Bouchiba and Kaddouri [9] found that, for the IEEE 14 bus network, the decision tree (DT) algorithm had lower accuracy (53%) compared to support vector machine (SVM) (87%) in fault classification. Mohanty *et al*. [10] highlighted that using DT based on post-fault current data can lead to overfitting, sensitivity to noise, and challenges in handling continuous variables. Abed *et al.* [11] demonstrated that the K-nearest neighbor (KNN) algorithm accurately diagnoses transmission line faults using phase current and voltage values. Awasthi *et al.* [12] further confirmed KNN's efficacy in fault classification and location in complex distribution systems with multiple DGs. Chen *et al.* [13] found that kernel density-based logistic regression (LogReg) improves accuracy compared to fuzzy KNN, SVM with a linear kernel, and standard multi-class LogReg, though it is more time-consuming. Venkata *et al.* [14] found that using time and frequency series data from currents and voltages for ML-based fault diagnosis, the Gaussian Naive Bayes (GNB) algorithm achieved the highest accuracy among classifiers. Asman *et al.* [15] compared SVM and KNN for fault categorization from lightning, insulator failure, and external invasions, finding SVM to be more accurate (97.1%) and faster than KNN (70.6%). Wu *et al.* [16] applied a random forest (RF) algorithm-based method to HVDC transmission lines, using S-transform variation index and energy sum ratio features to rapidly identify faults. Fonseca *et al.* [17] found that a notch filter-based RF algorithm classified transmission line faults eight times faster than neural networks, though with slightly lower accuracy. Jiashu *et al*. [18] used a convolutional neural network (CNN) model for fault classification and location, improving accuracy and robustness by minimizing data pollution, while Assadi *et al.* [19] demonstrated that MLP outperforms elman recurrent (ER) neural networks in shunt fault classification based on statistical evaluation parameters.

Recent literature highlights extensive research on ML algorithms for power system fault detection and classification, with popular methods including SVM, DT, KNN, Naive Bayes, and ensemble techniques. Several key metrics play a crucial role in quantifying efficacy and evaluation of these algorithms [20]-[22]. Models of these algorithms have been used with the data of three phase fault currents and voltages as an input conventionally. However, these researchers have not considered the limitations of current and voltage transformers (i.e. CTs and PTs) leaving the scope for further enhancement of protection schemes. This research paper uniquely focuses on a comparative analysis of ML algorithms applied to magnetic field data, rather than traditional current and voltage measurements, for fault identification in power systems. The study aims to develop a current-to-magnetic field transformation block for transmission line models, generate a novel magnetic field dataset, and apply both supervised and unsupervised ML techniques. The algorithms are evaluated based on various metrics to identify the most effective approach for developing a non-intrusive intelligent fault detection and classification system.

Organization of the paper follows the stages of research work: section 1 includes introduction, literature survey, and problem formulation, section 2 describes the proposed methodology, system simulation studies are discussed in section 3, section 4 presents the applied ML approach, section 5 presents the results and discussion on the obtained current waveforms, magnetic field patterns, and analytical comparison of various ML models applied for fault detection as well as fault classification, finally, section 6 concludes the research.

2. PROPOSED METHOD

Typically, in a power system protection scheme, a CT senses the fault current and a relay transmits a trip signal to the circuit breaker (CB) [23], [24]. In the proposed methodology, as shown in Figure 1, instead of the CT, magnetic field sensors are to be used along with an intelligent system trained using AI techniques. Power system simulated here incorporates current to magnetic field conversion block that is designed using its mathematical equations. Both in normal and fault circumstances, current is fed to this block as an input. The output of this block is a set of values of magnetic field components corresponding to currents. A novel dataset is generated using the values of magnetic field components collected from the workspace.

Different fault types generate distinct patterns, of magnetic fields which can be effectively recognized and classified using artificial intelligence (AI) techniques. To design the intelligent system, it is imperative to apply the ML algorithms for accurate fault prediction. We have used several supervised and unsupervised ML classifier models such as GNB, KNN, LogReg, RF, SVM, and XGB, DT, and MLP algorithms in the current work. These algorithms have been applied to the generated magnetic field dataset and evaluated separately: to deal with the problem of binary classification and multiclass classification in case of fault detection and fault type identification respectively. Functional description of these algorithms is available in the literature [7]-[22]. Finally, comparative analysis of applied algorithms based on various indices is performed.

