IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received November 23, 2019, accepted December 13, 2019, date of publication December 26, 2019, date of current version January 27, 2020.

Digital Object Identifier 10.1109/ACCESS.2019.2962510

Performance Analysis of Different Types of Machine Learning Classifiers for Non-Technical Loss Detection

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This work was supported in part by the construction under Grant EFOP-3.6.3-VEKOP-16-2017-00002, in part by the European Union, and in part by the by the European Social Fund.

ABSTRACT With the ever-growing demand of electric power, it is quite challenging to detect and prevent Non-Technical Loss (NTL) in power industries. NTL is committed by meter bypassing, hooking from the main lines, reversing and tampering the meters. Manual on-site checking and reporting of NTL remains an unattractive strategy due to the required manpower and associated cost. The use of machine learning classifiers has been an attractive option for NTL detection. It enhances data-oriented analysis and high hit ratio along with less cost and manpower requirements. However, there is still a need to explore the results across multiple types of classifiers on a real-world dataset. This paper considers a real dataset from a power supply company in Pakistan to identify NTL. We have evaluated 15 existing machine learning classifiers across 9 types which also include the recently developed CatBoost, LGBoost and XGBoost classifiers. Our work is validated using extensive simulations. Results elucidate that ensemble methods and Artificial Neural Network (ANN) outperform the other types of classifiers for NTL detection in our real dataset. Moreover, we have also derived a procedure to identify the top-14 features out of a total of 71 features, which are contributing 77% in predicting NTL. We conclude that including more features beyond this threshold does not improve performance and thus limiting to the selected feature set reduces the computation time required by the classifiers. Last but not least, the paper also analyzes the results of the classifiers with respect to their types, which has opened a new area of research in NTL detection.

INDEX TERMS Data mining, machine learning, classification algorithms, supervised learning, boosting.

I. INTRODUCTION

Non-Technical Loss (NTL) is the loss incurred due to the unlawful theft attempts by the malicious consumers of electricity. With the ever-growing demand of electricity, NTL identification is becoming mandatory to protect illegal theft of electricity which can save billions of dollars [1]. In the US, the total annual loss is 6 billion dollars while for India, it is 4.5 billion dollars [2]. Similarly, Brazil suffers 4.5 billion dollars annually due to NTL [3]. Pakistan's economy is also suffering from 0.89 billion dollars annually on account of NTL [4], which is mostly caused due to bypassing electric meter, which results in zero meter reading for the consumer. Other methods include direct hooking from the main lines, reversing the meter units after opening electric meter, using magnetic device to slow down the normal rotation of units disc, changing the direction of meter to stop the rotation of units disc and tapping the neutral wire in the meter to stop the normal rotation of units disc [4]. In almost all cases, the meter reader is also involved in malfunctioning the meter, which results in near-zero reporting of NTL. This becomes a dilemma for the power supply company as it becomes hard to identify individual households where NTL is happening. One way of reporting NTL is on-site inspection in

The associate editor coordinating the review of this manuscript and approving it for publication was Francesco Piccialli.

selected households. This, of course, is limited to inspecting few households due to manpower required for inspection. Another approach is using an observer meter for a community that monitors the difference between billed electricity and consumed electricity. This approach is limited to identifying the area where NTL is occurring and fails to pinpoint the culprits. In general, as compared to committed electricity thefts, the number of reported thefts is very small, which results in burdening the power supplier.

NTL detection involves training different machine learning classifiers with existing data that contains observations from both positive and negative classes. After training, the classifiers are then tested on a different set of test data. The test results are then evaluated using performance evaluation metrics. The use of machine learning classifiers for NTL detection has been an ongoing and interesting activity in the research community that has now span for over two decades. There are many types of the classifiers that have been tested for NTL detection. These include decision trees, ensemble methods, generalized linear models, linear and quadratic discriminant analysis, Naive Bayes, nearest neighbors, neural network models, stochastic gradient descent and support vector machines.

Machine learning classifiers are by far the most flexible way of NTL detection for many reasons [5]. Unlike manual on-site inspection, machine learning requires some technically skilled professionals who can work on real datasets to identify the occurrence of theft. The shortlisted theft cases can then be verified by manual inspection. Adding new theft cases to the learning models makes the models learn new cases. In this way, the performance of the classifiers keeps improving. These machine learning methods are also useful to identify real culprits unlike other network based techniques which are only able to identify an area where NTL is committed but fail to pinpoint the theft cases. Furthermore, a much less cost is incurred in using machine learning methods as compared to other procedures like manual on-site inspection. Automation of the NTL detection procedure is another added advantage of using machine learning. This advantage can not be gained while using other NTL detection schemes like manual on-site inspection.

The main problem is that a detailed comparative study of the machine learning classifiers on some real dataset is still missing which can particularly highlight the best performing machine learning classifiers and the best types of classifiers for NTL detection. This paper contributes in not only identifying NTL in a real dataset taken from a power supply company in Pakistan but it also highlights the best performing individual classifiers and the best performing types of the classifiers for NTL detection. NTL in power sector is given less importance in Pakistan and less effort is done for its detection. That is why an on-site inspection is the only measure deployed for the detection of NTL. This paper has initially taken approximately $80,000$ consumption records with positive and negative classes along with 71 features for a possible detection of NTL. In this paper, our objectives are as follows:

1) Present a taxonomy of the NTL detection techniques and categorize the strategies of NTL detection with respect to data, network, a combination of both and additional data. Moreover, identify and focus on a number of solutions based on unsupervised, supervised, semi-supervised and hybrid learning.
2) For NTL detection, use a real dataset taken from a power supply company in Pakistan. The contributions which use synthesized data for NTL detection generally contain equal distribution of classes that do not depict the natural class distribution. As our dataset is real, the ratio between positive and negative classes is imbalanced which represents the natural behavior. Investigate the performance of different types of machine learning classifiers and identify the type that performs best in NTL detection. Apart from the comparison of different types of the classifiers, perform extensive simulations and find the best individual classifier for NTL detection in terms of F-measure and Recall. It will open a potentially new area where NTL detection can be worked on. Moreover, identify a threshold of the number of participant features beyond which adding more features does not affect the efficiency of the classifiers.

The rest of the paper is as follows: Section II explains the state of the art techniques used in NTL detection. Section III explains the methods we have used for NTL detection, the data collection and feature selection process. Section IV explains the metric used for performance evaluation and discusses the results obtained. Section V presents conclusions and future work.

II. STATE-OF-THE-ART IN NTL

The use of machine learning classifiers in a variety of different domains of science and business is becoming as fruitful as ever before. The applications involve the analytical computations for big data like concentric computing model [6], event detection for preventive medication [7], text classification [8] and data centric analysis [9]. Moreover, real-time anomaly detection is also beneficial by using clustering mechanism for big data repositories [10], [11]. One of the applications of classification is fraud detection. In power industry, fraud occurs with the use of unlawful connections of electricity, which is the primary cause of NTL. Identifying the NTL in power industry is as important as any other classification task as it not only identifies potential fraudsters but it also helps in saving billions of dollars for a company. During the last few years, the research community has paid attention to the problem of NTL detection. To encounter this problem, supervised, unsupervised and semi-supervised learning methods have been used. Some of the authors have used customer's consumption history while others have used the grid and network data. Effort has also been made to use both types of data, i.e. consumer's consumption profile as well as the

