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Deep Ensemble Framework with Supervised Learning for Secure IoT Network

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ABSTRACT

Electricity theft represents a pressing problem that has brought enormous financial losses to electric utility companies worldwide. In the United States alone, $6 billion worth of electricity is stolen annually. Traditionally, electricity theft is committed in the consumption domain via physical attacks that includes line tapping or meter tampering. Therefore, this project evaluating performance of various deep learning algorithms such as deep feed forward neural network (DNN), recurrent neural network with gated recurrent unit (RNN-GRU) and convolutional neural network (CNN) for electricity cyber-attack detection. Now-a-days in advance countries solar plates are used to generate electricity and these users can sale excess energy to other needy users and they will be maintained two different meters which will record consumption and production details. While producing some malicious users may tamper smart meter to get more bill which can be collected from electricity renewable distributed energy. This attack may cause huge losses to agencies. To detect such attack, this project is employing deep learning models which can detect all possible alterations to predict theft.

Keywords: Electricity theft detection, energy metering system, neural network, deep neural network, convolution neural networks, Internet of things.

1. INTRODUCTION

Electricity theft is defined as the consumed amount of energy that is not billed by the consumers. This incurs major revenue losses for electric utility companies. All over the world, electric utility companies lose $96 billion every year due to electricity theft. This phenomenon affects all nations, whether rich or poor. For instance, Pakistan suffers 0.89 billion rupees of loss yearly due to non-technical losses (NTLs) [1] and in India, the electricity loss exceeds 4.8 billion rupees annually. Electricity theft is also a threat to countries with strong economies; i.e., in the U.S., the loss due to electricity theft is approximately $6 billion, and in the UK, it is up to £175 million per annum. In addition, electricity theft causes a voltage imbalance and can affect power system operations by overloading the transformers [2]. Moreover, the rising electricity prices increase the burden on honest customers when the utility asks them also to pay for the theft of energy. It also increases unemployment, the inflation rate and decreases revenue and energy efficiency, which has adverse effects on a country's economic state.

Today, electric power loss has become one of the most conspicuous issues affecting both conventional power grids and smart grids. From the statistics, it has been shown that transmission and distribution losses increased from 11% to 16% between the years 1980 to 2000. The electricity losses vary from country to country. The losses in the USA, Russia, Brazil, and India were 6%, 10%, 16%, and 18%, respectively, of their total energy production [3]. The difference between the energy produced in one system and the metered energy delivered to the users is known as the power loss. To determine the amount of electricity loss, smart meters in smart grids play a prominent role. Advanced energy meters

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obtain information from the consumers' load devices and measure the consumption of energy in intervals of an hour. The energy meter provides additional information to the utility company and the system operator for better monitoring and billing, and provides two-way communications between the utility companies and consumers [4]. However, it is also possible to limit the maximum amount of electricity consumption, which can terminate as well as re-connect the supply of electricity from any remote place.

2. LITERATURE SURVEY

Hasan et. a [5] implemented a novel data pre-processing algorithm to compute the missing instances in the dataset, based on the local values relative to the missing data point. Furthermore, in this dataset, the count of electricity theft users was relatively low, which could have made the model inefficient at identifying theft users. This class imbalance scenario was addressed through synthetic data generation. Finally, the results obtained indicate the proposed scheme can classify both the majority class (normal users) and the minority class (electricity theft users) with good accuracy.

Zheng et. al [6] combined two novel data mining techniques to solve the problem. One technique is the maximum information coefficient (MIC), which can find the correlations between the nontechnical loss and a certain electricity behavior of the consumer. MIC can be used to precisely detect thefts that appear normal in shapes. The other technique is the clustering technique by fast search and find of density peaks (CFSFDP). CFSFDP finds the abnormal users among thousands of load profiles, making it quite suitable for detecting electricity thefts with arbitrary shapes. Next, a framework for combining the advantages of the two techniques is proposed. Numerical experiments on the Irish smart meter dataset are conducted to show the good performance of the combined method.

Li et. al [7] presented a novel CNN-RF model to detect electricity theft. In this model, the CNN is similar to an automatic feature extractor in investigating smart meter data and the RF is the output classifier. Because a large number of parameters must be optimized that increase the risk of overfitting, a fully connected layer with a dropout rate of 0.4 is designed during the training phase. In addition, the SMOT algorithm is adopted to overcome the problem of data imbalance. Some machine learning and deep learning methods such as SVM, RF, GBDT, and LR are applied to the same problem as a benchmark, and all those methods have been conducted on SEAI and LCL datasets. The results indicate that the proposed CNN-RF model is quite a promising classification method in the electricity theft detection field because of two properties: The first is that features can be automatically extracted by the hybrid model, while the success of most other traditional classifiers relies largely on the retrieval of good hand-designed features which is a laborious and time-consuming task. The second lies in that the hybrid model combines the advantages of the RF and CNN, as both are the most popular and successful classifiers in the electricity theft detection field.

