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A Multilabel Approach for Fault Detection and Classification of Transmission Lines using Binary Relevance

Debshree Bhattacharya*, Dr. Manoj Kumar Nigam
* Research Scholar, MATS School of Engineering and Information Technology, Aarang
Professor, MATS School of Engineering and Information Technology, Aarang

Abstract: In Contemporary automation systems, Fault detection and classification of electrical transmission lines in grid systems are given top priority. The broad application of Machine Learning (ML) methods has enabled the substitute of conventional methods of fault identification and classification. These methods are more effective ones that can identify faults early on using a significant quantity of sensory data. So detecting simultaneous failures is difficult in the context of distracting the noise and several faults in the transmission lines. This study contributes by offering a unique way for concurrently detecting and classifying several faults using a multilabel classification approach based on binary relevance classifiers. The proposed binary relevance multilabel detection and classification models' performances are examined. Under both ideal and problematic circumstances, faults in the dataset are collected. A variety of multilabel fault types detection and classification determines the suggested method's effectiveness.

Keywords: Fault Detection, Machine Learning (ML), Binary Relevance Classifiers, Graph-Based Feature Selection, Multilabel Classification.

I. Introduction

The power transmission line is becoming longer and more sophisticated, and their challenging operational condition makes them vulnerable to a variety of fault occurrences that cause disruptions or stop power transmission. The main cause of faults must be categorized according to their features to address fault occurrences for power transmission maintenance and a dependable power source. Power transmission problems can occur from climate, animal activity, and component breakdowns, which are often determined by expert viewpoints on fault behavior and natural occurrences. Manually identification based on professional experience, although, is time-consuming and puts a high requirement on the caliber of the workforce. Since more sophisticated recording devices and tracking mechanisms are used to enhance fault detection, the accompanying multi-source fault information is too large to be manually interpreted. It is unavoidable for the power transmission line to have faults occur, and these faults often include crucial devices linked to high-overhead in transmission lines. It not only affects the transmission line of the grid system's dependability but also has a significant impact on consumers. As structures become complicated, securing transmission line becomes more difficult. Identifying types of faults with substantial accuracy increases the performance reliability and consistency of the transmission lines and aids in preventing serious system failures.

The solution for the above-aforementioned problem is well that highly effective devices are crucial in maximizing total performance [1]-[2]. Hence, it is highly indicated that reducing and forecasting faults that may arise in power transmission lines is crucial. Traditional fault identification and classification methods [3] are based on dynamic modeling [4]-[5] or intricate mathematical simulations [6]-[7]-[8] of the tracking network. The growing usage of ML approaches in industrial uses results from adaptive modernization [9]-[10]. To accommodate many fault occurrences or dynamically changing load levels in the case of imperfect or noise assessments, the most recent fault detection and classification systems have increased their requirement for artificial intelligent methods [11]. A typical method for making diagnoses and forecasts is current signature analysis, which involves looking at the output current of the transmission line when functioning steadily [12]-[13]. The relays that protect the electrical transmission line from blackouts can be used in the power transmission safety network. Solid damage detection and classification system offer a reporting function that is efficient, dependable, quick, and secure.

This study on the improvement in the detection and classification of faults for power transmission lines is motivated due to the suitability of multilabel classification of faults using ML techniques. The study contributes by offering a unique way for concurrently detecting several faults and assessing the problem degree within distracting

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settings. The technique uses a multilabel classification algorithm and compares the classification performance of these algorithms. The main contribution of this study is

- To collect the Phase Measurement Unit (PMU) IEEE 14-bus dataset. Data imbalance problem is addressed and solved.
- Optimal feature selection method is proposed in which graph-based technique (filter method) is used to select the best features from the edges of the graph.
- Propsoed a binary relevance model in which a hyper-tuned model is offered to classify the multilabel faults.
- Proposed method is compared with different multilabel classifiers like binary relevance with under-sampling and chain classifiers.