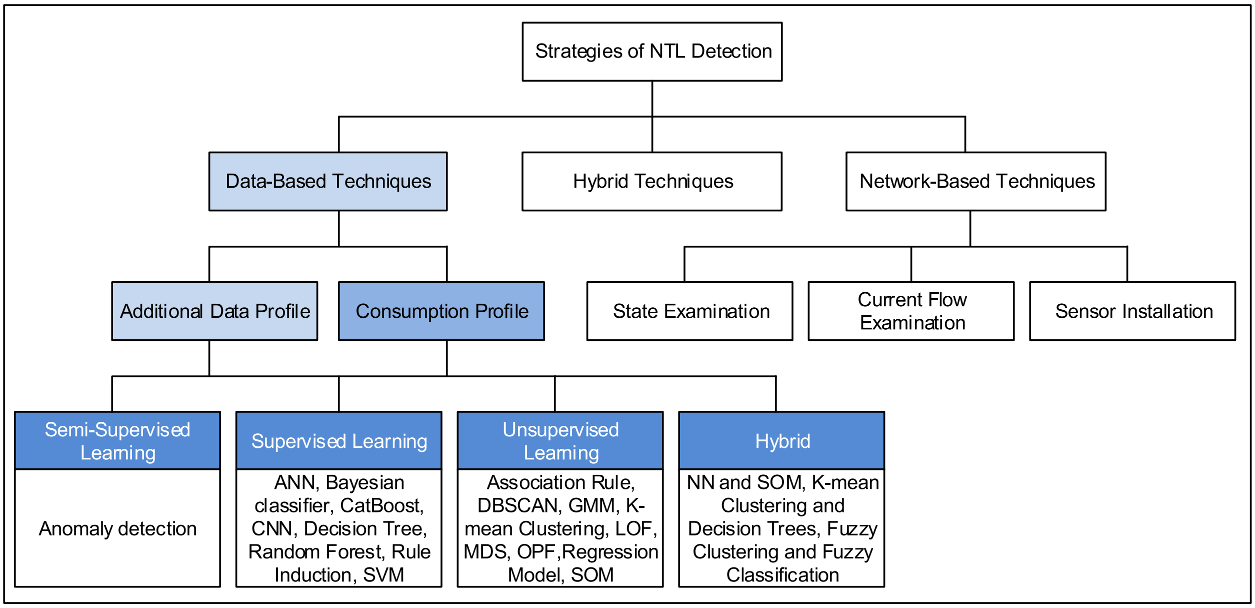

FIGURE 1. Strategies of NTL detection.

grid data which may contain current and voltage information supplied to different areas. At times, some additional data are also merged to the consumption data to see the effect of hit ratio of NTL detection. This additional data may comprise of environmental and temperature readings. A complete categorical division of the types of strategies and algorithms used in NTL is shown in Figure 1.

A survey on NTL can be found in [12]. The authors of this paper have categorized the techniques used in NTL into data oriented, network oriented and hybrid techniques. They have categorized the consumption data into multiple categories like time series data, raw data and geographical data. The authors have also discussed the classification and clustering techniques used for NTL and the performance evaluation metrics used to evaluate them.

A. DATA-BASED TECHNIQUES

Two different types of data profiles are used for NTL detection. Consumption profile contains hourly, daily or monthly consumption records of consumers which is used to detect a potential NTL. Additional data profile is also merged with consumption profile in an effort to increase accuracy in predicting NTL. The additional data profile may contain environmental and temperature features.

1) CONSUMPTION PROFILE

To address the problem of NTL, the research community has used unsupervised, supervised, semi-supervised and even a combination of supervised and unsupervised learning methods. Research contributions of some of them are discussed below.

a: UNSUPERVISED LEARNING

The authors of [13] have used consumption data collected from Endesa Distribucion, a power supply company in Spain. They have used association rule mining to cluster a group of customers responsible for electricity theft. The use of association rule mining has enabled them to perform an on-site inspection of a filtered few hundred consumers out of thousands of consumers. They have used support, confidence, TP, TN, FP and FN metrics to evaluate their result. They have claimed a 7% to 20% increase in detecting NTL. In [14], the authors have also used association rule mining by proposing an algorithm of their own which generates frequent patterns of the use of appliances. They have claimed to find associations between appliances of home and time series. Their work can further lead to NTL detection by filtering out those instances which disobey frequent pattern of a specific household area. They have stated that their results outperformed SVM and Multi-layer perceptron (MLP).

Benford curve, hierarchical clustering and Multi-dimensional scaling (MDS) are used in [15] to study the characteristics of consumption for a better detection of NTL in two companies. One of their findings is that in company 1, fraudsters have a different curve as compared to normal consumers with respect to Benford curve. No such indication is observed in company 2. This behavior is also indicated by the fact that using decision trees, company 1 has a good classification for fraudsters as compared to company 2.

Sharma *et al.* [16] have used the concept of local outlier factor (LOF) in density-based spatial clustering of applications with noise (DBSCAN) clustering algorithm to identify unusual load patterns in two datasets from USA and India. LOF is the ratio of density of a data point to the density of its k-nearest neighbors. A higher value of LOF shows that there is a noticeable difference between the densities of the point and its neighbors reflecting the point to be suspicious. They have used Silhouette coefficient and Davies Bouldin index to evaluate their technique but did not compare them with other clustering algorithms. A similar approach is used in [17]. The authors have proposed a distance matrix to observe the unusual profiles of consumers. They have used Area Under ROC Curve (AUC), accuracy and F1 measures to evaluate their proposed model and compared it with GMM, k-means and DBSCAN. Their results show that their technique outperformed the already known techniques. In [18], the authors have also proposed a density based clustering algorithm called DBMSCAN. It identifies low and peak loads which in turn help in detection of irregular consumption. The algorithm encounters anomalies by introducing irregularity variance. The authors have used silhouette coefficient for the comparison of DBMSCAN with the traditional DBSCAN and stated that their algorithm has outperformed DBSCAN.

Another unsupervised method, Optimum-path forest (OPF), is used in [19] to detect NTL in a Brazilian electricity data. The authors have also used semi-supervised learning method of anomaly detection that has the information of only one class. They have compared the accuracy of both techniques with SVM, Gaussian mixture model (GMM) and k-means and stated that OPF and anomaly detection techniques (semi-supervised learning) outperformed others. Yeckle and Tang [20] have used seven different outlier detection techniques to identify the occurrence of NTL in an Irish dataset. They have also performed k-means clustering algorithm in the pre-processing step to cutoff the number of transactions per day to three. They have tested the performance of the outlier detection techniques using AUC and claimed that reducing the number of meter readings by using k-means clustering has helped improving the performance of AUC.

b: SUPERVISED LEARNING

Similar attention is made in dealing NTL detection through supervised learning techniques. For example, Zheng *et al.* [21] have experimented wide and deep convolutional neural network (CNN) in a dataset collected from a Chinese electricity company. Wide framework of the neural networks handles the 1-D consumption records of each consumer, while the deep framework maintains weekly consumption. They have used AUC as the evaluation metric to compare their work with existing classifiers like SVM, logistic regression, random forest, and three sigma rule (TSR). They observed that their model outperforms these classifiers.

Fuzzy logic is used in [22] to detect potential electricity theft consumption. The authors have used consumption data from 2003 to 2017 in a series of five decades incrementing a year every time starting from 2003. Fuzzy suspicions are created based on the relationship of consumption between time-series data. Fuzzy logic is then used to calculate suspicion value for each consumer. If it passes a certain threshold, the consumer is considered a suspicious consumer. This work has shown a 14% of success percentage in finding the theft cases but it claims that the percentage of success will be increased after on-site inspection. A similar type of work is presented in [23] where authors have used fuzzy-based distance to check whether a consumer's distance has significantly crossed a consumption prototype. They have used consumption records of four thousand Irish households. The authors have claimed a true positive rate of 63.6% and a false positive rate of 24.3%.

Recently developed ensemble methods namely CatBoost, LGBoost and XGBoost are tested in [24]. The authors have used an Irish dataset that contains half-hourly meter readings for 420 days. They have generated six theft cases in the dataset to balance out the minority class. They have concluded that LGBoost and CatBoost outperformed XGBoost with respect to detection ratio, while LGBoost performed better than CatBoost and XGBoost with respect to False Positive Rate (FPR). However, they have not compared the three classifiers with other known classifiers. Moreover, their dataset is synthesized with equal positive and negative class representations. This, of course, does not reflect the real-world scenario where the observations of the positive class are very small as compared to the observations of the negative class. There is a need that these classifiers should also be tested on a real world dataset.

c: HYBRID OF SUPERVISED AND UNSUPERVISED LEARNING

Some of the authors have applied supervised and unsupervised learnings as a sequence of operations to deal with NTL. For example, in [25], the authors have taken a dataset of a Spanish electricity supply company and performed two modules. In the first module, they have used artificial neural networks to filter the consumers in a pre-processing step. In the next module, they have tested classification and regression tree (supervised learning) along with Self Organizing Maps (SOM), which is a technique used in unsupervised learning. The authors have claimed a three times rise of accuracy as compared with manual inspection. Similarly, authors of [26] have performed a mixture of unsupervised and supervised learning techniques in a dataset collected from a Chinese electric company. In the first step, they have performed k-means clustering algorithm to form different clusters of consumers based on their consumption patterns. In the second step, they have performed a reclassification step by applying decision tree, random forest, SVM and KNN to the filtered consumers obtained from the first step. The paper concludes that the classification step overcomes the weaknesses that appeared in the clustering step. Another approach is used in [27], which combines fuzzy clustering and fuzzy classification. This work first forms clusters of consumers having similar consumption patterns using fuzzy clustering. Then, using membership matrices, a fuzzy classification further classifies the consumers. Moreover, an expected consumption profile is calculated for each consumer and if the difference between the expected and real consumption profile passes a specific threshold, the consumer is shortlisted as a potential fraudster. However, the paper did not compare its findings with other techniques.