Nabil et. al [8] proposed an efficient and privacy-preserving electricity theft detection scheme for the AMI network and we refer to it as PPETD. Our scheme allows system operators to identify the electricity thefts, monitor the loads, and compute electricity bills efficiently using masked fine-grained meter readings without violating the consumers' privacy. The PPETD uses secret sharing to allow the consumers to send masked readings to the system operator such that these readings can be aggregated for the purpose of monitoring and billing. In addition, secure two-party protocols using arithmetic and binary circuits are executed by the system operator and each consumer to evaluate a generalized convolutional-neural network model on the reported masked fine-grained power consumption readings for the purpose of electricity theft detection. An extensive analysis of real datasets is performed to evaluate the security and the performance of the PPETD.

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Khan et. al [9] presents a new model, which is based on the supervised machine learning techniques and real electricity consumption data. Initially, the electricity data are pre-processed using interpolation, three sigma rule and normalization methods. Since the distribution of labels in the electricity consumption data is imbalanced, an Adasyn algorithm is utilized to address this class imbalance problem. It is used to achieve two objectives. Firstly, it intelligently increases the minority class samples in the data. Secondly, it prevents the model from being biased towards the majority class samples. Afterwards, the balanced data are fed into a Visual Geometry Group (VGG-16) module to detect abnormal patterns in electricity consumption. Finally, a Firefly Algorithm based Extreme Gradient Boosting (FA-XGBoost) technique is exploited for classification. The simulations are conducted to show the performance of our proposed model. Moreover, the state-of-the-art methods are also implemented for comparative analysis, i.e., Support Vector Machine (SVM), Convolution Neural Network (CNN), and Logistic Regression (LR). For validation, precision, recall, F1-score, Matthews Correlation Coefficient (MCC), Receiving Operating Characteristics Area Under Curve (ROC-AUC), and Precision Recall Area Under Curve (PR-AUC) metrics are used. Firstly, the simulation results show that the proposed Adasyn method has improved the performance of FA-XGboost classifier, which has achieved F1-score, precision, and recall of 93.7%, 92.6%, and 97%, respectively. Secondly, the VGG-16 module achieved a higher generalized performance by securing accuracy of 87.2% and 83.5% on training and testing data, respectively. Thirdly, the proposed FA-XGBoost has correctly identified actual electricity thieves, i.e., recall of 97%. Moreover, our model is superior to the other state-of-the-art models in terms of handling the large time series data and accurate classification. These models can be efficiently applied by the utility companies using the real electricity consumption data to identify the electricity thieves and overcome the major revenue losses in power sector.

Kocaman et. al [10] developed by using deep learning methods on real daily electricity consumption data (Electricity consumption dataset of State Grid Corporation of China). Data reduction has been made by developing a new method to make the dataset more usable and to extract meaningful results. A Long Short-Term Memory (LSTM) based deep learning method has been developed for the dataset to be able to recognize the actual daily electricity consumption data of 2016. In order to evaluate the performance of the proposed method, the accuracy, prediction and recall metric was used by considering the five cross-fold technique. Performance of the proposed methods were found to be better than previously reported results.

Li et. al [11] presented a novel approach for automatic detection by using a multi-scale dense connected convolution neural network (multi-scale DenseNet) in order to capture the long-term and short-term periodic features within the sequential data. They compare the proposed approaches with the classical algorithms, and the experimental results demonstrate that the multi-scale DenseNet approach can significantly improve the accuracy of the detection. Moreover, our method is scalable, enabling larger data processing while no handcrafted feature engineering is needed.

Aldegheishem et. al [12] developed two novel ETD models. A hybrid sampling approach, i.e., synthetic minority oversampling technique with edited nearest neighbor, is introduced in the first model. Furthermore, AlexNet is used for dimensionality reduction and extracting useful information from electricity consumption data. Finally, a light gradient boosting model is used for classification purpose. In the second model, conditional wasserstein generative adversarial network with gradient penalty is used to capture the real distribution of the electricity consumption data. It is constructed by adding auxiliary provisional information to generate more realistic data for the minority class. Moreover, GoogLeNet architecture is employed to reduce the dataset's dimensionality. Finally, adaptive boosting is used for classification of honest and suspicious consumers. Both models are

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trained and tested using real power consumption data provided by state grid corporation of China. The proposed models' performance is evaluated using different performance metrics like precision, recall, accuracy, F1-score, etc. The simulation results prove that the proposed models outperform the existing techniques, such as support vector machine, extreme gradient boosting, convolution neural network, etc., in terms of efficient ETD.