The paper's organization is as follows section 2 presents the previous related work for fault detection and classification. Section 3 presents the method of the proposed system, discusses about fault dataset and working of the proposed system. The result analysis and performance evaluation is presented in section 4. Finally, the conclusion and future scope are provided in section 5.

II. Related Work

Although the issue is typically noticeable like if a transmission line crosses the power line or a power transmission line fails, and the parts crash down, short circuits in a transmission line are usually the simplest to investigate. Another key features of overhead transmission line protection is how accurately it detects and categorizes several faults. The following are some fault classification techniques presented based on a recent studies.

In [14], the author proposed fault detection and classification based on a support Vector Regression approach to improve the performance of short-term estimate strategies based on the earlier power consumption data. In [15], the author proposed an Adaptive Neuro-Fuzzy Inference Framework for fault classification in transmission networks. In [16], the author discusses rapid fault detection and classification in power distribution systems using a hybrid of fuzzy logic and singular entropy concepts. Using ML is not constrained to power transmission industries. The Deep Learning (DL) approach to waveform classification and detection is a popular topic because high-voltage power grids require a waveform deviation tracking system that is extremely correct and durable [17]-[19]. In [20], relevant features were used as inputs for a hybrid approach that combined a Gated Recurrent Unit (GRU) with a Discrete Wavelet Transform for detecting and classifying several faults in transmission lines. Using Convolutional Neural Network (CNN) for fault detection and classification in microgrids was suggested in [21].

However, according to traditional signal processing methods for fault identification [22], several approaches have been developed in recent decades to apply intelligent methodologies [24]-[25], such as fresh methods for fault identification and isolation [26] using fuzzy logic, decision trees, artificial neural network, and more ML algorithms [27]-[28]. Most systems depend on the tracking and analysis of vibrations in transmission line signals, which requires the use of a single vibration sensor and increases the cost of implementation and upkeep [29]-[30]. To use these sensors effectively, an operator also needs training and knowledge [31]-[32]. Also, it was claimed that the ESA could identify several relationships between the system features. Hence, ML approaches are suited for analyzing such collected data. Recently, various intelligent techniques have been developed to enhance fault identification and classification prediction rate. In [33], investigating the mechanical fault signals of misaligned and imbalanced using the multilayer perceptron system with 3 levels can categorize the several faults. Some have observed that training the proposed model on massive dataset results in good accuracy. CNN is used to classify faults effectively [34]. It is noticeable that most pattern-matching techniques function under the possibility of a single fault occurrence. Very few studies provide adaptive and all-encompassing strategies for several fault detection.

The capabilities of the decision tree combined with the suggested wavelet approach also offer a potential strategy for fault identification [35]. To discover pattern matching, [36] analyses a huge number of different wavelets. For certain applications, choosing a good wavelet transformation approach is still difficult. In [37], the author developed the model for detecting and classifying the faults in electrical power systems based on several DL approaches such as Long Short Term Memory (LSTM), Recurrent Neural Network (RNN), and GRU. The RNN approach outperformed the other methods. The outcomes showed that the suggested RNN model may be improved and could be used in the secondary electrical power system for fault identification and classification[38]-[39]-[40].

III. Methodology

This section describes the overall method of the proposed model and the number of steps involved in fault detection and classification. Figure 1 shows the overall architecture of the proposed model for fault detection in transmission lines based on binary relevance classifiers. This study used the

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PMU IEEE 14 bus electrical fault dataset extracted from Kaggle. There are steps required to pre-process data to keep missing data and remove redundant or duplicate data. The median can replace the missing data values. Relevant features were selected based on graph-based feature selection methods. The complete architecture of the proposed model for fault detection and classification is shown in figure 1.