2) ADDITIONAL DATA PROFILE

Some authors have also tested merging consumption data with some additional data like data related to environment and temperature. For example, in [28], the authors have merged weather data with the consumption data obtained from an electric distribution company in Luxembourg. They have created multiple consumption profiles for each customer based on time, e.g, monthly, weekly and daily profiles and used them in live machine learning for consumer classification. They have claimed that the additional data coupled with live machine learning and maintaining multiple consumer profiles has helped reduce false positive rate (FPR).

B. NETWORK-BASED TECHNIQUES

Some interest has been developed in using network data to identify potential NTL. For example, Chauhan [29] have proposed a framework to monitor current between poles. Given a constant voltage, the current between the poles will remain almost the same. If there is a large difference between the current readings of two poles, then it indicates that there is a possible unlawful connection between the poles. To some extent, this method can identify unlawful meter bypassing but it can not detect NTL which is caused by slowing down meters or wrong meter readings. The authors have not used any performance evaluation metric. A similar strategy is proposed in [30]. The paper has proposed to install an observer meter for a community. Using this meter, the difference between the electricity billed and actual electricity consumed can be calculated. However, this solution can filter a locality where NTL is occurring but it fails to identify the specific consumers responsible for NTL. In [31], the authors have proposed to remotely detect NTL by monitoring the difference between the electricity distributed and the electricity consumed. The electricity consumed at the consumer end is monitored by radio transceivers and communicated back to the distribution pole using Wi-Fi space. If the difference between the distributed and used electricity passes a certain threshold, a potential NTL is identified. However, this framework fails to identify NTL caused by meter bypassing. Moreover, a heavy cost is also associated with the installation of radio transceivers at every consumer's meter.

C. HYBRID TECHNIQUES

Efforts have been made to combine the consumption data and network data in a bid to better achieve NTL detection results. Meira *et al.* [2] have categorized the consumption and network features in four categories based on their similarity, time period, neighborhood and transformer data. They have tested three classifiers on these different sets of features. The performance evaluation metric used is AUC. The paper concludes that predicting NTL using the raw data from consumption profile is better than using a combination of consumption and network data. In [32], the authors have used a combination of regression model and SVM. The regression model is used to analyze the state of the meters and the grid. A large deviation of a specific meter in the regression indicates a possibility of NTL. The consumption data is used to train the SVM classifier for a prediction of NTL. The authors have used true positive rate (TPR) and true negative rate (TNR) as the performance evaluation metrics and concluded that consumption data requires less configuration which makes it relatively easier to implement.

D. MODELS

A variety of different machine learning algorithms are tested for NTL detection which also include recently developed ensemble methods namely CatBoost, LGBoost and XGBoost. We investigated the types of classifiers mentioned in Figure 2 to find the best classifiers for NTL detection. The figure represents the classifiers and their types that are used in our experiments.

1) NAIVE BAYES CLASSIFIERS

All classifiers belonging to this type use Bayes' algorithm along with a 'Naive' assumption regarding the class conditional independence. The definition of Bayes' theorem as described in [33] is as follows:

$$P(C = i|X = x) = \frac{P(X = x|C = i)P(C = i)}{P(X = x)} \quad (1)$$

where $P(C = i|X = x)$ is the class posterior probability given the feature vector X. Notice that $P(X = x)$ is the same for all classes and thus can be ignored. Thus, Equation 1 is reduced to the following equation:

$$P(C = i|X = x) = P(X = x|C = i)P(C = i) \quad (2)$$

When the number of features are too many, computing $P(X = x|C = i)$ becomes exponentially expensive. For this reason, assumption of the class conditional independence is made. This assumption states that the features are independent of each other which means that the values of one feature is not dependent on the values of any other feature. This assumption simplifies the Equation 2 to the following equation:

$$P(C = i|X = x) = \prod_{j=1}^{n} P(X_j = x_j|C = i)P(C = i) \quad (3)$$

Despite the assumption being over-simplified, Naive Bayes (NB) still performs better on many real datasets. Different classifiers use NB approach while the difference between them is the assumptions they use for finding the posterior probability $P(X_j = x_j|C = i)$, where x_j is the j^{th} feature and $C = i$ is the i^{th} class label. We have used Gaussian Naive Bayes [34] and Bernoulli Naive Bayes [35] classifiers in our simulation.

2) LDA AND QDA

Linear Discriminant Analysis (LDA) [36] and Quadratic Discriminant Analysis (QDA) [37] belong to a separate type of supervised machine learning classifiers. As their names suggest, LDA generates linear decision boundaries and QDA

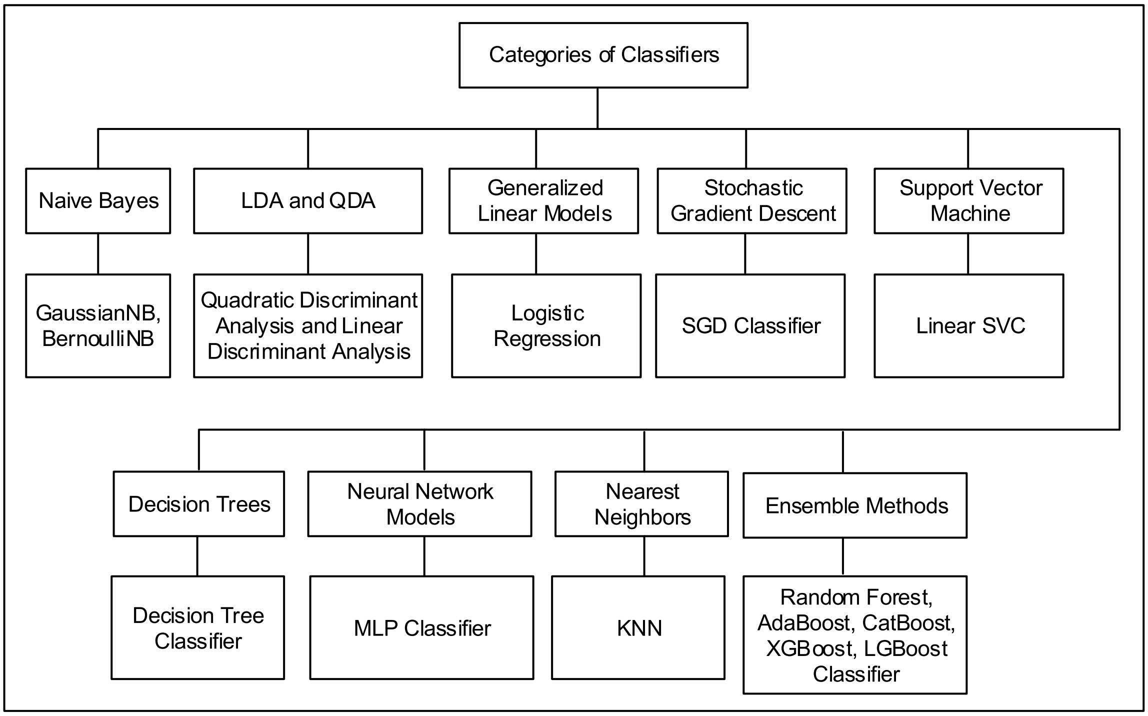

FIGURE 2. Hierarchy of classifiers.

generates quadratic decision boundaries. These classifiers are used in practice due to their advantage of multi-class support, computationally less expensive with no requirement of hyper-parameter tuning.

The difference between the two classifiers is that LDA uses the same co-variance matrix for all classes while QDA computes separate co-variance matrix for each class. Thus, at one hand, QDA is computationally expensive as compared to LDA but on the other hand it is more flexible and informative with respect to decision boundaries. In general, LDA works better with a small training set and thus has a low variance while QDA performs better with a large training set and thus has a high variance.

3) GENERALIZED LINEAR MODELS

For Generalized Linear Models, we have chosen logistic regression to simulate on our data. Unlike its name, logistic regression is used for classification instead of regression. The mathematical notation for logistic regression model [38] is given in Equation 4.

$$\hat{y}(w, x) = w_0 + w_1 x_1 + \cdots + w_n x_n \tag{4}$$

where $\hat{y}$ is the predicted value, $x = (x_1, x_2, \ldots, x_n)$ is the feature vector, $w = (w_1, w_2, \ldots, w_n)$ is the coefficient vector and w_0 is the intercept.