3. PROPOSED SYSTEM

The smart grid paradigm opens the door to new forms of electricity theft attacks. First, electricity theft can be committed in a cyber manner. With the advanced metering infrastructure (AMI), smart meters are installed at the customers' premises and regularly report the customers' consumption for monitoring and billing purposes. In this context, malicious customers can launch cyber-attacks on the smart meters to manipulate the readings in a way that reduces their electricity bill. Second, the smart grid paradigm enables customers to install renewable-based distributed generation (DG) units at their premises to generate energy and sell it back to the grid operator and hence make a profit. In this context, two approaches are adopted when renewable DG units are integrated in the power grid, namely, the net metering system and the feed-in tariffs (FITs) policy. In the net metering system, the excess generation from the DG can be stored as future credit for customers. On the other hand, in the FIT policy, which is referred to as clean energy cashback, customers sell all their generated energy to the grid and get paid in exchange. The incentives offered by the FIT programs are more effective compared with net metering for promoting renewable energy. Hence, FIT requires two meters to be installed in the customer premises, one meter is a selling meter that monitors the energy generated from the DG unit, which is directly injected (sold) to the grid, and the other meter is a buying meter that monitors the consumption. Thus, consumption and generation can be charged independently. In this two-metering system, malicious customers can manipulate the integrity of the reported energy generation data to claim higher supplied energy to the grid and hence falsely overcharge the electric utility company. Such a malicious act is possible due to the weak authentication firmware that is installed in most smart meters deployed worldwide. While several research works have investigated electricity theft cyber-attacks at the consumption domain, such a research problem is not well investigated in the DG domain and requires a better attention.

Dataset description

This dataset contains information of the amount of electricity each consumers used. Columns contains the dates and Rows refers to the consumers. This dataset contains the electricity consumption for a year 2015.

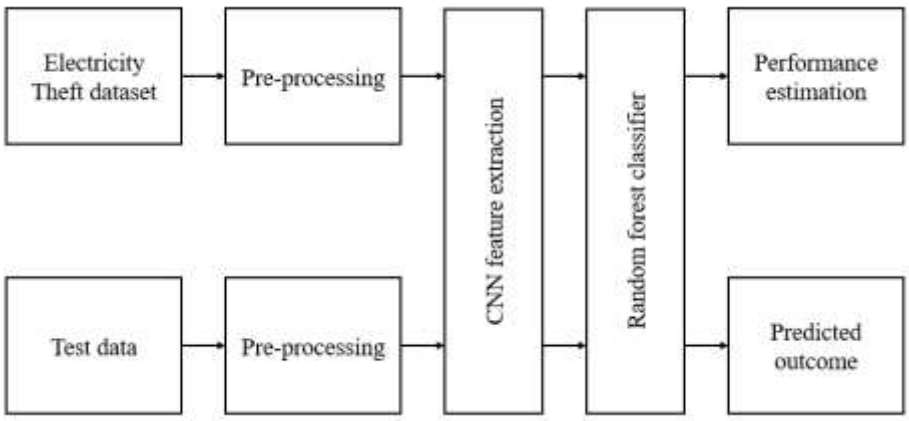

Fig. 1: Block diagram of proposed system.

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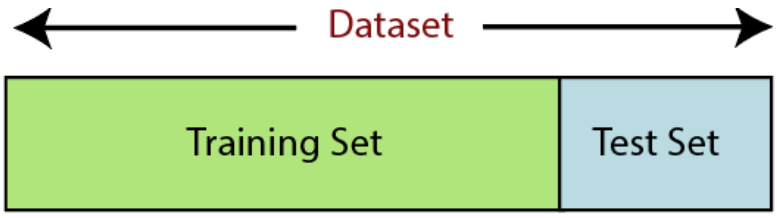
Data Preprocessing in Machine learning

Data pre-processing is a process of preparing the raw data and making it suitable for a machine learning model. It is the first and crucial step while creating a machine learning model. When creating a machine learning project, it is not always a case that we come across the clean and formatted data. And while doing any operation with data, it is mandatory to clean it and put in a formatted way. So, for this, we use data pre-processing task.

Splitting the Dataset into the Training set and Test set

In machine learning data pre-processing, we divide our dataset into a training set and test set. This is one of the crucial steps of data pre-processing as by doing this, we can enhance the performance of our machine learning model. Suppose if we have given training to our machine learning model by a dataset and we test it by a completely different dataset. Then, it will create difficulties for our model to understand the correlations between the models. If we train our model very well and its training accuracy is also very high, but we provide a new dataset to it, then it will decrease the performance. So we always try to make a machine learning model which performs well with the training set and also with the test dataset. Here, we can define these datasets as:



Training Set: A subset of dataset to train the machine learning model, and we already know the output.

Test set: A subset of dataset to test the machine learning model, and by using the test set, model predicts the output.

CNN Classifier

According to the facts, training and testing of CNN involves in allowing every source data via a succession of convolution layers by a kernel or filter, rectified linear unit (ReLU), max pooling, fully connected layer and utilize SoftMax layer with classification layer to categorize the objects with probabilistic values ranging from. Convolution layer is the primary layer to extract the features from a source image and maintains the relationship between pixels by learning the features of image by employing tiny blocks of source data. It's a mathematical function which considers two inputs like source image $I(x, y, d)$ where x and y denotes the spatial coordinates i.e., number of rows and columns. d is denoted as dimension of an image (here d=3 since the source image is RGB) and a filter or kernel with similar size of input image and can be denoted as $F(k_x, k_y, d)$..