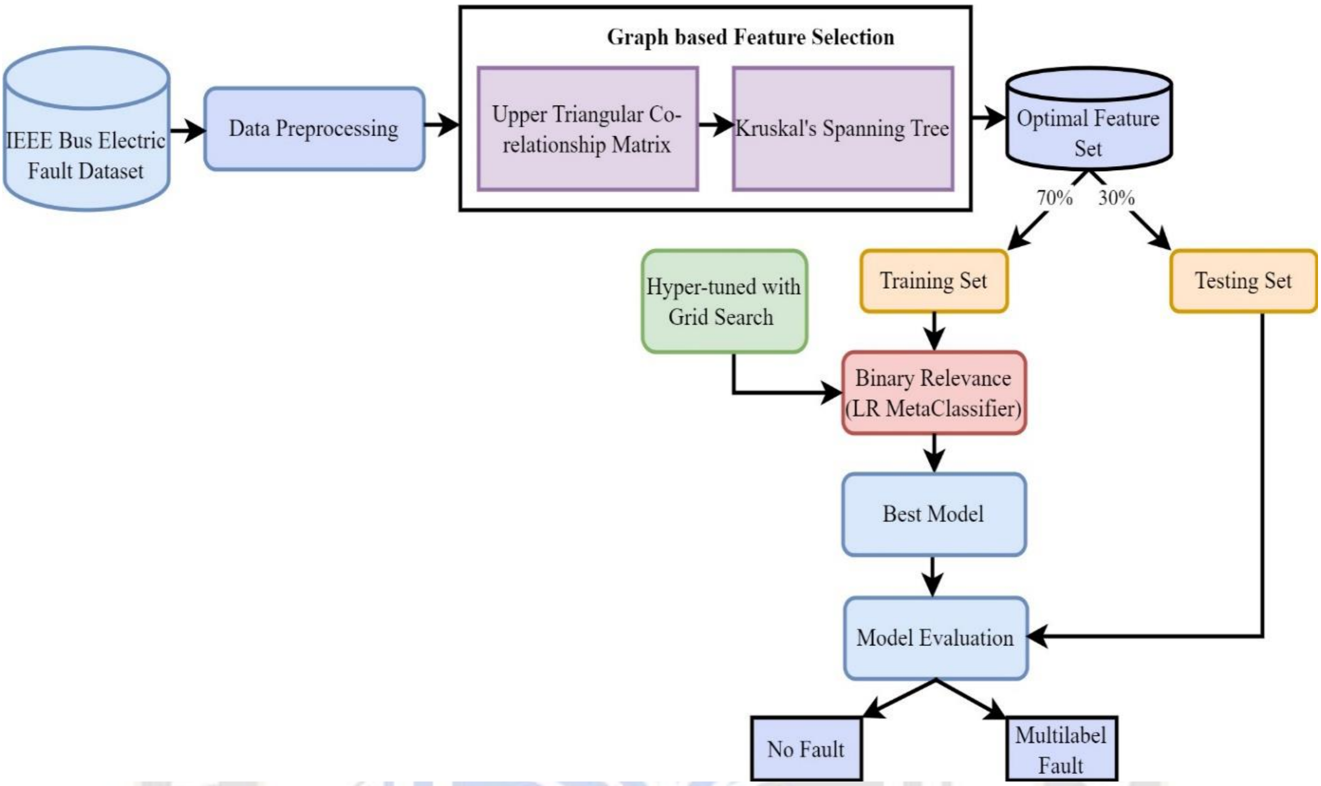

Figure 1: Complete Architecture of proposed model for fault detection in Transmission line

3.1 Dataset Description

In addition to the power transmission variables, the technique development needs voltage and current at every transmission line's two or three inputs as well as the state and trigger data. The electrical firms' field-recorded PMU values obtained and generated data from a grid system. This study used the PMU IEEE 14 bus electric fault dataset (figure 2) that has five faults such as LF, LL, LLG, LLL, and LLLG Fault with one No fault. Each fault has several instances 1129, 1004, 1134, 1096, 1133, and 2365 respectively. Each instance has the mix labeled faults. The dataset contains variables that are combined for processing based on their magnitude and angle, such as Ia', 'Ib,' 'Ic,' 'Va,' 'Vb,' and 'Vc.' Because the PMU was typically far from the point of failure for the majority of events in the dataset. After careful observation of field-recorded current magnitude assessments, it was determined that the difference in current magnitude was not noticeable enough to be detected and expressed voltage level. So electric currents were not used.