For a binary classification, the value of $\hat{y}$ must be between 0 and 1. For this, a conversion function sigmoid is used. The mathematical notation of sigmoid is given in Equation 5.

$$s = \sigma(w_0 + w_1 x_1 + \cdots + w_n x_n) = \sigma(z) = \frac{1}{1 + e^{-z}} \tag{5}$$

where s is the sigmoid function. For a large positive value of z, $s = 1$ and for a small or large negative value of z, $s = 0$ and for $z = 0$, $s = 0.5$.

4) STOCHASTIC GRADIENT DESCENT

Stochastic Gradient Descent (SGD) [39] is a type of linear models that has a support of classification as well as regression. SGD is particularly attractive for problems having large number of observations and large number of features. Despite dealing with large data and high dimensionality, SDC is efficient and offers many options for tuning parameters like number of iterations and regularization parameters. However, one of the prerequisites of using SGD is that the data must be normalized before use which means it is sensitive to scaling. We have used SGD classifier in our simulation, which offers a lot of options for loss functions and their penalties. A training sample looks like $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$, where $x_i \in \mathbf{R}^m$ and $y_i \in \{-1, 1\}$. Let us take a linear function which we want to learn

$$f(x) = w^T x + b \tag{6}$$

where $w \in \mathbf{R}^m$ and $b \in \mathbf{R}$ is the intercept. The training error, as described in [40], is evaluated using Equation 7:

$$E(w, b) = \frac{1}{n} \sum_{i=1}^{n} L(y_i, f(x_i)) + \alpha R(w) \tag{7}$$

where L is the loss function that estimates the difference between the expected and the actual output, R is a regularization step used to penalize on occurrence of error and $\alpha > 0$ is a hyper-parameter. Two most commonly used regularization choices are $L1$ and $L2$ regularizations given in Equations 8 and 9:

$$L1\ Regularization = \sum_{i=1}^{n} |w_i| \tag{8}$$

$$L2\ Regularization = \frac{1}{2}\sum_{i=1}^{n} w_i^2 \tag{9}$$

5) SUPPORT VECTOR MACHINE

Vapinik has proposed Support Vector Machine (SVM) classifier [41] that creates a margin between the two classes and tries to maximize this margin. This type of classifier is a set of machine learning methods which offers support for outlier detection, regression and classification. SVMs are widely used in the field of data mining [42], [43] due to their high predicting power and reliability in supervised machine learning problems. For classification problem, we have used Linear SVC classifier in our simulation. The main strengths of SVM are its effectiveness on high dimensional data and on datasets where the number of features is greater than the number of observations, less memory consumption due to the use of support vector (which is a subset of training observations and not the whole training set) and the use of a variety of kernel functions, which are used in the decision function. However, for a dataset where the difference between the number of features and number of observations is too big, SVM tends to overfit the model.

6) DECISION TREES

Decision Trees (DT) are a set of machine learning methods used in classification and regression. The data provided to the decision tree is used to infer if-then-else rules. These rules become complex with the increase in depth of the tree. The strength of decision trees include its simple interpretation of the rules, no requirement of data normalization, computationally less expensive and handling of numerical as well as categorical data. However, its weaknesses include creation of over-complex tree in some cases resulting in overfitting, instability of the tree when new data is added and the problem of NP-completeness for an optimal decision tree.

7) NEURAL NETWORK MODEL

The Neural Network (NN) model offers Multi-layer Perceptron (MLP) classifier which is vastly used for classification. The objective of MLP classifier is to learn a function $f(.)$: $R^m \rightarrow R^n$ with a feature set $X = x_1, x_2, \cdots x_m$ and an output y where m is the number of features and n is the number of values for the output y. The difference between MLP classifier and logistic regression is that MLP classifier can have one or more hidden layers between input and output layers. The input layer transforms the input to the hidden layers where a linear summation like $w_1x_1 + w_2x_2 + \cdots + w_mx_n$ occurs. The output layer takes the input from the hidden layer and converts it to the output values using the sigmoid function. The main advantage of using MLP classifier is its compatibility with non-linear models. However, it requires a number of hyper-parameters to be tuned [44].

8) NEAREST NEIGHBORS

A set of supervised and unsupervised machine learning methods use nearest neighbors, which is based on calculating distances from the neighbors [45]. This technique is widely used in solving many real-world problems like physical activity classification [46]. In nearest neighbors, both classification and regression are supported. The key idea of nearest neighbors is to find a predefined (k) number of training observations which are closest to the new observation and then find the value of the output variable y for this new observation based on the nearest neighbors. There are many metrics used to find the distance between neighbors. The most commonly used metric is standard Euclidean method.

9) ENSEMBLE METHODS

Ensemble methods combine the predicted results of multiple base estimators. This way the results are improved as compared to some individual estimator. There are two main streams of ensemble methods. The first stream includes techniques which take into account results from many individual estimators and combine their results using average. This way the combined results of individual estimators turn out to be better as compared to the results of individual estimators. Examples of this stream are bagging and random forests. The second stream includes techniques which combine many weak estimators in order to get a powerful result of an ensemble. This in turn also reduces the bias. Examples of this stream are AdaBoost, CatBoost, LightGBM and XGBoost. We have experimented random forest, AdaBoost, CatBoost, LightGBM and XGBoost in our simulation.

Random forest [47] is a combination of randomized decision trees. These decision trees are built with separate training observations and their results are then combined using average. AdaBoost [48] is a technique to repeatedly apply new data to weak estimators. This includes increasing weights for the training observations that had wrong predictions and decreasing weights for the training observations that had correct predictions. This way, with every new iteration, the estimator is restricted to concentrate on those training observations that had wrong predictions in the previous iteration.

Derived from the terms 'Category' and 'Boosting', CatBoost [49] is a recently developed open-source machine learning algorithm. The term 'Category' refers to the fact that it handles categorical features on its own. Other machine learning techniques require pre-processing steps to convert categorical data into numbers but CatBoost requires only the indices of categorical features. It then automatically performs one-hot encoding to transform the categorical data into numerical data [50]. The term 'Boost' refers to the fact that it is based on gradient boosting algorithm which itself is widely used in different machine learning problems like recommendation systems, fraud detection and forecasting, etc. Moreover, unlike deep learning, CatBoost does not require

TABLE 1. Observations after applying random permutation.

Records	Class-Bill	Class Label
1	Home	0
2	Industrial	0
3	Home	1
4	Home	1
5	Government	1
6	Industrial	1
7	Home	0

TABLE 2. Observations after transforming categorical data into numerical values.

Records	Class-Bill	Class Label
1	0.05	0
2	0.05	0
3	0.025	1
4	0.35	1
5	0.05	1
6	0.025	1
7	0.5125	0

huge datasets for extensive training. Despite having a number of hyper-parameters like regularization, learning rate, number of trees, tree depth etc., CatBoost does not require exhaustive hyper-parameter tuning which reduces the likelihood of over-fitting.

CatBoost uses three steps to transform categorical features having number of categories greater than a specified number into numerical features.

1) The set of input observations are randomly permuted multiple number of times.
2) The label values are transformed from categorical or floating point to integer values.
3) The categorical features are transformed to numerical features using the formula given in Equation 10:

$$Average\_target = \frac{InClassCounter + Prior}{TotalCounter + 1} \tag{10}$$

where *InClassCounter* represents the number of times the class label is 1 for all those records having the current feature value. *Prior* is the starting value for the numerator and is defined during initialization of parameters. *TotalCounter* is the total number of records (upto the previous record) having the same categorical value as that of the current categorical value.

Suppose *Class-Bill* is a feature that contains categorical values representing the category of the consumer. The feature can contain three categories namely home, industrial or government. Table 1 shows the observations after applying random permutation. Table 2 shows the transformed categorical values of *Class-Bill* into numerical values using Equation 10. In this case, we have set *Prior* to 0.05.

Light Gradient Boosting Machine (LGBoost) is another gradient-based boosting algorithm which uses decision trees [51]. Like CatBoost, it is used in many machine learning problems involving classification and prediction. Instead of level-by-level tree growth, LightGBM uses depth-first approach in splitting the tree which may cause an increase in complexity and overfitting. To avoid this disadvantage, maximum depth of the tree can also be set. The training time of LightGBM is significantly improved as it converts continuous feature values into discrete bins using a histogram approach. However, it is not advisable to use LightGBM for smaller datasets as it tends to overfit them.