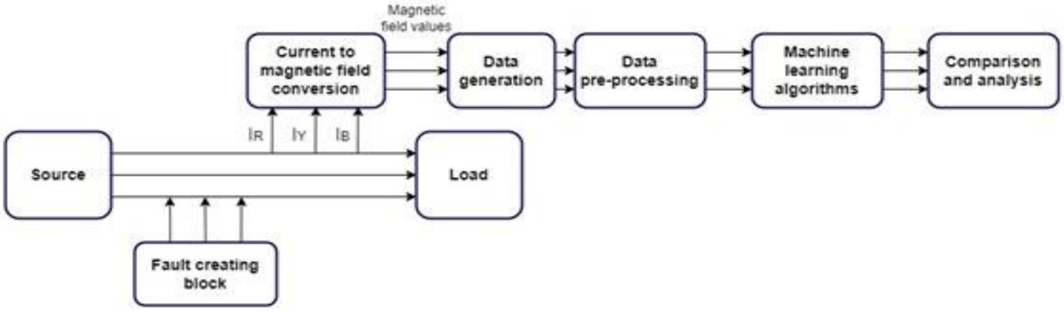

Figure 1. Block diagram of the proposed non-contact electromagnetic fault diagnosis scheme

Magnetoresistance (MR) effect-based sensors detect the change in resistance with respect to variations in magnetic field strength [25]. Thereby, magnetic field sensor based on this effect can be a direct and precise tool to accurately measure the magnetic field produced around the conductor due to current flowing in transmission line [26]. As the sensor would be located at some distance from the quantity to be measured, it offers the advantage of safety by avoiding direct contact. Also, it can be swiftly taken out for the maintenance. These features make it suitable to be used in substation in place of CTs [27]. The interference due to external factors is certainly a topic of research and have been kept beyond the scope of this paper.

The proposed system assumes a couple of magnetic field sensors in the vicinity of the conductors at specific positions such that one of them will detect the magnetic field in horizontal direction and other in vertical direction. This system resolves the magnetic field to obtain the local 2D pattern. In this paper, we present a comparative assessment of several ML algorithms applied to non-intrusive electromagnetic current measurements for power system fault diagnosis. The performance of these algorithms is investigated based on various evaluation metrices across different fault scenarios. We aim to offer valuable insights towards optimal selection and deployment of ML algorithms in order to identify and categorize the faults in the context of smart grid with electromagnetic current sensing capability.

3. SYSTEM SIMULATIONS

3.1. Modelling of 154 kV transmission line

In this study, the system specifications listed in [28] are used to model an actual 28 kms, 154 kV transmission line is simulated in MATLAB/Simulink. A three-phase fault block is used to create various fault conditions namely triple line to ground, triple line, double line to ground, double line, single line to ground. Here, the phase conductors in three phase transmission lines are termed as R, Y, and B as generally preferred in India. Parameters used in the equations in section 4 have been symbolized relating to these phases. Faults were created at the middle of the line at 14 kms from the sending end. Switching time of the fault block was 0.04s to 1s.

3.2. Current to magnetic field conversion

Currents flowing through the phase conductors R, Y, and B are $I_R \sin(2\pi ft + \varphi_R)$, $I_Y \sin(2\pi ft + \varphi_Y)$, and $I_B \sin(2\pi ft + \varphi_B)$ respectively. The section discusses the mathematical equations behind the current to magnetic field conversion block. The proposed set up consists of two magnetic field sensing coils at right angles to each other. Out of which, one coil senses horizontal component H_h and the other senses verticle component H_v of the generated magnetic field. According to laboratory experimentation in [29] that explored the potential of current to magnetic field conversion for power quality analysis, the relation between current and corresponding magnetic field is given by (1):

$$[H] = [M][i] \tag{1}$$

where,

$$[H] = \begin{bmatrix} H_h \\ H_v \end{bmatrix} \quad [i] = \begin{bmatrix} i_R \\ i_Y \\ i_B \end{bmatrix} \quad [M] = \begin{bmatrix} D_R & D_Y & D_B \\ Q_R & Q_Y & Q_B \end{bmatrix} \tag{2}$$