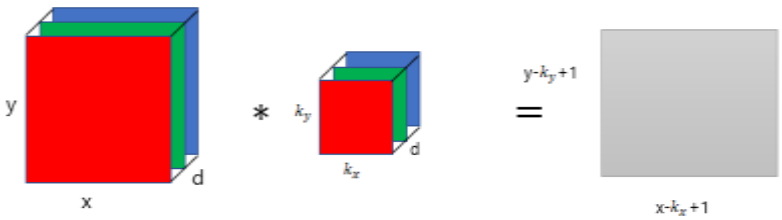


Fig. 2: Representation of convolution layer process.

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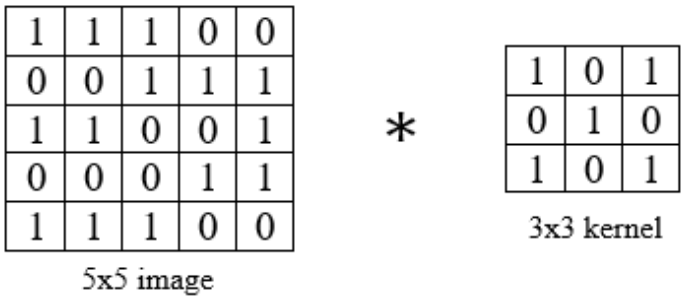
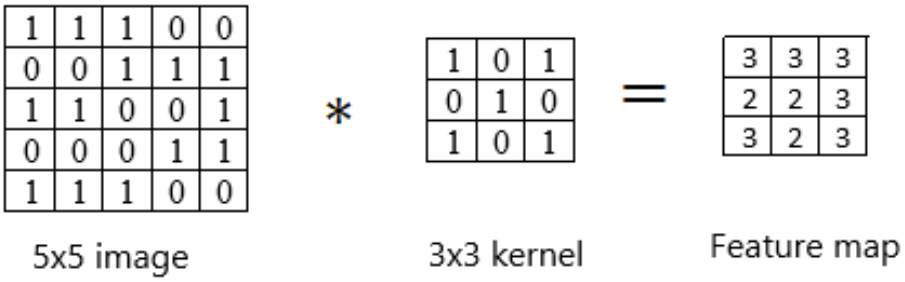
The output obtained from convolution process of input image and filter has a size of $C\left((x-k_x+1),(y-k_y+1),1\right)$, which is referred as feature map. Let us assume an input image with a size of 5×5 and the filter having the size of 3×3. The feature map of input image is obtained by multiplying the input image values with the filter values.



(a)



(b)

Fig. 3: Example of convolution layer process (a) an image with size 5×5 is convolving with 3×3 kernel (b) Convolved feature map.

ReLU layer

Networks those utilizes the rectifier operation for the hidden layers are cited as rectified linear unit (ReLU). This ReLU function $\mathcal{G}(\cdot)$ is a simple computation that returns the value given as input directly if the value of input is greater than zero else returns zero. This can be represented as mathematically using the function $max(\cdot)$ over the set of 0 and the input x as follows:

$$\mathcal{G}(x) = \max\{0, x\}$$

Max pooing layer

This layer mitigates the number of parameters when there are larger size images. This can be called as subsampling or down sampling that mitigates the dimensionality of every feature map by preserving the important information. Max pooling considers the maximum element form the rectified feature map.

Random Forest Algorithm

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of ensemble learning, which is a process of combining multiple classifiers to solve a complex

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problem and to improve the performance of the model. As the name suggests, "Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset." Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output. The greater number of trees in the forest leads to higher accuracy and prevents the problem of overfitting.

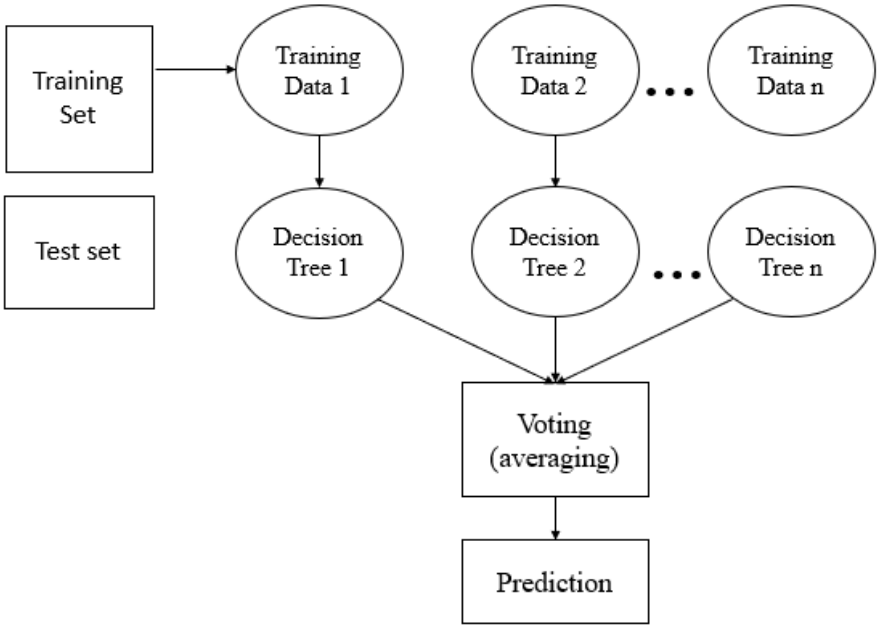

Fig. 4: Random Forest algorithm.