3.2 Pre-processing

The dataset included measurements from 43 PMUs taken in the field over the years 2017–2018. Only 38 PMUs are chosen for extracting features due to significant poor data within the dataset. The dataset contains missing and duplicate values, so we need to pre-process the data. The missing values are replaced by the median. Data are normalized using the standard normalization method. After normalization of the data, the data were correlated for a weighted graph. Assigned a column as a vertex and converted it to an upper triangular matrix.

Table 2 shows the data imputation after filling in the missing values to keep most values of the dataset. Table 3 shows the correlation between all the feature of power transmission line. The correlatin between Va and Vb , Va and Vc, have values more than 0.6 and these feaures are highly correlated if consider, the threshold values is 0.6.

3.3 Graph-based Feature Selection

The broad topic of feature extraction includes feature selection methods. In contrast to feature selection techniques, which only generate a subset of relevant features, feature selection generates new features using the original features in the dataset. This study used the graph-based approach to selecting the best feature for fault detection and classification. Minimum features were selected based on the upper triangular co-relationship matrix and Kruskal's spanning tree. Table 4 shows the weighted triangular matrix. Apply the Kruskal minimum spanning tree algorithm to the weighted triangular matrix to construct the minimum spanning tree.

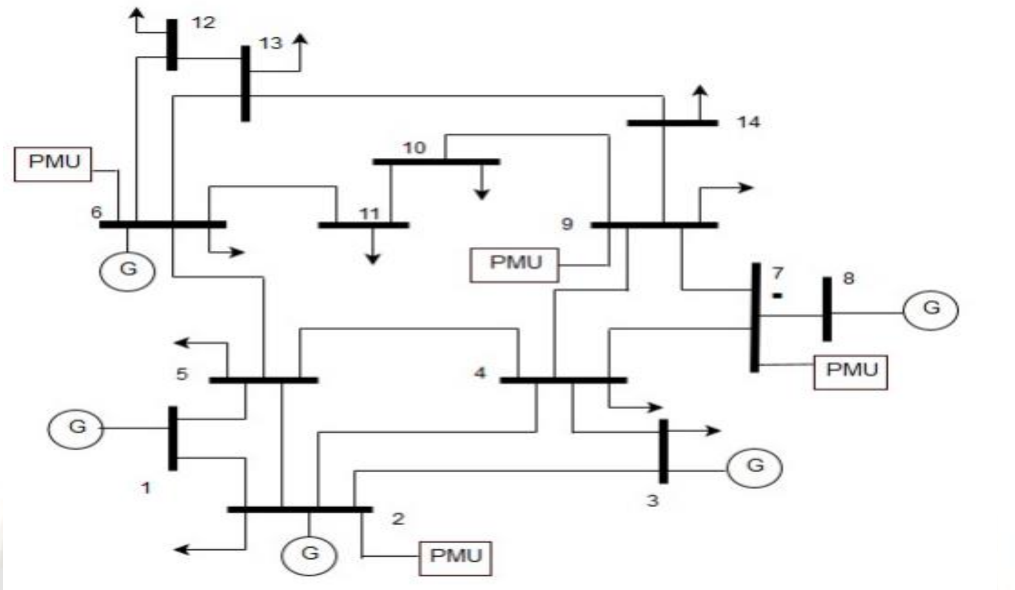

Figure 2: IEEE PMU 14-bus Power System [23]

Table 1: Summary of Fault Occurrences

	Ia	Ib	Ic	Va	Vb	Vc
count	7861.000000	7861.000000	7861.000000	7861.000000	7861.000000	7861.000000
Mean	13.721194	-44.845268	34.392394	-0.007667	0.001152	0.006515
Std	464.741671	439.269195	371.107412	0.289150	0.313437	0.307897
Min	-883.542316	-900.526952	-883.357762	-0.620748	-0.608016	-0.612709
25%	-119.802518	-271.845946	-61.034219	-0.130287	-0.159507	-0.215977
50%	2.042805	5.513317	-4.326711	-0.005290	0.001620	0.009281
75%	227.246377	91.194282	49.115141	0.111627	0.153507	0.239973
Max	885.738571	889.868884	901.274261	0.595342	0.627875	0.600179