D and Q in (2) are positional coefficients associated with horizontal and vertical magnetic field respectively. M is called as position matrix. As shown in Figure 2, magnetic field sensing coils are located at horizontal distances d_R, d_Y, and d_B, and heights h_R, h_Y, h_B from the phase conductors R, Y, and B respectively. Knowing this, angles σ_R, σ_Y, σ_B are calculated by (3):

$$\sigma_R = tan^{-1}\frac{d_R}{h_R}, \qquad \sigma_Y = tan^{-1}\frac{d_Y}{h_Y}, \qquad \sigma_B = tan^{-1}\frac{d_B}{h_B} \tag{3}$$

with the knowledge of these angles, we can determine positional coefficients D_R, D_Y, D_B and Q_R, Q_Y, Q_B by using (4) and (5) respectively.

$$D_R = \frac{cos^2\sigma_R d_R}{2\pi h_R}, \qquad D_Y = \frac{cos^2\sigma_Y d_Y}{2\pi h_Y}, \qquad D_Y = \frac{cos^2\sigma_Y d_Y}{2\pi h_Y} \tag{4}$$

$$Q_R = \frac{cos\ \sigma_R sin\ d_R}{2\pi h_R}, \qquad Q_Y = \frac{cos\ \sigma_Y sin\ d_Y}{2\pi h_Y}, \qquad Q_B = \frac{cos\ \sigma_B sin\ d_B}{2\pi h_B} \tag{5}$$

Finally, the matrix of magnetic field is computed by (6).

$$\begin{bmatrix} H_h \\ H_v \end{bmatrix} = \begin{bmatrix} D_R & D_Y & D_B \\ Q_R & Q_Y & Q_B \end{bmatrix} \begin{bmatrix} I_R \sin(2\pi ft + \varphi_R) \\ I_Y \sin(2\pi ft + \varphi_Y) \\ I_B \sin(2\pi ft + \varphi_B) \end{bmatrix} \tag{6}$$

Magnetic field analysis will vary with location of the sensor [30]. In this particular study, the sensor has been assumed to be kept at right- and left-hand side of the conductors. Though, only one case is discussed here as shown in Figure 2, as the results obtained in both circumstances are same due to symmetry. Detailed study on different locations of the sensing coils can be performed to identify optimal position that gives best performance in future work. Based on the mathematical analysis above, the values of horizontal as well as vertical magnetic field components are determined taking into account the location of sensor at both left and right positions. These values vary with the type of faults and accordingly generate a different pattern when plotted on graph.

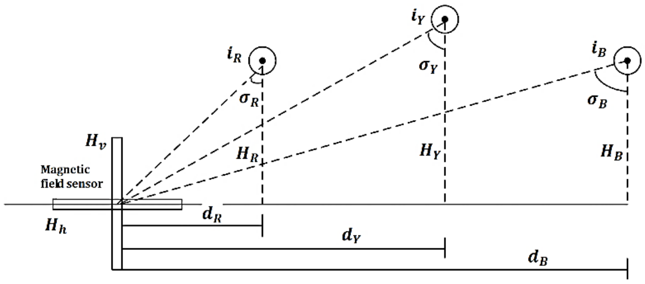

Figure 2. Magnetic field sensor placed at left side of the conductor

4. MACHINE LEARNING APPROACH

4.1. Data generation and pre processing

In the simulated power system model, twelve types of faults and non-fault conditions with various specifications were created. The magnetic field values H_h and H_v corresponding to these conditions were collected, and binary fault indicators were added to the dataset: 0 for normal and 1 for fault conditions to generate the novel datasets. For fault detection, the dataset includes magnetic field components and a binary fault indicator. For fault classification, along with H_h and H_v, the dataset includes four columns representing lines (R, Y, B, G) with binary indicators for fault presence in each line, with the dependent variable being the fault type.

