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OPTIMIZING THE UTILIZATION OF RENEWABLE ENERGY RESOURCES IN SMART GRIDS USING DEEP LEARNING

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Abstract - Electric power networks have undergone considerable changes to meet a range of needs, including environmental compliance, energy conservation, improved grid stability, production performance, and customer service. Microgrid development and optimal operation is a vital step in increasing solar power utilization, improving grid resilience, and expanding the amount of electrical power available in poor countries. Micro grids combine local energy generation and storage, as well as load requirements, and can operate independently or in conjunction with a grid. The idea of a micro grid has been proposed to anticipate the decision in selecting the source to the grids using Machine Learning approach in this article, which outlines a system that delivers day-to-day grid power generation from energy sources (MLTs). We employed four distinct methods to validate the performance of the techniques in this research. In comparison to other methods, we achieved good results with the support vector machine approach.

Keywords – Renewable Energy, Wind Energy, Smart Grid, K-Nearest Neighborhood, Deep Learning, Optimization.

Introduction

New topics of investigation in the application of Deep (ML) for raising the detection rate and performance of micro grids are opening up as a result of recent developments in computer technology and the increasing availability of enormous amounts of data in smart grids and smart towns. However, as the amount of different machine learning techniques grows, so does their efficiency and applicability.Even if many various options are used for each task, made by mixing models usually outclass single ML-based structures because machine learning can manage huge amounts of data with large data, allowing the detection of hidden characteristics of (even) complex systems; even if many different approaches are used for each assignment, mixed models typically outperform single ML-based systems even though machine learning can handle huge amounts of data with high - dimensional, allowing the detection of hidden characteristics of (even) complicated systems.

A micro grid is a low- or medium-voltage distribution network made up of numerous distributed generating units (DGs), storage devices, and regulated loads that can be linked to the grid or islanded.

Microgrids are self-contained (small) electric systems that are powered by local units (distributed generation).

Micro grids are defined as locally restricted and autonomously managed electric power grids with a distribution design that combines loads and distributed generation—local distributed generators and energy storage devices—allowing the micro grid to function as a standalone entity or as part of a larger network (DGs range from a few KW to a MW).
Machine learning is a type of data gathering in which machines are taught how to make choices based on past experiences. As the volume of information has risen, machine learning has become a vital problem-solving approach. Many machine learning techniques may now be applied in smart grid applications because to the continual progress of computing capabilities, notably in data management and analysis. It's the final piece of the smart grid puzzle, which is powered by data collection, analysis, and decision-making.
Machine learning algorithms provide a useful method for assessing and making suitable grid decisions, allowing the smart grid to function as intended. Among the features of machine learning are:

- consumption price predictions
- power generation
- future optimal scheduling
- fault identification and repair

Related Work

Machine learning is a type of data gathering in which machines are taught how to make choices based on past experiences. As the volume of information has risen, machine learning has become a vital problem-solving approach. Many neural network models may now be applied in smart grid applications due to the continual progress of computing capabilities, notably in information management.
Mir HadiAthari et al [2] presented that, As power networks are reorganised and renewable production is increasingly integrated into the grid, power system uncertainties are becoming more relevant. Several techniques to uncertainty modelling have been described in the literature in order to improve choices for the effective operation of a power system. The primary goal of these approaches is to create a statistical depiction for a variety of sources of uncertainty, such as load, generation, and connections. However, for applications like as voltage control, frequency control/stability, and grid vulnerability analysis signals, an uncertainty model capable of capturing the frequency components of uncertainty is required.
MahshidKhoshlessan et al [3], Intelligent micro-grids are projected to be an important component of future smart grids due to their local intelligence and capacity to host distributed energy resources. To ensure that power is spread properly and important loads are provided reliably, a sophisticated decision-making system should be employed to run a community of micro-grids. The system will make smart, precise, and fast judgments using machine learning algorithms, contributing in the achievement of the above mentioned aims. Five machine learning methods are applied to data from a neighborhood made up of three micro-grids in this article.The data set, which comprises test and testing dataset, is created by combining voltage level, weather, the state of charge (SOC) of the storage solution in both the microgrid and its surrounding unit, as well as the time of day. The operating modes are accomplished through rational choices that result in a diverse variety of energy redistribution from easily accessible

sources to the most preferred loads. The five alternative strategies for governing energy distribution will be compared: Randomized Forests, Decisions Trees, Linear Regression, SVM, and Gradient Boosting.