Extreme Gradient Boost (XGBoost) [52] is another boosting-based machine learning algorithm. Unlike CatBoost, it does not transform categorical data into numbers by its own. Consequently, before applying XGBoost, a pre-processing step must include encoding techniques like one-hot encoding, mean encoding or label encoding to convert categorical features into numerical features. It also has a built-in feature of handling missing values. A specific parameter is reserved to supply a different value than the usual values which is used by the algorithm when it encounters a missing value.

III. METHODOLOGY

The literature in NTL detection does not properly contribute in identifying the types of classifiers which are best suitable for NTL detection. Moreover, a feature selection strategy is also needed which can identify the best combination of features for NTL detection in a real dataset. Our contribution in this regard is highlighted in this section, which outlines the data collection, feature selection strategy and the metrics used to evaluate the performance of the classifiers.

A. DATA COLLECTION

For NTL detection, a real dataset is collected from a power supply company in Pakistan. Due to sensitive nature of the data, consumers' information is kept anonymous. This dataset contains consumers' monthly consumption records over a period of 15 months spanning between January 2015 and March 2016. It comprises of $80,244$ records. The dataset is randomly split into train and test sets with the ratio of 80% and 20%, respectively. The training set contains $64,195$ records out of which $61,456$ are normal records with no theft and $2,739$ are abnormal records where the users have committed stealing of electricity. Test set contains $16,049$ records out of which $15,366$ are normal consumption records and 683 records contain NTL. The percentage of NTL in both sets is 4%. As the number of normal users is always much greater than the number of abnormal users (thieves), this data is considered imbalanced and biased towards major representation of normal users. This behavior is shown in Figure 3 and a detailed characteristic chart of train and test data is presented in Table 3.

B. PRE-PROCESSING

Initially, a set of 71 features is selected that span across six major categories as illustrated in Appendix A. These include normal amount, normal units, additional amount, additional units, bill info and extra info. The category 'Normal amount' contains all features describing characteristics related with billed amount like regular amount, opening amount, closing amount and surcharge. The category 'Normal Units' contains features describing characteristics of billed units like regular

FIGURE 3. Imbalanced data representation.

TABLE 3. Data characteristic chart.

Sr. No	Parameter	Unit
1	Number of observations	80244
2	Number of features	71
3	Train percent split	80%
4	Test percent split	20%
5	Train size	64195
6	Test size	16049
7	Normal consumption in Train set	61456
8	Theft cases in Train set	2739
9	Normal consumption in Test set	15366
10	Theft cases in Test set	683
11	Percentage theft in Train set	4.45%
12	Percentage theft in Test set	4.44

units and average units. The category 'Additional amount' contains features describing any additional amount billed like late payment surcharge across different time-lines. The category 'Additional units' contains features describing any additional units billed. The category 'Bill info' consists of features describing characteristics of bills like billing month and billing class. The category 'Extra info' contains features describing any characteristic which is not directly part of the bill. An example of such a feature is 'last disconnection reason', which describes the reason electricity was disconnected last time.

C. SELECTING TOP-K FEATURES

One of the contributions of this paper is to find the optimum number of k features that can provide best theft prediction in a real dataset. It is observed that not every feature has an equal or comparable participation in predicting the NTL. Some features have a high role while others have a negligible role. Also, using all 71 features to predict NTL will increase the computational complexity of the classifiers. It turns out that there should be a threshold for the contributing features beyond which including or excluding features should not affect the efficiency of the classifier. For this, we first sort the feature set in descending order with respect to feature importance [53]. It is a measure that uses accuracy to filter attributes which are most suitable for correctly identifying the target variable. Thus, it gives an insight to the relative importance of every feature with respect to the target variable. For a theoretical definition of feature importance, the reader can refer to [47]. Then, we apply Gini Index to find the top-k number of features for which the F-measure is the highest where k ranges from 1 to 71. Finally, the k^{th} value for which the best F-measure is found is selected. For our data set, the value of k with best F-measure is 14. This indicates that using this set of top 14 features to find NTL has the same behavior as using all 71 features. This simulation has not only identified key features that are participating in predicting NTL in the real dataset but it also has helped to significantly reduce the execution time of the classifiers. Table 6 lists 71 features and their corresponding feature importance. The cumulative percentage of feature importance of top 14 features is presented in Figure 4, which shows that the contribution of top 14 features in predicting NTL is 77%.

D. NTL AND EVALUATION METRIC

NTL detection is an application of imbalance problem domain. It is a problem where the dataset is highly biased towards one of the outcomes of the target variable while the other outcome(s) remains least representative. Interestingly, the focus is on the least representative outcome. This leads to the requirement of an appropriate selection of the evaluation metric. Taking the example of NTL detection, most of the users are not thieves (True Negative) while few are thieves (True Positive). Now selecting accuracy as an evaluation metric would be a wrong choice as the results will be highly biased towards the most representative class, i.e. TN. In fact, we need a measure which should comprehensively give an insight to the actual number of thieves (recall) as well as the actual number of predicted thieves (precision) along with the combination of the two. For this, F-measure is used which combines precision and recall. In this work, we have used precision, recall and F-measure as our performance evaluation metrics. Equations 11-13 define these terms:

$$Precision = \frac{TP}{TP + FP} \tag{11}$$

$$Recall = \frac{TP}{TP + FN} \tag{12}$$

$$F - measure = \frac{2 \times (Precision \times Recall)}{Precision + Recall} \tag{13}$$

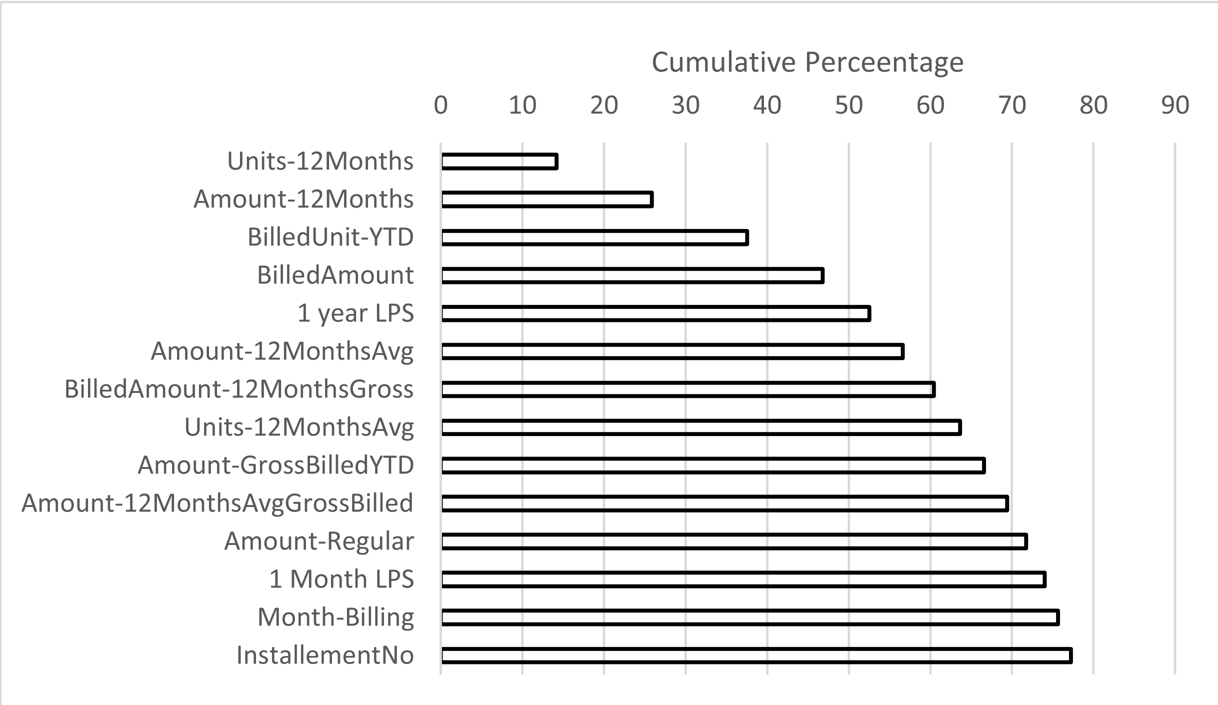

FIGURE 4. Cumulative percentage of feature importance of top 14 features.

where TP, FP and FN are True Positive, False Positive and False Negative, respectively. FP is the number of normal users predicted as thieves by the classifier and FN is the number of thieves predicted as normal by the classifier.