4.2. Performance evaluation criteria

Performance evaluation provide insights into the effectiveness and capabilities of various algorithms. Important metrices used in the evaluation of ML algorithms are accuracy, error rate, precision, recall, F1 score [31], and receiver operating characteristic - area under curve (ROC-AUC) [32]. Also, fit time and score time are crucial criteria of ML model's computational efficiency [33].

4.3. Steps applied in machine learning approach

A systematic approach followed to apply ML algorithms to magnetic field component dataset. The script imports essential libraries for machine learning, including scikit-learn, NumPy, and Pandas, and defines a function to evaluate multiple models. It initializes various ML models and performs 5-fold cross-validation, followed by training and testing on an 80-20 data split. Additionally, it uses bootstrap sampling for stability analysis and organizes cross-validation results, test predictions, and detailed classification reports for each model.

5. RESULTS AND DISCUSSION

5.1. Magnetic field patterns

Figure 3 shows the instantaneous current waveforms and magnetic field patterns under various states of transmission line. These patterns are obtained by plotting values of H_h and H_v values along X-axis and Y-axis respectively corresponding to currents. Figures 3(a), 3(b), and 3(c) are the waveforms of currents at normal, RYBG fault, and RYB fault respectively while Figures 3(d), 3(e), 3(f) illustrate corresponding magnetic field pattern. Similarly, Figures 3(g), 3(h), and 3(i) are the waveforms of currents at RYG fault, RY fault, and RG fault respectively with Figures 3(j), 3(k), and 3(l) showing corresponding magnetic field pattern. As in Figure 3(a), under normal state, the pattern of plot is a perfect circle. However, this shape gets disturbed on creating faults. Notably, each type of fault yields a distinct magnetic field pattern which lays the foundation of fault identification and classification.