Sharif Atique et al [4], [21]-[23], Microgrids have gained popularity as a viable means of combining disparate energy resources, a claim bolstered by their flexibility and autonomy. Microgrids, on the other hand, are still a relatively new field of study, and there are a number of obstacles to overcome before they can be widely integrated into present power networks. The newest advancements and uses of two fascinating disciplines of research, machine learning and game theory, in dealing with constructing autonomous microgrid solutions are examined in this review paper. In general, machine learning applications in microgrid research have been examined based on a few key microgrid characteristics: detection, system design.

Miftah Al Karim et al [5] presented that, when it comes to integrating variable power sources, a stand-alone microgrid is especially prone to volatility. When a microgrid develops a short circuit while operating at full capacity, expense system restoration becomes difficult. Predictive analysis can be used to improve system restoration techniques in such cases. A machine learning algorithm is used in this research to develop a system that anticipates the security of a solitary microgrid and, based on the predictions, plans several backup generating units in the event of a primary generating unit failure.

Laurine Duchesne et al [6] stated that, a failure of the primary generating unit

This research looks at recent work that looks at how machine learning can be used to analyse and control the dependability of energy systems, according to Laurine Duchesne et al [6], [24]-[26]. We highlight both the achievements and the stated goals. To date, as well as critical future research objectives, while also providing a solid basis in computer vision and which included. The goal is to promote cooperation between these two industries while also accelerating the deployment of machine learning approach in energy network and management reliability. We focus on and use large-scale power grid as example. However, we feel that approaches, procedures, and other elements are equally significant.

JirapornCharoenpong, BusayamasPimpunchat et al [7], suggested that, Machine learning is one sort of data mining. In recent years, machine learning has been employed in a range of disciplines, including cancer research, education, agriculture, environmental protection, and business. This research looks at the algorithms of commonly used Machine Learning for the aforementioned applications. The many types of machine learning software are contrasted and evaluated. Other freeware, open-source, and non-free apps are provided, including Tensor Flow, Weka, RapidMiner, R Programming, and others. Most software has the advantage of shortening the time it takes to develop a Machine Learning Model, while others are used as more user-friendly design tools.

Iqbal H. Sarker et al [8] identified that, using specific phone log data, we plan to evaluate the performance of several machine learning category models for estimating tailored usage. In our context-aware study, we began with eleven well-known ai techniques categorization methods: ZeroR, Naive Bayes, Logistic Regression, Random Forest, Support Vector Machine, K-Nearest Neighbors, Adaptive Boosting, Repeated Incremental Pruning to Produce Error Reduction, Ripple Down Rule Learner, and Logistic Regression classifiers Furthermore, we conduct a comparison study and provide empirical assessments of a classification model based on Convolutional Neural Networks, which is commonly used in pattern recognition.

Yang Zhang et al [9], We intend to assess the efficacy of multiple machine learning classification models for projecting personalized consumption using specific phone log data. We begin with ten well-known machine learning classification methods in our situationally analysis: Repeated Incremental Trimming to Produce Error Rates, Ripple Down Rule Learner, and Logistic Regression classifiers, ZeroR, Naive Bayes, Decision Tree, Random Forest, Support Vector Machine, K-Nearest Neighbors, Adaptive Boosting. In addition, we conduct a comparison study and offer empirical evaluations of a classification model based on Artificial Neural Networks, which is frequently employed in deep learning.

Anish Jindal et al [10],[18], [19] According to the report, large-scale fraudulent electricity use could exacerbate the requirement mismatch. As a result, a mechanism for detecting these thefts in the complex power networks must be developed. Based on decision trees (DT) and support vector machines (SVM), this paper presents a comprehensive top-down technique that addresses these challenges (SVM). Unlike existing technology, the proposed technique can detect and locate real-time power loss at all levels of power systems. The recommended method combines a combination of DT and SVM classifiers to properly analyze the obtained power usage data.