Table 2: Data Imputation

	Ia	Ib	Ic	Va	Vb	Vc
0	-151.291812	-9.677452	85.800162	0.400750	-0.132935	-0.267815
1	-336.186183	-76.283262	18.328897	0.312732	-0.123633	-0.189099
2	-502.891583	-174.648023	-80.924663	0.265728	-0.114301	-0.151428
3	-593.941905	-217.703359	-124.891924	0.235511	-0.104940	-0.130570
4	-643.663617	-224.159427	-132.282815	0.209537	-0.095554	-0.113983

Table 3: Correlation among the features

	Ia	Ib	Ic	Va	Vb	Vc
Ia	1.000000	-0.313346	-0.268672	0.097179	0.264615	-0.378368
Ib	-0.313346	1.000000	-0.538012	-0.411064	0.145906	0.354769
Ic	-0.268672	-0.538012	1.000000	0.326151	-0.560504	0.156396
Va	0.097179	-0.411064	0.326151	1.000000	-0.602942	-0.618880
Vb	0.264615	0.145906	-0.560504	-0.602942	1.000000	-0.253499
Vc	-0.378368	0.354769	0.156396	-0.618880	-0.253499	1.000000

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Table 4: Weighted Triangular Matrix

Array	1	-0.31334605	0	0	0	0
	-0.31334605	1	-0.53801222	0	0	0
	-0.26867194	-0.53801222	1	0.32615074	0	0
	0.09717931	-0.41106364	0.32615074	1	-0.60294225	0
	0.26461487	0.14590568	-0.56050385	-0.60294225	1	-0.25349939
	-0.37836784	0.35476944	0.15639606	-0.61888014	-0.25349939	1

Following are edges in the constructed minimum spanning tree. Edges in the constructed MST

Vc -- Va == -0.618880 (1)

Va -- Vb == -0.602942 (2)

Vb -- Ic == -0.560504 (3)

Ib -- Ic == -0.538012 (4)

Vc -- Ia == -0.378368 (5)

Cost of Minimum Spanning Tree -2.698706285354955

Considering the threshold to be -0.31 for Removing edges whose weights are greater than the threshold. After removing edges in the minimum spanning tree, the remaining edges with their weight are

Vc -- Va == -0.618880 (6)

Va -- Vb == -0.602942 (7)

These are the best feature used for further processing.

Algorithm 1: Graph-based Feature Selection

Input: Fault Dataset $FD = \{FD_1, FD_2 \, FD_3 \ldots . FD_n\}$
∅ = Threshold Value
C = Cost
Output: FS = Minimum Selected features

Minimum Spanning Tree using Kruskal's Algorithm
1. G = NULL; //G is the complete weighted graph
 C = 0; // Initial Cost is zero
2. **For** $each\ feature\ \{Ia, Ib, Ic, Va, Vb, Vc\} \in FS$ **do**
3. if $(T - Relevance = SU\ (FD_i, C))$ is satisfied
 if (T-Relevance > ∅)
 Select the features
 else
 Discard the features
4. Perform F-Correlation $(FD_i\ and\ FD_j (FD_i, FD_j$ €^ F ^ $i \neq j\ ))$ on SU (FD_i', FD_j') for each feature from step 3
5. Build Minimum Spanning Tree using Kruskal's Algorithm
 minSpanTree = Kruskal's(G)
6. Partition the tree constructed using step 5
7. Elect a Representative from the featured selected using step 6
8. End.

Table 5 shows the reduced dataset after selecting the relevant features from the original dataset based on the upper triangular correlation ship matrix and Kruskal's minimum spanning tree. The best feature dataset can be split into two training and testing data. 70% as training and 30% as testing data. 70% of training data is fed to train the proposed model.