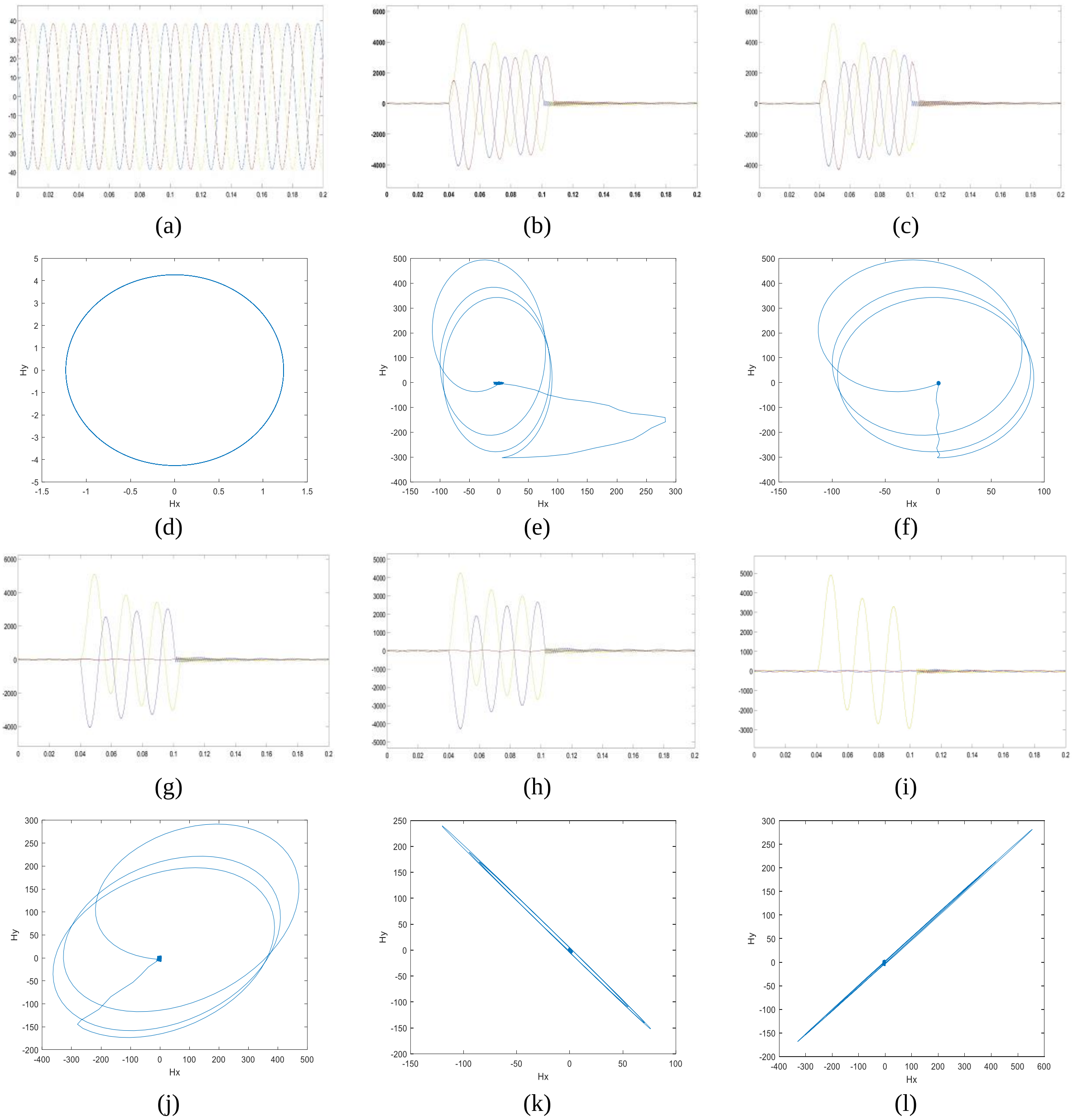

Figure 3. Current waveforms (a), (b), (c), (g), (h), (i) and corresponding magnetic field patterns (d), (e), (f), (j), (k), (l) at normal condition, RYBG, RYB, RYG, RY, and RG faults respectively

5.2. ML algorithms applied for fault detection–binary classification

Values of the accuracy and error rate, evaluation metrices, fit time, and score time obtained for applied ML algorithms in results have been discussed separately for fault detection in this subsection 5.2 and classification in next subsection 5.3. Table 1 presents the obtained values of various performance indicators of ML models applied to fault detection. The XGB algorithm achieved the highest accuracy of 99.98% and an error of 224.4417µ. The GNB and KNN algorithms also performed well, with accuracies of 99.97% and 99.94%, and errors of 336.6626µ and 561.1043µ, respectively. RF and SVM showed respectable accuracies of 85.99% and 99.03%, while LogReg had the lowest accuracy at 78.41%, serving as a useful baseline.

It shows that the GNB, KNN, RF, and XGB algorithms achieved high mean scores across all evaluation metrics. Notably, GNB and KNN excelled with mean ROC AUC scores of 0.99944 and 0.999907, respectively, along with high weighted recall, F1-score, and precision values, indicating their effectiveness in fault detection. While the SVM algorithm performed well, LogReg had comparatively lower scores, suggesting limited suitability for this application.

Table 1. Comparative of ML algorithm’s performance indicators in fault detection

ML Algorithm	Accuracy	Error	Precision	Recall	F1 score	ROC AUC	Fit time	Score time
GNB	0.999663	336.6626µ	0.999834	0.999834	0.99983	0.99944	0.005778	0.016093
KNN	0.999439	561.1043µ	0.999613	0.999613	0.99961	0.999907	0.010653	0.254415
LogReg	0.7840871	0.2159129	0.838484	0.790437	0.74615	0.617385	0.024490	0.022612
RF	0.8599484	336.6626µ	0.999945	0.999945	0.99995	0.999907	0.683868	0.080307
SVM	0.990349	0.009650993	0.988581	0.988391	0.98832	0.994641	0.619416	0.181288
XGB	0.999776	224.4417µ	0.999834	0.999834	0.99983	0.999821	0.096144	0.027415

Regarding fit and score times, it highlights that GNB algorithm emerged as the most computationally efficient algorithm. In contrast, RF and SVM algorithms exhibit longer fit times. Random Forest, despite its ensemble nature, requires relatively higher computational resources. Similarly, SVM algorithm demands computational effort during model training. Interestingly, the KNN algorithm stands out with a relatively low fit time but a significantly higher score time. This discrepancy suggests that while KNN algorithm requires minimal effort during training, it incurs a computational cost during the prediction phase, especially for larger datasets.