Hang Xu et al [11], [28] followed that, On smart grids with smart gateways, a distributed and connected machine learning platform is used. It can track passenger movement, generate short-term energy estimates, and allocate renewables. A real-time presented system with Wi-Fi data gathering captures the passenger profile, while a real-time system with electrical load data analysis extracts the energy profile. The 24-hour inhabitant profiles and energy profile are then integrated with prediction using online distributed machine learning and real-time data updates. The predicted population mobility pattern and energy usage profile are utilized to allocate solar energy.

Oyeniyi Akeem Alimi et al [12], [20] proposed that The necessity for efficient solutions for faster identification and detection of these problems has long been a source of worry for energy stakeholders. Recently, MLTs have been demonstrated to be effective in a variety of uses, including power system analysis. Various MLTs, such as neural networks (ANN), Decision Trees (DT), and support vector machines (SVM), have been proposed in the literature, leads to effective decision making and taking the actions in the secure and stable operation of the power system. This article presents a complete evaluation of the most recent studies in which MLTs for power systems have been established, in light of this tendency.

Methodology

The proposed method is illustrated in figure 1 as a model diagram. The flow of the research undertaken while constructing the model is depicted graphically. The most widely used data mining or machine learning methods are often classed as supervised or unsupervised learning based on whether each item in datasets has a label, as indicated in Table 5. Using the given data, the data analytics model for supervised learning algorithms can be trained to recognise the relationship between data properties and associated categories or values. The purpose of a data analytics model is to detect Data Mining Procedures that aren't labelled.In the smart grid, data analytics is utilised to extract useful information from historical data for use in directing operations and maintenance by comparing it to real-time data. Data management systems organise and store the massive volumes of data collected by smart metres and sensors. After the mathematical model has been developed, it can be utilised to create potential groupings among all of the objects.

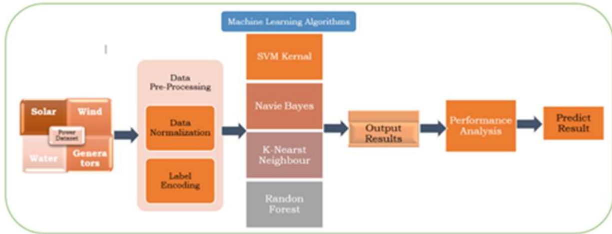

Fig 1: Architecture of smart grid Power resource prediction model

Data preparation is an important stage in Machine Learning since it improves data quality and makes it easier to derive relevant insights from it. Preprocessing (cleaning and arranging) raw data in order to create and train Machine Learning models is referred to as data preprocessing in Machine Learning. In Machine Learning, data preprocessing is a data mining strategy for turning raw data into a usable and understandable format.

Machine Learning Data Preprocessing Steps:

1. Obtain the data set
2. Install the required libraries
3. Add the data to the spreadsheet
4. Recognizing and resolving missing values
5. Partitioning the data
6. Scaling of features

The first stage in preparing machine learning data is to obtain the dataset. The first step in creating and using Machine Learning models is to obtain the necessary dataset. This dataset will be built from data obtained from a number of sources and then combined in the appropriate way to make a dataset. The format of a dataset varies depending on the application.

This technique's dataset is based on grid reliability reproduction findings and includes 12 features and two dependent variables derived from solar, wind, generator, and water energy resources. The dataset contains 15,000 different energy resources, as indicated in Table 1.

Features relating to overall strength. This model includes stability, production reaction time, and energy rate defiance.

Specific data preparation activities can be carried out using Python libraries. The second stage of machine learning data preparation is importing all of the necessary libraries. The three most popular Python libraries for data preprocessing in Machine Learning are as follows:

a) Import the data.

b) Encoding the categorical data

c) Splitting the dataset

d) Machine Learning Techniques

Import datasets

In order to create machine learning data, you must first import the dataset. Another critical stage in the dataset import process is extracting dependent and independent variables. Separating the independent variables (feature matrix) and dependent variables in a dataset is important for each Machine Learning model. Missing values are found and corrected. Missing values must be identified and managed efficiently during data preparation; failing to do so may result in erroneous and flawed findings and inferences.

Encoding the categorical data

Within a dataset, categorical data is information that is split into distinct categories. The aforementioned dataset has two category variables: nation and purchased.

Mathematical equations serve as the foundation for Machine Learning models. As a result, because the equations only require integers, it's easy to see how including category data could cause problems.