Table 5: Reduced Dataset

	Ia	Va	Vb	Vc
0	-0.055554	0.002301	-0.000763	-0.001537
1	-0.220970	0.000906	-0.000358	-0.000548
2	-0.324341	0.000493	-0.000212	-0.000281
3	-0.337632	0.000365	-0.000163	-0.000202
4	-0.322858	0.000302	-0.000138	-0.000164

3.4 Binary Relevance (Logistic Regression (LR) MetaClassifier)

This study used multilabel classification instead of two classes of fault or No fault. We have multiple faults in datasets, so we need to correctly classify faults in the transmission line. According to the name of faults, algorithm adaptation applies single-label classification to setting multiple labels, often via altering the value or decision parameters. Compared to binary relevance, this technique needs fewer classifiers since it adjusts the proposed classifiers to the labeling space. The label pairing must be included in the training dataset for prediction to be possible, and splitting may protect labels that are correctly classified.

Multilabel Classification

Let L represent the finite set of labels $(L_1, L_2, \ldots \ldots \ldots, L_n)$, and F is the input space, and Q is the output space defined as the set of subsets of labels L.

Definition-1: A ML classification job is given by a dataset

$$FD = \{(p_1, q_1), \ldots \ldots, (p_n, q_n)\} \in P \times Q \qquad (8)$$

of pair of inputs p_i belongs to P and subsets of labels q_i belongs to Q as outputs.

The fault labels assigned to every input are known as relevant labels. Sometimes, the input space is Euclidean space of x-weights; the classifier learning task can be done by ideal features set.

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$$FD = (P, Q), \qquad (9)$$

in which $P = (p_1, \ldots., p_2)$ and $Q = (q_1, \ldots\ldots. q_2)$. To make the notation clearer, each element of Q, q_{ij}, is 1 when label j is relevant such as i, and 0 otherwise.

An assumption formulated below is intended to be induced by ML classification job FD.

Definition-2: An ML assumption is a function f from the input space to the output space, The power set of labels P(L);

$$f: P -> Q = P(L) = \{0,1\}^L \qquad (10)$$

Hence $f(p)$ is the set of relevant labels classified by f for the fault p. Sometimes used $f(P) = Q$ to represent that prediction of f is applied to the input set given by matrix P are a set of labels coded by matrix Q.

IV. Results and Discussion

This section presents the evaluating parameters and discusses the performance analysis of the proposed binary relevance model. This study also proposed the classifier chain model and compared it to binary relevance and binary relevance with the under-sampling approach. Performing the proposed classifier can be measured by several evaluating parameters such as accuracy and F1-score.

$$Accuracy = \frac{(T\_P + T\_N)}{(T\_P + F\_N + F\_P + T\_N)} \qquad (11)$$

$$F1 - Score = \frac{T\_P}{T\_P + 1/2\,(F\_P + F\_N)} \qquad (12)$$

Table 6 shows the accuracy score of binary relevance classifiers with or without hyper tunning in the under-sampling approach. It shows that the binary relevance classifier with under-sampling after hyper tunning achieves a 95.65% accuracy score. Performing the proposed classifier is better as compared to other classifiers.

Table 6: Accuracy score of Binary Relevance classifiers with or without hyper tunning

Classifiers	**Accuracy Score (%)**
Binary Relevance Algorithm	61.94
Binary Relevance Algorithm After hyper tunning	61.94
Binary Relevance Algorithm with Under-Sampling	64.14
Binary Relevance Classifier with Under-sampling After hyper tunning	95.65

Table 7 and Table 8 show the performance evaluation of various classifiers under binary relevance and binary relevance with under-sampling in terms of accuracy and F1 score. It found that random forest achieves the 98.81% and 95.71% accuracy scores under the binary relevance and binary relevance with under-sampling in table 7. Random forest classifier performed well as compared to other classifiers. In terms of the F1-score decision tree achieves the 95.47% and 95.51% scores in table 8. Decision trees perform better as compared to other classifiers in terms of the F1-score.