Random Forest algorithm

Step 1: In Random Forest n number of random records are taken from the data set having k number of records.

Step 2: Individual decision trees are constructed for each sample.

Step 3: Each decision tree will generate an output.

Step 4: Final output is considered based on Majority Voting or Averaging for Classification and regression respectively.

Important Features of Random Forest

- **Diversity**- Not all attributes/variables/features are considered while making an individual tree, each tree is different.
- **Immune to the curse of dimensionality**- Since each tree does not consider all the features, the feature space is reduced.
- **Parallelization**-Each tree is created independently out of different data and attributes. This means that we can make full use of the CPU to build random forests.
- **Train-Test split**- In a random forest we don't have to segregate the data for train and test as there will always be 30% of the data which is not seen by the decision tree.
- **Stability**- Stability arises because the result is based on majority voting/ averaging.

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Assumptions for Random Forest

Since the random forest combines multiple trees to predict the class of the dataset, it is possible that some decision trees may predict the correct output, while others may not. But together, all the trees predict the correct output. Therefore, below are two assumptions for a better Random Forest classifier:

- There should be some actual values in the feature variable of the dataset so that the classifier can predict accurate results rather than a guessed result.
- The predictions from each tree must have very low correlations.

Below are some points that explain why we should use the Random Forest algorithm.

- It takes less training time as compared to other algorithms.
- It predicts output with high accuracy, even for the large dataset it runs efficiently.
- It can also maintain accuracy when a large proportion of data is missing.

Types of Ensembles

Before understanding the working of the random forest, we must look into the ensemble technique. Ensemble simply means combining multiple models. Thus, a collection of models is used to make predictions rather than an individual model. Ensemble uses two types of methods:

Bagging– It creates a different training subset from sample training data with replacement & the final output is based on majority voting. For example, Random Forest. Bagging, also known as Bootstrap Aggregation is the ensemble technique used by random forest. Bagging chooses a random sample from the data set. Hence each model is generated from the samples (Bootstrap Samples) provided by the Original Data with replacement known as row sampling. This step of row sampling with replacement is called bootstrap. Now each model is trained independently which generates results. The final output is based on majority voting after combining the results of all models. This step which involves combining all the results and generating output based on majority voting is known as aggregation.

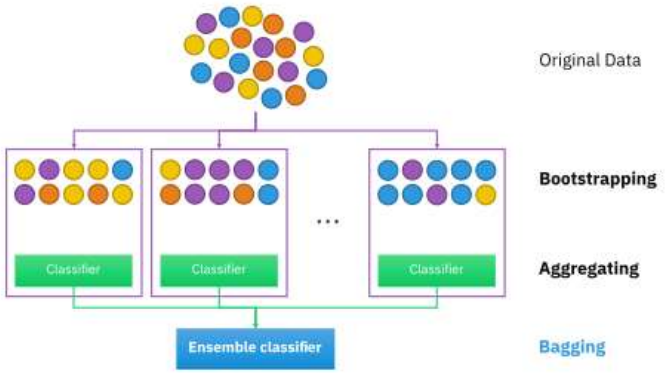

Fig. 5: RF Classifier analysis.

Boosting– It combines weak learners into strong learners by creating sequential models such that the final model has the highest accuracy. For example, ADA BOOST, XG BOOST.

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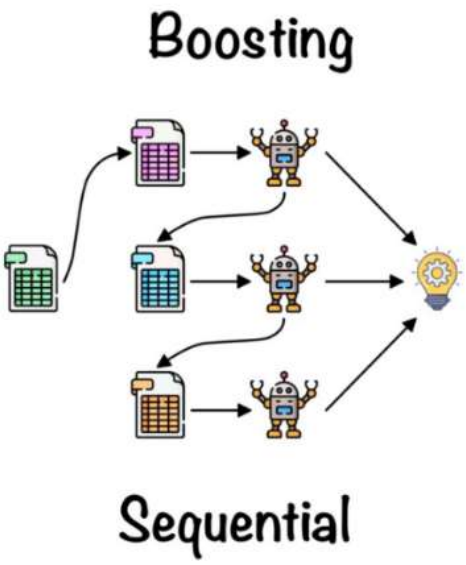

Fig. 6: Boosting RF Classifier.