Splitting the dataset

The dataset is separated as the following phase in the machine learning data preparation technique. A Machine Learning model's dataset must be separated into two distinct sets: training and testing.

A training set is a portion of a dataset that is used to train a machine learning model. In this case, the outcome is known. In contrast, a test set is a subset of the dataset used to verify the machine learning technique. The machine learning model predicts outcomes using the test set. The data was divided into 80:20 proportions. Specifically, 80 percent of the information is utilized to train the model, while the other 20% is used to test the model. The technique for splitting the dataset differs depending on its shape and size.

Feature scaling is the final step in the data preparation process in Machine Learning. It is a strategy for keeping the different factors in a dataset within a specific range. To put it another way, feature scaling limits the number of factors that may be assessed on an equal basis

ML Techniques

On four different energy resource datasets, several machine learning algorithms have been applied. Working with the various data sets described below reveals the algorithm's performance and evaluation.

Naive Bayes Classifier The method of classification The premise behind Naive Bayes is that all variables are separate and unrelated. It proves that the position of one feature in a class has no bearing on the status of some other feature in that class. It is regarded as a powerful classification method because it is based on conditional probability. It performs well with missing value data and data that is unbalanced. The Bayes Theorem is used by Naive Bayes, a machine learning classifier. Calculating posterior probability using the Bayes theorem PA(c), PA(x), andPA (x|c) can be multiplied to get PA (c|x). Asa result, PA (c|x) = (PA (x|c) PA(c))/PA (x|c)/PA (x|c)/PA (x|c)/PA (x|c)/PA (x|c) (x) where PA (c|x) is the target classprobability. PA (x|c) denotes the predictor class of probability. The chances that c is correct is denoted by PA(c). The prior probability predictor is denoted by PA(x).

Decision Tree ClassifierA supervised machine learning method for dealing with classification difficulties is the Decision Tree algorithm. In this study, the major goal of using Decision Tree is to forecast the target class using a decision rule generated from previous data. It predicts and classifies using nodes and internodes. Instances are classified by root nodes based on a variety of parameters. The root node may contain two or more branches, whereas the leaf node represents categorization. At each level, the Decision Tree selects a node based on the best information gain across all features.

K Nearest Neighbor: Assign the most frequent label among the k most similar training inputs to a test input xx.

K Nearest Neighbor

To find the best match, a non-parametric approach is used that employs the least degree of dissimilarity between new and tagged items in various classifications. These parameters are used by the algorithm.

- Test point: x
- Denote the set of the k nearest neighbors of x as Qx.

Formally Qx is defined as Qx⊆DSx⊆D such that |Qx|=k and ∀ (x′, y′) ∈D\Qx
dist(x, x′) ≥max (x″, y″) ∈Qxdist(x, x″),
(i.e. every point in D but not in Sx is at least as far away from xx as the furthest point in Qx).
We can then define the classifier h() as a function returning the most common label in Qx:
h(x) =mode ({y″ :(x″, y″) ∈Qx})
Where mode () denotes choosing the label with the most occurrences.
The k-nearest neighbour classifier is built on a distance metric. The categorization will be more accurate if that measure appropriately measures label similarity. The most widely used method is the Minkowski distance.
$dist\ (x, y) = (\sum_{1=d}^{r} |Xr - Zr|p)$1/p

Support Vector Machine (SVM) SVM It stands for supervised machine learning model and is often used in categorization. A support vector machine's goal is to discover the best hyperplane that separates with the greatest margin across two classes given a two-class training sample. For more consistency, the hyper - plane should not be closer to data points from the other class. A hyperplane that is far distant from the data points in each category should be picked. The support vectors are the points closest to the classifier's edge. By optimizing the distance between the two decision boundaries, the SVM determines the optimal separation hyperplane.

The distance between the wt x + c = 1 hyperplane and the wt x + c = 1 hyperplane will be optimized using mathematics. This distance is 2 w in length. As a result, we simply need to solve 2 w. As an alternative, we may use min w | 2. The SVM should be able to classify all x I correctly, implying that yi (wt xi + c) >= 1, I_1, n.