IV. EXPERIMENTAL RESULTS

In this section, we validate our work by performing extensive simulations using Python 3.4 on a 64-bit Windows Server with hardware specification including an Intel Xeon 2.2 GHz processor and 32 GB RAM. Other than CatBoost, LGBoost and XGBoost, all the classifiers are trained and tested using the scikit-learn [54] open source library for Python. CatBoost [49], LGBoost [51] and XGBoost [52] are also open source libraries which are available in GitHub for Python. Secondly, we perform a detailed analysis of the results of the classifiers which span across 9 different types. A list of simulation parameters of the classifiers is presented in Appendix B.

The top-14 features identified in feature selection process are used to calculate the confusion matrix, precision, recall and F-measure of different machine learning classifiers. The confusion matrix for all classifiers is presented int Table 4.

One of our contributions is that we compare the results of the classifiers with respect to the types of the classifiers. Another contribution is that we compare the efficiency of recently developed CatBoost, LightGBM and XGBoost with other supervised machine learning classifiers including Gaussian Naive Bayes, Bernoulli Naive Bayes, Quadratic Discriminant Analysis (QDA), Stochastic Gradient Descent (SGD), Decision Trees, Random Forest, K-Nearest Neighbors (KNN), Adaboost, Multi-Layer Perceptron (MLP) classifier, Linear SVC, Logistic regression and Linear Discriminant Analysis (LDA). The precision, recall and F-measure for all the classifiers are presented in Table 5.

A. PERFORMANCE ANALYSIS OF DIFFERENT TYPES OF CLASSIFIERS FOR NTL DETECTION

It is interesting to observe that considering F-measure as the classifiers' efficiency measure, ensemble methods outperformed all other types of classifiers. In fact, top three classifiers having best F-measures belong to the ensemble methods namely CatBoost, Random Forest and XGBoost, while Naive Bayes performed worst with lowest two F-measures. A reason for this behavior is that ensemble methods are robust to overfitting as compared to Naive Bayes classifiers which tend to overfit the model. Thus, any method which overfits the model will suffer. Two classifiers are experimented in 'LDA and QDA' type. The F-measure of LDA is quite low, that is, 0.471 while the F-measure of QDA is observed to be 0.782 which shows a percent increase in the performance of 66% while the percent increase in the performance from Naive Bayes to 'LDA and QDA' type is 248%. The type 'Generalized Linear Models' performed no better than the type 'LDA and QDA'. The F-measure obtained from its classifier, that is, Logistic Regression, is 0.787. The percent increase in the performance from 'LDA and QDA' to the type of 'Generalized Linear Models' is only 0.64%. One classifier from each of SGD, SVM, DT, NN and Nearest Neighbors is tested. Their F-measures are observed as 0.945, 0.972, 0.977, 0.979 and 0.980 respectively. Notably, all these readings are above 0.90.

TABLE 4. TP, TN, FP and FN of all classifiers.

Type of Classifier	Classifiers	TP	TN	FP	FN
Naive Bayes	BernoulliNB	1	15365	1	682
	GaussianNB	58	15249	117	625
LDA and QDA	LDA	230	15302	64	453
	QDA	566	15167	199	117
Generalized Linear Models	LogisticRegression	453	15351	15	230
SGD	SGDClassifier	639	15336	30	44
Support Vector Machine	LinearSVC	672	15338	28	11
Decision Tree	DecisionTreeClassifier	672	15346	20	11
Neural Network Models	MLPClassifier	679	15341	25	4
Nearest Neighbors	KNeighborsClassifier	678	15343	23	5
Ensemble Methods	AdaBoostClassifier	660	15350	16	23
	RandomForestClassifier	677	15347	19	6
	LGBoost	606	15356	10	77
	XGBClassifier	674	15349	17	9
	CatBoostClassifier	677	15352	14	6

TABLE 5. Precision, recall and F-measure of all classifiers.

Type of Classifier	Classifiers	Precision	Recall	F-measure
Naive Bayes	BernoulliNB	0.500	0.001	0.003
	GaussianNB	0.331	0.085	0.135
LDA and QDA	LDA	0.782	0.337	0.471
	QDA	0.740	0.829	0.782
Generalized Linear Models	LogisticRegression	0.968	0.663	0.787
SGD	SGDClassifier	0.955	0.936	0.945
Support Vector Machine	LinearSVC	0.960	0.984	0.972
Decision Tree	DecisionTreeClassifier	0.971	0.984	0.977
Neural Network Models	MLPClassifier	0.964	0.994	0.979
Nearest Neighbors	KNeighborsClassifier	0.967	0.993	0.980
Ensemble Methods	AdaBoostClassifier	0.976	0.966	0.971
	RandomForestClassifier	0.973	0.991	0.982
	LGBoost	0.984	0.887	0.933
	XGBClassifier	0.975	0.987	0.981
	CatBoostClassifier	0.980	0.991	0.985

LGBoost has the worst F-measure among ensemble methods which is 0.933 while the F-measure of AdaBoost is 0.971. The percent increase in the performance from the worst to the best classifier in the ensemble methods is only 5.5% which shows that the performance of all classifiers in ensemble methods is close to each other. The comparison of all types of classifiers using F-measure is shown in Figure 5 where T-1 to T-9 correspond to the types of Naive Bayes, LDA and QDA, Generalized Linear Models, SGD, SVM, DT, NN, Nearest Neighbors and Ensemble Methods, respectively.

Considering recall as the efficiency measure of the classifiers, NN outperformed other types with MLP Classifier having a recall of 0.994. The worst two recalls are observed for the Naive Bayes. For the type 'LDA and QDA', LDA has a recall as low as 0.337 while the recall of QDA is 0.829 which shows a performance increase of 146%. The type 'Generalized Linear Models' performed no better than 'LDA and QDA'. The classifier used for this type is Logistic Regression. Its recall is 0.663. An interesting point is that the counterpart of logistic regression, that is, MLP Classifier which belongs to the type of NN, has the highest recall. Thus, the percentage increase in performance from the Logistic Regression to MLP Classifier is 50%. The only difference between the two classifiers is the number of hidden layers between input and the output layer. This observation has led us to a new future direction of testing deep learning in our real dataset. The recalls of each of the classifiers from SGD, SVM, DT and Nearest Neighbors are observed as 0.936, 0.984, 0.984 and 0.993 respectively. The recalls of ensemble methods are 0.966, 0.991, 0.887, 0.987 and 0.991. These recalls are for the classifiers AdaBoost, Random Forest, LGBoost, XGBoost and CatBoost respectively. Other than LGBoost, the recalls of all ensemble methods are above 0.960 which shows that the performance of ensemble methods is very good for our data. The percent increase from the worst to the best classifier in the ensemble methods is 11.7%. The comparison of different types of classifiers using recall is shown in Figure 6.

Considering precision as the efficiency measure of the classifiers, all the classifiers used in ensemble methods outperformed rest of the types. LGBoost has the best precision of 0.984, which interestingly also has the lowest recall and F-measure among the ensemble methods. This indicates that LGBoost has the lowest FP. The other classifiers of AdaBoost, Random Forest, XGBoost and CatBoost from ensemble methods have precision reading as 0.976, 0.973, 0.975 and 0.980, respectively. There is an increase of only 1.1% of the performance from the worst to