5.3. ML algorithms applied for fault classification–multiclass classification

Results obtained for various performance indicators of ML algorithms in fault classification are tabulated in Table 2. It shows that the MLP algorithm achieved the highest accuracy at 89.16% with a low error rate of 2.68%, highlighting its effectiveness in fault classification for transmission lines. The KNN algorithm followed with an accuracy of 87.62% and a slightly higher error rate of 3.51%. Both DT and RF algorithms performed well with accuracies of 85.69% and 85.99%, respectively, but had higher error rates. GNB and SVM achieved accuracies of 81.79% and 74.72%, with GNB having a lower error rate but slightly inferior accuracy compared to SVM.

The KNN algorithm achieved the highest overall performance, with a mean test ROC AUC of 0.8869 and strong weighted recall, F1-score, and precision values of 0.8858, 0.8867, and 0.8893, respectively, effectively differentiating fault types in transmission lines. The MLP algorithm also performed well, with a mean test ROC AUC of 0.8803, recall of 0.8844, F1-score of 0.8720, and precision of 0.8803, indicating its capability to learn complex correlations in the data. RF and DT algorithms showed competitive results with mean test ROC AUC values of 0.8730 and 0.8683, respectively. GNB and SVM had lower performances with ROC AUC values of 0.8187 and 0.7003, while LogReg exhibited the lowest performance with a mean test ROC AUC of 0.6705, suggesting its limited suitability for this task.

DT and GNB algorithms demonstrated the fastest training and prediction times, making them ideal for applications needing high computational efficiency. KNN had low fit times but high prediction times, indicating greater computational demand during use. LogReg and RF showed moderate fit and score times, balancing efficiency, and performance. While MLP and SVM required more training resources, they delivered competitive performance, suitable for applications prioritizing accuracy over computational constraints. Summarizing the discussion, study revealed that algorithms like GNB, KNN, RF, and XGB excel in fault detection, while MLP and KNN are superior in fault classification using magnetic field data. Positioned within the broader context, this work corroborates previous findings on the limitations of CTs and advances the use of electromagnetic sensing for smart grid applications.

Table 2. Comparative of ML algorithm's performance indicators in fault classification

ML Algorithm	Accuracy	Error	Precision	Recall	F1 score	ROC AUC	Fit time	Score time
D-Tree	0.8685	4.173942	0.868367	0.8685	0.86800	0.868342	0.022346	0.010544
GNB	0.820831	3.12378	0.819705	0.82083	0.81354	0.8187277	0.005807	0.010839
KNN	0.885802	3.50836	0.889301	0.88580	0.88668	0.886897	0.008894	0.192897
LogReg	0.726884	7.137358	0.59854	0.72688	0.62966	0.6704932	0.257884	0.010408
MLP	0.8915947	2.680956	0.880261	0.88439	0.872	0.8802617	9.031673	0.020286
RF	0.872351	4.166199	0.874238	0.87235	0.87295	0.872972	1.319228	0.077882
SVM	0.7471664	6.076759	0.636513	0.74679	0.67106	0.7002912	73.054609	0.010420

6. CONCLUSION

This research addresses critical challenges in smart grid fault diagnosis. The study highlights significant potential of MF sensors as a non-contact, effective, compact, safe, and economical alternative to traditional CTs, which are often limited by size, cost, and installation complexities. Supervised and unsupervised machine learning algorithms have been applied to the magnetic field values for superior fault detection and classification in power systems, and their effectiveness was assessed and compared analytically. In the fault detection studies, GNB, KNN, RF, and XGB algorithms performed exceptionally that underlines their ability to leverage features derived from magnetic field components to effectively identify fault conditions. Findings of the fault classification studies suggest that overall, MLP and KNN algorithms consistently outperformed other methods making them promising algorithms for the classification of transmission line faults based on magnetic field components. The overarching takeaway of the research is MF sensors, integrated with machine learning, represent a promising direction for modern power system protection technologies. Future research should explore optimized algorithm configurations, sensor positioning effects, and cross-domain interference to further refine this approach.

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