Power system uncertainties are increasing as power networks are renovated and renewable energy is being integrated into the grid. Several uncertainty modelling methodologies have been reported in the literature to aid choosing for efficient power system operation. Developing These techniques' primary goal is to offer a statistical representation for numerous sources of uncertainty, such as load, generation, and line capacity.
Performance Evaluation

A confusion matrix is a way of summarizing the performance of a classification algorithm.
When each class has an unequal amount of observations or the dataset has more than two classes, classification accuracy alone can be deceiving. Calculating a confusion matrix can

assist you in determining where the classification model succeeds and where it fails. The confusion matrix constructed for four energy resources test data of size 3000 is shown in Table 2.

The number of times the classifier correctly classifies the positive class as positive is referred to as true positive (TP).

True Negative refers to the number of times the classifier properly predicts the negative class as negative (TN).

False Positive (FP): The number of times a classifier incorrectly predicts a negative class as a positive.

False Negative (FN): The number of times the classifier predicts a positive class as a negative class incorrectly.

Table 2: Confusion matrix of four energy resources test data set

CONFUSION MATRIX								
Test data Set size 3000	TP				FP			
	NBs	DT	KNN	SVM	NBs	DT	KNN	SVM
Solar Power	1090	900	819	1321	1455	1610	1312	1274
Wind Power	980	832	901	1316	1490	1499	1285	1262
Generators	894	987	789	1090	1503	1567	1503	1455
Water Energy	1287	871	864	900	1087	1598	1304	1610
Test data Set size 3000	FN				TN			
	NBs	DT	KNN	SVM	NBs	DT	KNN	SVM
Solar Power	115	125	258	118	340	365	611	304
Wind Power	171	169	271	115	359	500	543	307
Generators	102	132	467	112	501	314	241	343
Water Energy	207	145	244	125	419	386	588	365

4.1. Results:

Precision, sensitivity, specificity, FPR, fmeasure, accuracy, and f2 Score are determined for different energy resources based on the values derived from the confusion matrix using the following equations, and the performance evaluation of the four energy resources is displayed in Table 3. The graphs in Figures 2,3,4, and 5 are plotted based on the performance evaluation.

Precision (TPR)=$\frac{TP}{(TP+EP)}$

Recall / Sensitivity =$\frac{TP}{(TP+FN)}$

Specificity =$\frac{TN}{(FP+\quad)}$

FPR=$\frac{FP}{(TN+\quad)}$

F-Measure = $\frac{2*Precision*Recal}{(Precision+Reca\ )}$

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

f2 Score-f2 Measure=$\frac{((1+2*2)*Precision*Recal}{(2*2*Precision+Rec\quad)}$

Table 3: Performance evaluation of the Solar power, Wind power, Generators Power and Water Energy resources.

MLTs	Precision	Sensitivity	Specificity	FPR	fmeasure	Accuracy	f2 Score
Solar Power							
NBs	0.428290766	0.904564315	0.18941504	0.810585	0.581333333	0.848333333	0.58133
DT	0.358565737	0.87804878	0.18481013	0.81519	0.509193777	0.836666667	0.50919
KNN	0.384326607	0.760445682	0.31773271	0.682267	0.510598504	0.710333333	0.5106
SVM	0.509055877	0.91799861	0.19264892	0.807351	0.654933069	0.860125953	0.65493
Wind Power							
NBs	0.396761134	0.851433536	0.194159	0.805841	0.541286937	0.823333333	0.54129
DT	0.356928357	0.831168831	0.25012506	0.749875	0.49939976	0.777	0.4994
KNN	0.412168344	0.768771331	0.29704595	0.702954	0.536628946	0.728666667	0.53663
SVM	0.510473235	0.919636618	0.19566603	0.804334	0.656522824	0.859333333	0.65652
Generators Power							
NBs	0.372966208	0.897590361	0.25	0.75	0.526967286	0.799	0.52697
DT	0.386452623	0.882037534	0.16693248	0.833068	0.537435339	0.851333333	0.53744
KNN	0.344240838	0.628184713	0.13818807	0.861812	0.44475761	0.764	0.44476
SVM	0.428290766	0.906821963	0.19076752	0.809232	0.581798772	0.848333333	0.5818
Water Energy							
NBs	0.542122999	0.861445783	0.27822045	0.72178	0.665460186	0.791333333	0.66546
DT	0.352774403	0.857283465	0.19455645	0.805444	0.499856528	0.823	0.49986
KNN	0.398523985	0.779783394	0.31078224	0.689218	0.527472527	0.722666667	0.52747
SVM	0.358565737	0.87804878	0.18481013	0.81519	0.509193777	0.836666667	0.50919