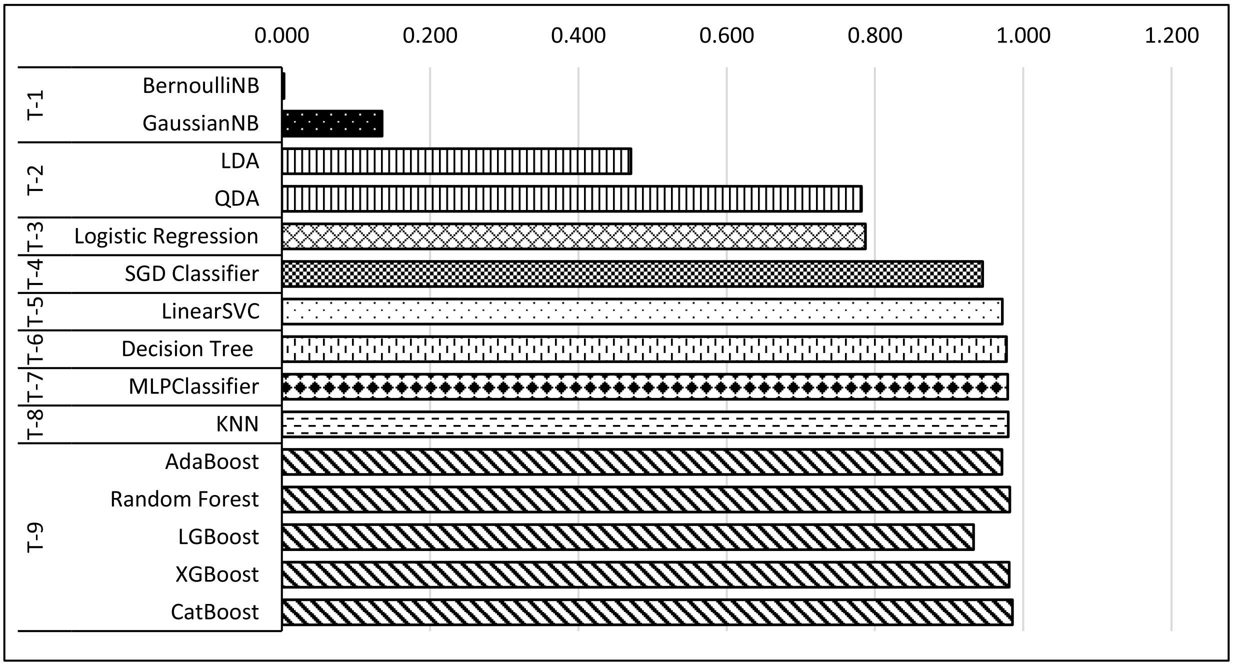

FIGURE 5. Comparison of different types of classifiers using F-measure.

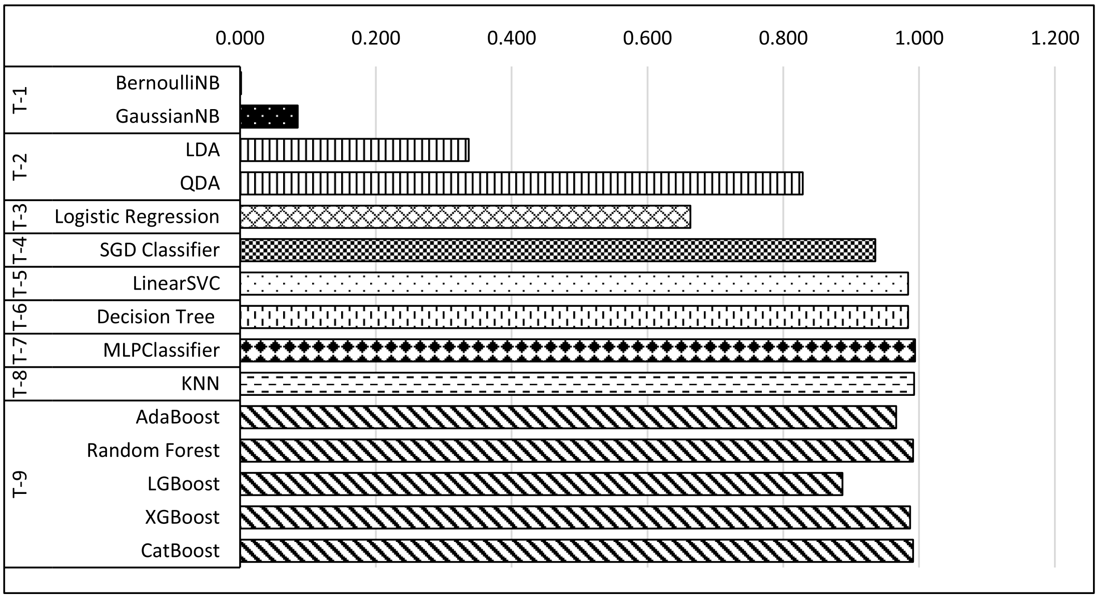

FIGURE 6. Comparison of different types of classifiers using recall.

the best classifier among the ensemble methods. This shows that not only all classifiers in this type performed better but also their performance is very close to one another. In [24], the authors have used a similar approach in finding the NTL in a synthesized dataset. They have used detection rate and False Positive Rate (FPR) as the performance evaluation metrics. They have found that LGBoost and CatBoost outperformed XGBoost with LGBoost being the fastest but it has the highest FPR, while CatBoost is the slowest but it has the lowest FPR. The worst two precisions in our experiment are for the type 'Naive Bayes'. The two classifiers from the type 'LDA and QDA' has the precision of 0.782 and 0.740. This shows an increase of 48% in the performance from Naive Bayes type to 'LDA and QDA' type. Each of the classifiers from the types of Generalized Linear Models, SGD, SVM, DT, NN and Nearest Neighbors has precision readings as 0.968, 0.955, 0.960, 0.971, 0.964 and 0.967, respectively.

B. PERFORMANCE ANALYSIS OF INDIVIDUAL CLASSIFIERS FOR NTL DETECTION

We have used precision, recall and F-measure as the performance evaluation metrics. The best F-measure is 0.985

TABLE 6. Feature set.

FID	Feature	Description	Category	F. Importance
1	Units-12Months	Units consumed during last 12 months	Normal units	0.141807732008
2	Amount-12Months	Total amount billed during last 12 months	Normal amount	0.116774856878
3	BilledUnit-YTD	Units billed in current year	Normal units	0.116751907486
4	BilledAmount	Amount billed in current month	Normal amount	0.092791430138
5	1 year LPS	Late payment surcharge in last one year	Additional amount	0.057126632724
6	Amount-12MonthsAvg	Average monthly amount in last 12 months	Normal amount	0.040861765397
7	BilledAmount-12MonthsGross	Total payment made in last 12 months	Normal amount	0.038509950395
8	Units-12MonthsAvg	Average monthly units in last 12 months	Normal units	0.032045710111
9	Amount-GrossBilledYTD	Total payment made in current year till date	Normal amount	0.029088274439
10	Amount-12MonthsAvgGrossBilled	Total average monthly payment made in last 12 months	Normal amount	0.028248805369
11	Amount-Regular	Payable amount for regular units	Normal amount	0.023397470434
12	1 Month LPS	Late payment surchare in last 30 days	Additional amount	0.022879096842
13	Month-Billing	Month of billing	Bill info	0.016062708402
14	InstallementNo	Number of installements	Additional amount	0.015831709285
15	Units-Regular	Sum of all units	Normal units	0.015017339757
16	Billing-MonthYear	Month and year of billing	Bill info	0.014896074379
17	6-12MonthLPS	Late payment surcharge in last 6-12 months	Additional amount	0.013971961284
18	3-6MonthLPS	Late payment surcharge in last 3-6 months	Additional amount	0.012784735142
19	Billed-LPS	Late payment surcharge billed	Additional amount	0.011929939987
20	Amount-Installement	Amount of installements	Additional amount	0.011181126362
21	2-3MonthLPS	Late payment surcharge in last 2-3 months	Additional amount	0.010289314501
22	Bill Day	Day of billing	Bill info	0.009823534830
23	1-2MonthLPS	Late payment surchrge in last 1-2 months	Additional amount	0.009627897668
24	Balance-Closing	Current month bill dues	Normal amount	0.009071362880
25	Date-Last Payment	Date of last payment received	Bill info	0.008636211093
26	Balance-Opening	Previous month bill dues	Normal amount	0.008609312214
27	Date-Last Disconnection	Date of last disconnection	Extra info	0.006633772523
28	1-2YearLPS	Late payment surcharge in last 1-2 years	Additional amount	0.006118613036
29	2-3YearLPS	Late payment surcharge in last 2-3 years	Additional amount	0.005575965464
30	Class-Bill	Bill class as per type of customer	Bill info	0.005432932386
31	Amount-Last Payment	Amount of last payment received	Normal amount	0.005270394928
32	Meter Company	Meter manufacturer company	Extra info	0.004691091511
33	Amount-12MonthsNetCredit	Total credit amount in 12 months	Normal amount	0.004654967355
34	Amount-12MonthsAvgNetCredit	Average monthly credit amount in 12 months	Normal amount	0.004596220721
35	4-5YearLPS	Late payment surcharge in last 4-5 years	Additional amount	0.004532165693
36	3-4YearLPS	Late payment surcharge in last 3-4 years	Additional amount	0.004304066086
37	Above5YearLPS	Late payment surcharge before 5 years	Additional amount	0.003930719617
38	Amount-NetCreditYTD	Amount received in current year till date	Additional amount	0.003590748039
39	Last Discon Reason	Reason for last disconnection	Extra info	0.003512856482
40	Partner	Partner agency	Extra info	0.003249072825
41	Type-Premise	House hold type like house, flats, market etc.	Bill info	0.003050005819
42	Meter Category	Meter category	Extra info	0.002990504483
43	Category-Rate	Category for rate like resedential, commercial etc.	Bill info	0.002828424755
44	Load-Sanctioned	Allowed load	Extra info	0.002666668370
45	BankComm	Bank commission	Normal amount	0.002146206356
46	LoadConnected	Actual load	Extra info	0.001827458080
47	Industry Class	Type of industry	Extra info	0.001569211472
48	Payment Received	Payment received by customer	Additional amount	0.001457066958
49	Conn Phase	Connection phase	Extra info	0.001277748626
50	Amount-LPSWaived	Waived amount of late payment surcharge	Additional amount	0.001175315316
51	Amount-Adjustment	Pending bill adjustment	Additional amount	0.000894321102
52	Amount-Normal	Amount against consumed untis	Normal amount	0.000798917360
53	Units-Normal	Consumed units	Normal units	0.000554570642
54	Ordinary IP	Type of power supply in ordinary industry (AC)	Extra info	0.000542179330
55	Amount-Set Aside	Disputed amount	Additional amount	0.000473512563
56	DC Ordinary IP	Type of power supply in ordinary industry (DC)	Extra info	0.000418416649
57	Type-Consumer	Connection type	Bill info	0.000393096677
58	Code-Set Aside	Code for disputed amount	Additional amount	0.000386602460
59	Units-Adjusted	Adjusted units for previous month	Additional units	0.000138101530
60	Allowance-PreviousYear	Any allowance for previous year	Additional amount	0.000136395061
61	Units-Average	Guessed units written for any month	Normal units	0.000084363601
62	Amount-Average	Amount against guessed units	Normal amount	0.000062844597
63	Amount-Adjusted	Amount for adjusted units	Additional amount	0.000015937667
64	Amount-Clearing	Amount needed to clear account	Additional amount	0.000001677576
65	Connection-Status	State of connection like in-active, active	Extra info	0.000000006279
66	Type-Bill	Type of bill	Bill info	0.000000000000
67	Category-DC Rate	Rate category of DC	Extra info	0.000000000000
68	Request-Installement	Installement request	Additional amount	0.000000000000
69	Amount-DownPayment	Down payment amount	Additional amount	0.000000000000
70	Amount-OutStndDPayment	Remaining down payment	Additional amount	0.000000000000
71	1YearLPS	Late payment surcharge in last 1 year	Additional amount	0.000000000000