Advantages of proposed system

- It can be used in classification and regression problems.
- It solves the problem of overfitting as output is based on majority voting or averaging.
- It performs well even if the data contains null/missing values.
- Each decision tree created is independent of the other thus it shows the property of parallelization.
- It is highly stable as the average answers given by a large number of trees are taken.
- It maintains diversity as all the attributes are not considered while making each decision tree though it is not true in all cases.
- It is immune to the curse of dimensionality. Since each tree does not consider all the attributes, feature space is reduced.

5. RESULTS AND DISCUSSION

To implement this project, we have designed following modules.

1) Upload Dataset: using this module we will upload dataset to application.
2) Preprocess Dataset: using this module we will read dataset and then remove missing values and then convert all non-numeric data into numeric as deep learning accept only numeric data. Processed dataset will be split into train and test where 80% dataset used for training and 20% for testing.
3) Feed Forward Neural Network: processed train data will be input to DNN algorithm to train attack detection model and this model will be applied on test data to calculate prediction accuracy.
4) Deep Learning CNN: processed train data will be input to CNN algorithm to train cyberattack detection model and this model will be applied on test data to calculate prediction accuracy.
5) CNN + Random Forest: using this module we will extract features from CNN and then retrain with Random Forest algorithm to build a hybrid model and then test data will be applied on hybrid model to calculate its accuracy.
6) Predict Cyberattack: using this module we will upload test data and then proposed algorithm will predict weather test data is normal or contains attack signatures
7) Performance Evaluation: using this module we will plot comparison graph of all algorithms

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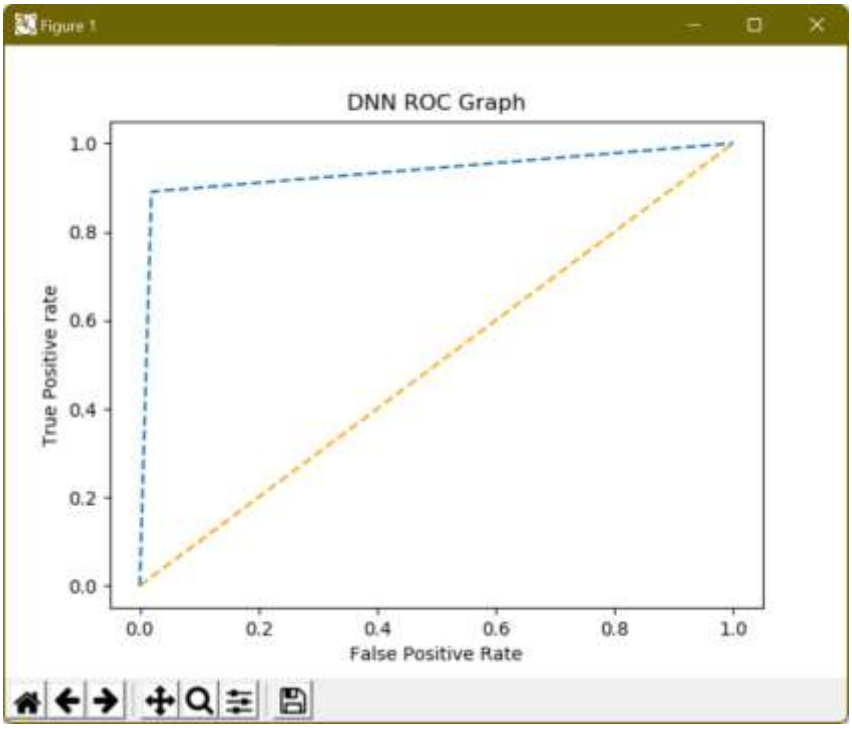
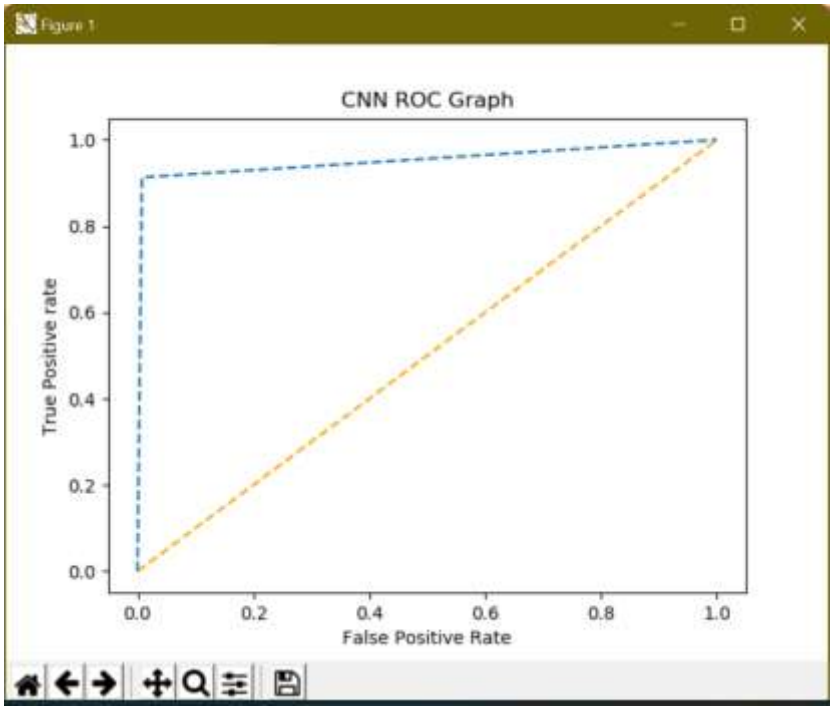