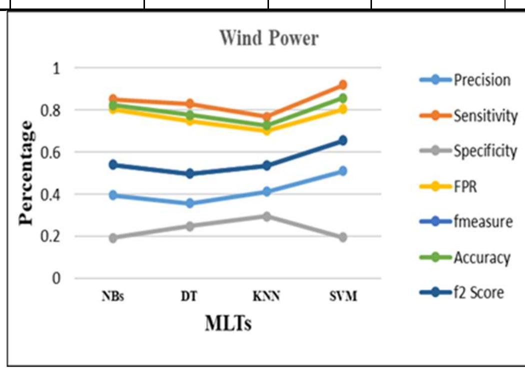

Fig 2: MLTs' Solar Power Energy Performance

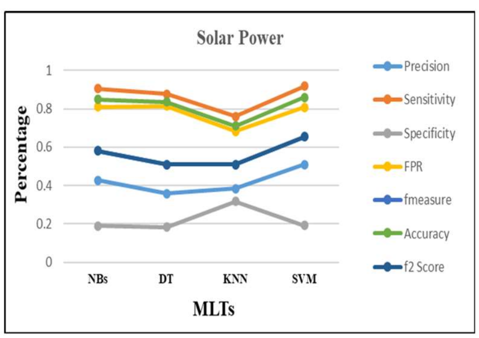

Fig 3: MLTs' Wind Power Energy Performance

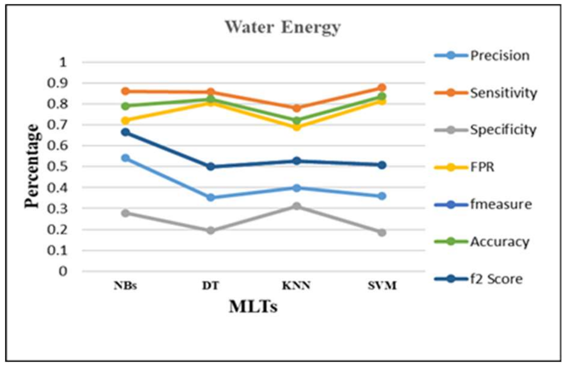

Fig 4: Performance of MLTs for Generators Power energy.