for CatBoost classifier, which narrowly outperforms Random Forest and KNN. These three classifiers have corresponding high precision and recall values indicating small FP and small FN values, respectively.

The F-measure of LGBoost classifier is 0.933, which is comparatively less than the F-measure of CatBoost classifier, i.e 0.985, while the corresponding figure for XGBoost is 0.981. There is an increase of 5.6% in the F-measure from

TABLE 7. List of simulation parameters.

Classifier	Simulation Parameters
BernoulliNB	alpha=1.0, binarize=0.0, fit_prior=True, class_prior=None
GaussianNB	priors=None, var_smoothing=1e-09
LDA	solver='svd', shrinkage=None, priors=None, n_components=None, store_covariance=False, tol=0.0001
QDA	priors=None,reg_param=0.0, store_covariance= False,tol=0.0001
Logistic Regression	penalty='l2', dual=False, tol=0.0001, C=1.0, fit_intercept=True, intercept_scaling=1, class_weight=None, random_state=None, solver='warn', max_iter=100, multi_class='warn', verbose=0, warm_start=False, n_jobs=None, l1_ratio=None
SGD Classifier	loss='hinge', penalty='l2', alpha=0.0001, l1_ratio=0.15, fit_intercept=True, max_iter=1000, tol=0.001, shuffle=True, verbose=0, epsilon=0.1, n_jobs=None, random_state=None, learning_rate='optimal', eta0=0.0, power_t=0.5, early_stopping=False, validation_fraction=0.1, n_iter_no_change=5, class_weight=None, warm_start=False, average=False
Linear SVC	penalty='l2', loss='squared_hinge', dual=True, tol=0.0001, C=1.0, multi_class='ovr', fit_intercept=True, intercept_scaling=1, class_weight=None, verbose=0, random_state=None, max_iter=1000
DT Classifier	criterion='gini', splitter='best', max_depth=None, min_samples_split=2, min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features=None, random_state=None, max_leaf_nodes=None, min_impurity_decrease=0.0, min_impurity_split=None, class_weight=None, presort=False
MLP Classifier	hidden_layer_sizes=(100,), activation='relu', solver='adam', alpha=0.0001, batch_size='auto', learning_rate='constant', learning_rate_init=0.001, power_t=0.5, max_iter=200, shuffle=True, random_state=None, tol=0.0001, verbose=False, warm_start=False, momentum=0.9, nesterovs_momentum=True, early_stopping=False, validation_fraction=0.1, beta_1=0.9, beta_2=0.999, epsilon=1e-08, n_iter_no_change=10
KNN	n_neighbors=5, weights='uniform', algorithm='auto', leaf_size=30, p=2, metric='minkowski', metric_params=None, n_jobs=None
AdaBoost	base_estimator=None, n_estimators=50, learning_rate=1.0, algorithm='SAMME.R', random_state=None
Random Forest	n_estimators='warn', criterion='gini', max_depth=None, min_samples_split=2, min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features='auto', max_leaf_nodes=None, min_impurity_decrease=0.0, min_impurity_split=None, bootstrap=True, oob_score=False, n_jobs=None, random_state=None, verbose=0, warm_start=False, class_weight=None
LGBoost	application='binary', is_unbalance='true',objective='binary', learning_rate=0.003, boosting_type='gbdt',metric=binary_logloss,num_leaves=10, min_data=50, max_depth=10
XGBoost	base_score=0.5,booster='gbtree',colsample_bylevel=1,colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,max_depth=3, min_child_weight=1, missing=None, n_estimators=100,n_jobs=1, nthread=None, objective='binary:logistic', random_state=0,reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,silent=True, subsample=1
CatBoost	learning_rate=0.047, depth=9, loss_function='Logloss'

LGBoost to CatBoost. Overall, precision and recall obtained for CabBoost, XGBoost and LGBoost classifiers are above 0.97 except that the recall of LGBoost is 0.887.

The F-measures is significantly increased from 0.471 to 0.782 when choosing QDA instead of LDA, which indicates that QDA outperforms LDA. This is because when multiple classes have a different co-variance relationship then LDA suffers while QDA remains a better option. This gives an insight to the characteristics of features of this real data set, that is, for NTL, there is a room to explore more about the co-variance relationship for individual classes.

V. CONCLUSION AND FUTURE WORK

This paper has used a real-world dataset of a power supply company in Pakistan for NTL detection. The dataset contains approximately 80, 000 monthly consumption records along with 71 features. We have tested 15 machine learning classifiers, which span across 9 types for a potential detection of NTL.

One of our findings is that, with respect to F-measure, ensemble methods outperformed other types and with respect to Recall, ANN outperformed other types of the classifiers. Considering individual classifier analysis, CatBoost outperformed all other classifiers when taking F-measure into account while MLP Classifier performed best when considering Recall as the performance evaluation metric. One of the observations is that recall increases by 50% when MLP Classifier is used instead of Logistic Regression. This shows that testing deep learning with many hidden layers can be a potential future contribution in NTL detection. Using feature importance along with Gini Index, we have derived a mechanism to identify the top-14 features, out of 71 features, which are contributing 77% in NTL detection. This has not only significantly reduced the execution time but also has identified useful features for NTL detection in a real dataset. There is still a need for creating a benchmark dataset which can widely be used in NTL detection. Another future direction is using penalized machine learning models in which weighted classifiers [55] are used. The best classifiers identified in this study can also be implemented on different feature selection approaches.

APPENDIXES

APPENDIX A

FEATURE SET

The list of 71 features along with their categories, feature description and feature importance values is described in Table 6.

APPENDIX B

SIMULATION PARAMETERS

Table 7 contains the list of parameters of the classifiers used in the simulation.

ACKNOWLEDGMENT

The authors would like to thank to the power supply company in Pakistan that has provided us their data for NTL detection.

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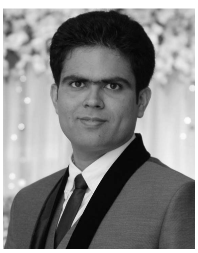

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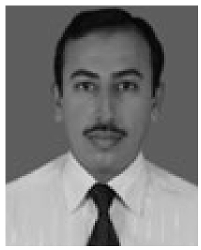

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