In above screen with DNN feed forward algorithm we got 93.99% accuracy and in ROC graph x-graph represents False Positive Rate and y-axis represents True Positive Rate and if blue line comes below orange line then we can say prediction is false and if blue line comes on top of orange line then prediction consider as CORRECT.



In above screen with CNN we got 95.78% accuracy and blue lines fully on top of orange line so its predictions are correct.

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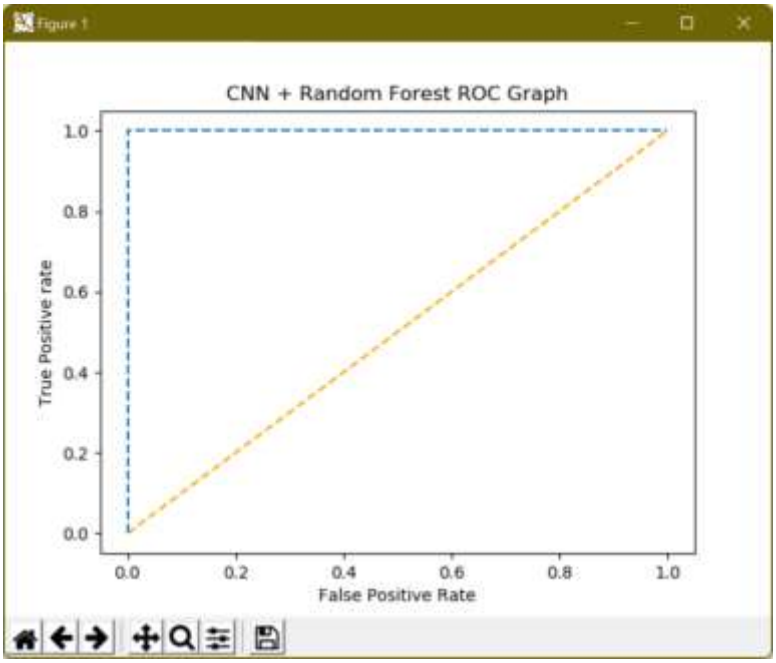
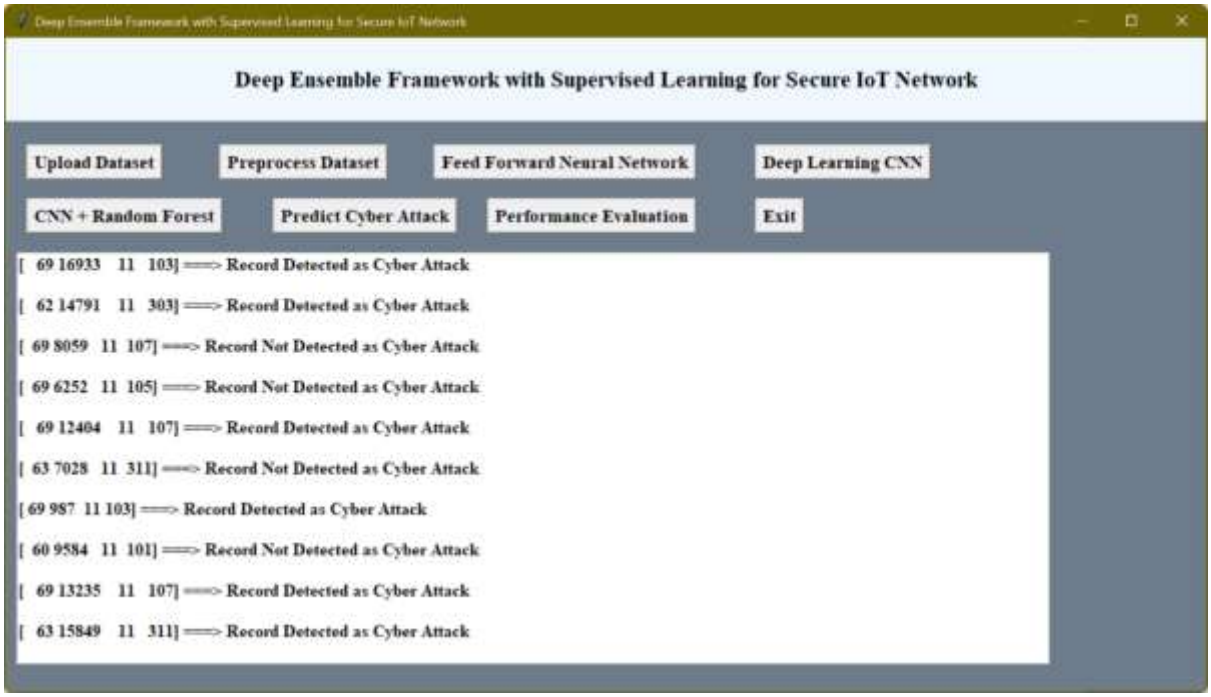


In above screen with hybrid algorithm, we got 99.85% accuracy.