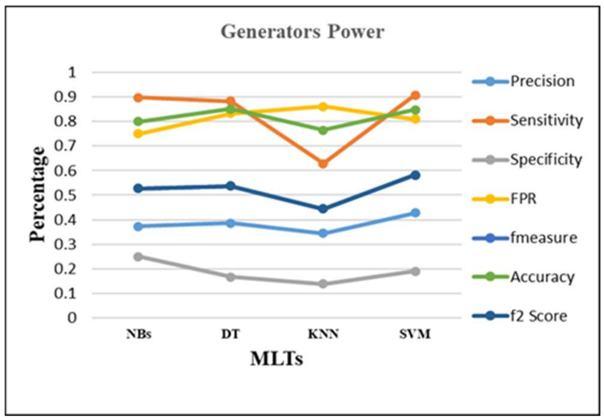

Fig 5: Performance of MLTs for Water Energy

	Table 1: Represents the sample data sets for the solar power generation, wind power, generators and water resource													
Sample Data count	SOLAR POWER													
	WEEK1			WEEK2			WEEK3			WEEK4				
	Day-1	Day-2	Day-3	Day-1	Day-2	Day-3	Day-1	Day-2	Day-3	Day-1	Day-2	Day-3	Differential Eqn. output	Binary label
1	2.95906	3.079885	8.381025	9.780754	3.763085	-0.782604	-1.257395	-1.723086	0.650456	0.859578	0.887445	0.958034	0.055347	UnBalanced
2	9.304097	4.902524	3.047541	1.369357	5.067812	-1.940058	-1.872742	-1.255012	0.413441	0.862414	0.562139	0.78176	-0.005957	Balanced
3	8.971707	8.848428	3.046479	1.214518	3.405158	-1.207456	-1.27721	-0.920492	0.163041	0.766689	0.839444	0.109853	0.003471	UnBalanced
4	0.716415	7.6696	4.486641	2.340563	3.963791	-1.027473	-1.938944	-0.997374	0.446209	0.976744	0.929381	0.362718	0.028871	UnBalanced
5	3.134112	7.608772	4.943759	9.857573	3.525811	-1.125531	-1.845975	-0.554305	0.79711	0.45545	0.656947	0.820923	0.04986	UnBalanced
	WIND POWER													
1	0.754512	1.415836	9.723392	9.264871	5.029876	-1.801387	-1.281568	-1.946921	0.44867	0.251181	0.413843	0.273108	-0.036986	Balanced
2	5.825547	2.644971	6.153305	9.215683	4.749492	-1.876166	-1.491278	-1.382048	0.528459	0.458131	0.155706	0.156222	-0.023089	Balanced
3	2.750088	1.373404	8.767781	4.517367	2.700511	-0.922647	-0.58731	-1.190554	0.471845	0.249577	0.428823	0.596576	-0.021277	Balanced
4	6.253534	7.550439	6.625686	0.613047	4.305593	-1.360955	-1.52939	-1.415248	0.376768	0.408225	0.686419	0.598896	0.009619	UnBalanced
5	1.800725	8.576087	1.185765	1.515843	4.255226	-1.015092	-1.270079	-1.970055	0.34115	0.653949	0.623442	0.247956	-0.038621	Balanced
	GENERATORS													
1	6.530527	4.349695	8.673138	6.78179	3.492807	-1.532193	-0.570329	-1.390285	0.073056	0.378761	0.942631	0.505441	0.045263	UnBalanced
2	2.95906	3.079885	9.780754	8.381025	3.763085	-0.782604	-1.723086	-1.257395	0.650456	0.859578	0.958034	0.887445	0.055347	UnBalanced
3	9.304097	4.902524	1.369357	3.047541	5.067812	-1.940058	-1.255012	-1.872742	0.413441	0.862414	0.78176	0.562139	-0.005957	Balanced
4	8.971707	8.848428	1.214518	3.046479	3.405158	-1.207456	-0.920492	-1.27721	0.163041	0.766689	0.109853	0.839444	0.003471	UnBalanced
5	0.716415	7.6696	2.340563	4.486641	3.963791	-1.027473	-0.997374	-1.938944	0.446209	0.976744	0.362718	0.929381	0.028871	UnBalanced
	WATER ENERGY													
1	5.825547	2.644971	9.215683	6.153305	4.749492	-1.876166	-1.382048	-1.491278	0.528459	0.458131	0.156222	0.155706	-0.023089	Balanced
2	2.750088	1.373404	4.517367	8.767781	2.700511	-0.922647	-1.190554	-0.58731	0.471845	0.249577	0.596576	0.428823	-0.021277	Balanced
3	6.253534	7.550439	0.613047	6.625686	4.305593	-1.360955	-1.415248	-1.52939	0.376768	0.408225	0.598896	0.686419	0.009619	UnBalanced
4	1.800725	8.576087	1.515843	1.185765	4.255226	-1.015092	-1.970055	-1.270079	0.34115	0.653949	0.247956	0.623442	-0.038621	Balanced
5	7.15043	2.089166	3.244408	4.837233	4.539624	-1.181821	-1.375972	-1.981831	0.31928	0.577839	0.842072	0.072775	-0.027978	Balanced

Conclusion

In this work, we focused mainly on the different requirements of electrical energy in the network to customer using the machine learning algorithm to choose based on the necessity of the customer, the data fromthe various energy resources from the DataGrid are collected and loaded to the ML algorthims. In thisMachine, Nave Bayes, Decision Tree, and K-Nearest Neighbor. Enormous amount of data set has been used to validate the performance of the different sources with various parameters. In all the above four algorithms SVM performance is much higher compared with other algorithms with respect to varies energy resources. SVM sensitivity to the dataset for all the sources is very effective decision making with an average 80%to 90% it varies in all sources. But SVM algorithm is not effective for specificity apart from specificity in other parameters like f2 score, fmeasure, FPR, accuracy and sensitivity reslutd gives a good performance.

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