Table 7: Performance evaluation of Classifiers in terms of Accuracy Score

Classifiers	**Binary Relevance**	**Binary Relevance with Under-Sampling**	**Chains Classifier**
Decision Tree	95.70	95.53	95.51
Random Forest	95.81	95.71	95.78
Logistic Regression	61.94	63.87	62.81
GaussianNB	80.39	80.37	80.67
kNN	94.45	94.54	94.45
SVM	85.63	84.19	81.46

Table 8: Performance evaluation of Classifiers in terms of F1-Score

Classifiers	**Binary Relevance**	**Binary Relevance with Under-Sampling**	**Chains Classifier**
Decision Tree	95.47	95.51	95.28
Random Forest	95.18	95.20	95.17
Logistic Regression	56.52	63.27	55.38
GaussianNB	82.35	82.34	82.54
kNN	93.66	93.99	93.66
SVM	83.79	84.72	78.16

Figure 3 shows the compares the accuracy score of different classifiers with BR and BRUS. It is clearly observed that BRUS classsifer is better perform as compared to BR.

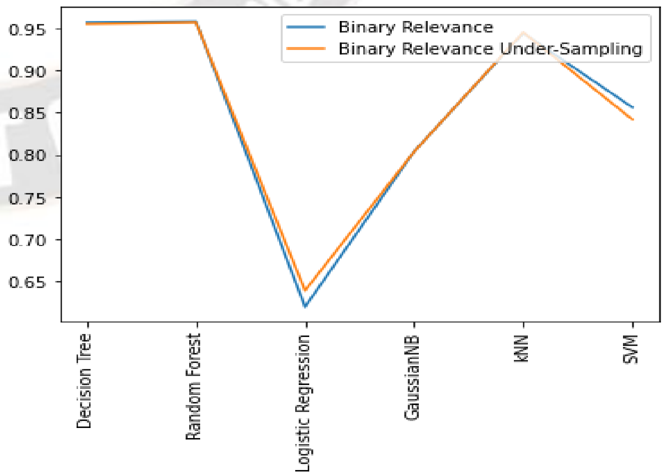

Figure 3: Accuracy Score of different classifiers with binary relevance (BR) and binary relevance under-sampling (BRUS)

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Figure 4 shows the compares the F1 score of different classifiers with BR and BRUS. It is clearly observed that BRUS classsifer is better perform as compared to BR.

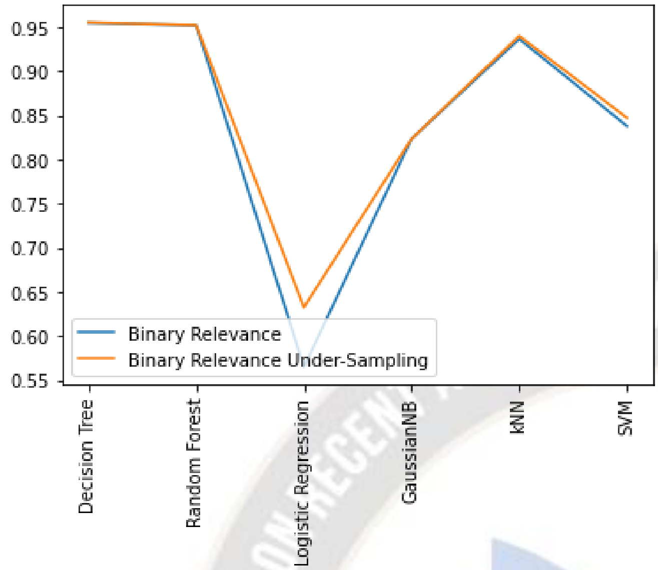

Figure 4: F1-score of different classifiers with binary relevance and binary relevance under-sampling

Figure 5 shows the comparative analysis of different classifier in term of accuracy score. It is clearly observed decision tree and random forest performe better as compare to SVM and LR classifier under the BR and classifier chain.