In above screen in square bracket, we can see TEST data and after arrow =➔ symbol we can see CYBER ATTACK detection and 'NOT DETECTED'. Now click on 'Performance Evaluation' button to get below graph.

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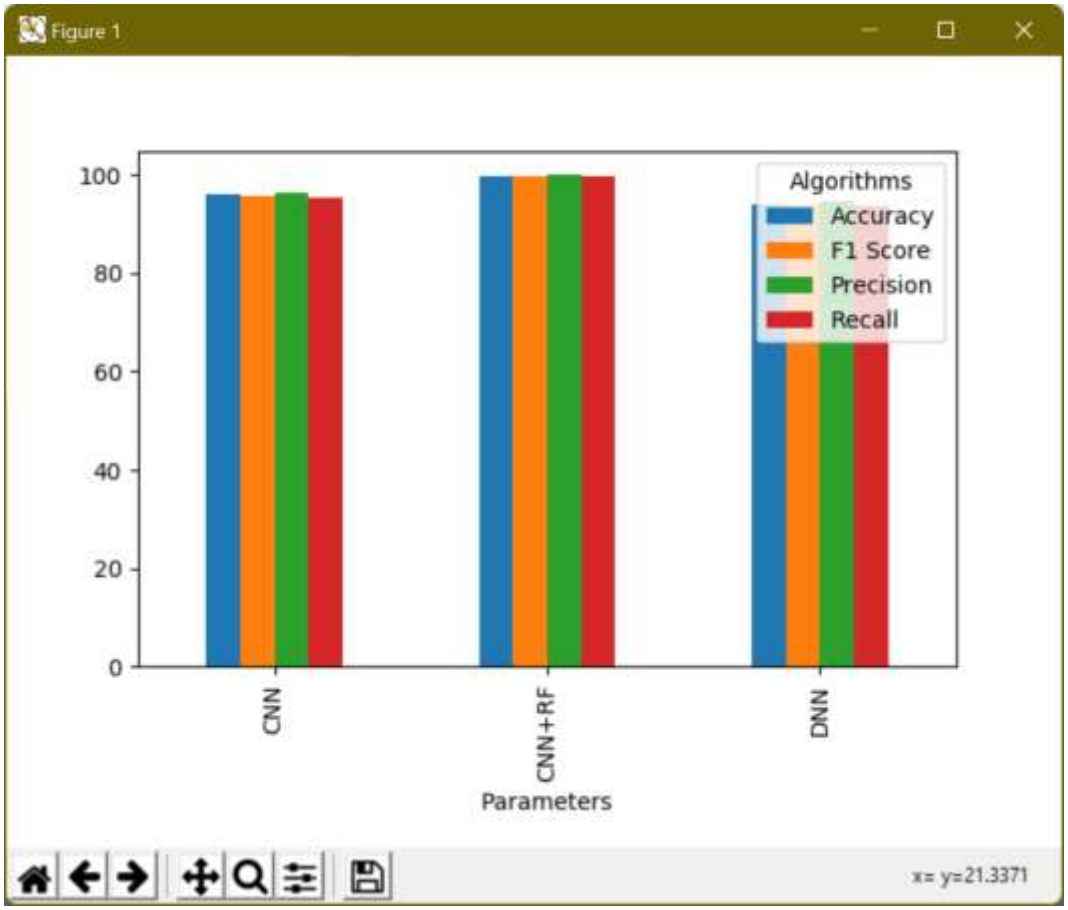

In above graph x-axis represents algorithm names with each different colour bar represents different metric such as 'accuracy, precision, recall and FSCORE' and Y-axis represents score values. In all algorithms proposed optimized ensemble framework got high performance.

5. CONCLUSION

Global energy crises are increasing every moment. Everyone has the attention towards more and more energy production and also trying to save it. Electricity can be produced through many ways which is then synchronized on a main grid for usage. Weather losses are technical or non-technical. Technical losses can abstract be calculated easily, as we discussed in section of mathematical modeling that how to calculate technical losses. Whereas nontechnical losses can be evaluated if technical losses are known. Theft in electricity produce non-technical losses. To reduce or control theft one can save his economic resources. Smart meter can be the best option to minimize electricity theft, because of its high security, best efficiency, and excellent resistance towards many of theft ideas in electromechanical meters. So, in this paper we have mostly concentrated on theft issues. Therefore, this project evaluated performance of various deep learning algorithms such as deep feed forward neural network (DNN), recurrent neural network with gated recurrent unit (RNN-GRU) and convolutional neural network (CNN) for electricity cyber-attack detection.

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