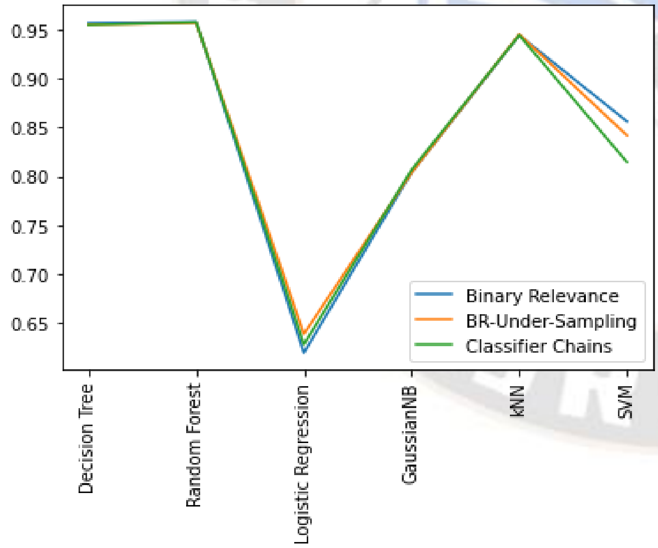

Figure 5: Comparative Analysis of different Classifiers in terms of Accuracy

Figure 6 shows the comparative analysis of different classifier in term of F1 score. It is clearly observed decision tree and random forest performe better as compare to SVM and LR classifier under the BR and classifier chain.

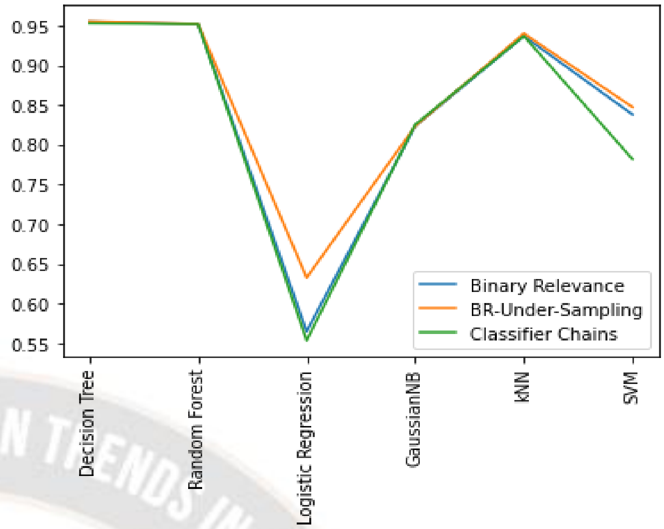

Figure 6: Comparative Analysis of different Classifiers in terms of F1-score

V. Conclusion

In the modern power transmission system, complexity is enhanced as various sensors are used in transmission lines and grown on a large scale. The smart and intelligent solution for detecting the faults in transmission lines requires many sensors for tracking the power system, which results in the cost-efficient and easy diagnosis of the faults. Suggested a well-developed approach for fault detection task of transmission line are carried out. The design of a proper methodology capable of reliably and timely detecting faults of the transmission system based on electrical data. The researcher addressed the several approaches for fault detection that were published in the previous literature. The pros and cons of the traditional fault detection approach have been proved. In the last few decades, fault detection and classification research has focused on prediction techniques that can detect and classify the relevant fault features. As such, methods or techniques depend on technology. Fault detection and classification algorithms have been developed for analyzing the relation between causes and fault features in transmission lines. It is found that the binary approach can easily represent such a system. Various researchers developed a new approach used to detect multiple faults and analyze the noisy and uncertain faults in transmission lines. There is a possible solution used in fault detection and classification problems. The ML and DL classifiers are presented in the related work in section 2. However, these methods require more development and enhancement toward fault detection accuracy and reliability. In addition, the ML approach to sensor data is not well established and needs strong and intelligent data analysis. In this study, the ML techniques were well explored, and a binary relevance model with hyper tuning parameters was developed to compare the effectiveness of other classifiers. The result shows that the accuracy score and F1-score of the binary relevance classifier with under-sampling after hyper tunning for the PMU dataset achieve the 95.65% and, hence it proved that the performance of the binary relevance classifier with under-sampling after hyper tunning is better than other classifiers. The proposed classifiers are best suited for fault detection and classification in the transmission line.

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