# ADAPTIVE HIERARCHICAL CYBER ATTACK DETECTION AND LOCALIZATION IN ACTIVE DISTRIBUTION SYSTEM

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## ABSTRACT

*Since dispersed renewable energy sources are increasingly being integrated into the grid, developing a cyber security plan for active distribution systems has become more difficult. This article describes an approach to using electrical waveform analysis to identify and localise cyberattacks in distributed active distribution systems. The cornerstone for cyber-attack detection is a sequential deep learning model, which allows the identification of even the slightest intrusions. The targeted cyberattack is initially localised inside the estimated cyberattack sub-region in a two-stage process. We present a network splitting approach based on a modified form of spectral clustering for "coarse" localisation of hierarchical cyber-attacks. To further localise the origin of a cyber assault, it is advised to define a number of waveform parameters and apply a normalised effect score based on statistical metrics of the waves themselves.Finally, a thorough quantitative assessment based on two case studies demonstrates that the proposed framework yields accurate estimations in contrast to both classic and state-of-the-art methods. Search Term Suggestions: Support Vector Machine; Random Forest; Gradient Boosting; Logistic Regression; Cyber Attack Detection.*

## I. INTRODUCTION

Systems that store or process sensitive information have been a frequent target of more sophisticated cyberattacks in recent years. Protecting essential national infrastructures against cyberattacks is a major issue for businesses and governments alike since increasingly important data and services rely on them. Intrusion detection systems (IDS) are used as a supplement to primary preventative security measures like authentication and access control.Using a predetermined set of rules or patterns, IDS can tell the difference between safe and dangerous actions[1].

The increasing prevalence of IoT-enabled applications, such as smart grids, makes power electronics converters increasingly vulnerable to cyber/physical assaults. There is a vital need to develop methods for power electronics converters to detect and identify cyber/physical assaults in many safety-critical applications, yet cyber expertise is scarce in the power electronics business. If these malicious attacks are not detected quickly, they may result in catastrophic failure and significant financial loss [2]. A hierarchical design for anomaly detection in smart grids, using data from a large number of smart metres. The proposed technique is meant to spot outliers at the transmission, substation, and distribution levels of the smart grid [3].

The cyberphysical safety of today's electric vehicle (EV) powertrain technologies. A number of vulnerabilities in EV power train systems are discussed in this research [4]. These include vulnerabilities in the communication networks, electric motor control, and battery management system. Support vector machines (SVMs) are a hierarchical intrusion detection system (IDS) that may be used to ICS/SCADA networks. The proposed method is meant to detect and classify different forms of intrusion, including reconnaissance assaults, denial-of-service attacks, and data alteration attacks. In order to locate single-phase grounding defects in distribution networks, the models use a data-driven method based on synchronised phasor measurement to discern between normal and abnormal network

behaviour, such as packet size and frequency. A smart method that use deep learning to identify bogus data injection attacks in real time in smart grids is proposed, with the synchronised phasor data being used to ascertain the fault's position and kind and to compute the fault's resistance [6]. The proposed method employs a neural network with long short-term memory (LSTM) to detect anomalous changes brought on by fake data injection attacks and to understand the temporal patterns of the data pertaining to the power system. [7].

## II. RELATED WORK

An innovative intrusion detection system (IDS) based on the decision tree and rules-based principles of the REP Tree, the JRip algorithm, and the Forest PA classifier. The outputs of the first and second classifiers, together with the characteristics from the original data set, are used as inputs for the third classifier. Experimental findings on the CICIDS2017 dataset presented by Mehmood et al [1] demonstrate that the proposed IDS outperforms state-of-the-art methods in terms of accuracy, speed, false positives, and overhead.Physical and digital attacks pose a threat to the reliability of the distribution power infrastructure. One of the rapidly expanding renewable energy sources, photovoltaics (PVs), comes with its own set of security concerns. In this research, we present an existing system that, using electric waveform data gathered by waveform sensors in the distribution power networks, develops a unique high-dimensional data-driven cyber physical attack detection and identification (HCADI) technique.

Power companies cannot improve efficiency and dependability without real-time monitoring and management of smart grids (SGs). We develop a system that uses information obtained from smart metres (SM) in customers' homes to identify anomalies in real time. The goal of the method is to detect out-of-the-ordinary events at the lateral and consumer levels. Li, G., Lu, Z., et al. [3] suggested a generative model for anomaly detection that takes into account the network's hierarchical structure in addition to data collected from SMs.

Because of their widespread deployment in IoT-enabled applications like linked electric vehicles (EVs), power electronics systems have grown increasingly vunerable to cyber-physical threats. A cyber-physical security project (PELS) was recently launched by the IEEE Power Electronics Society in response to this growing demand. J.Ye, L. Guo, and others [4] hypothesised that as Vehicle-to-everything (V2X) and the number of electronic control units proliferate, the cyber-physical security risk posed by connected electric cars will increase.

Standard Ethernet is increasingly employed in industrial control systems as a result of developments in information technology. It eliminates the ICS's inherent isolation but provides no additional security. Today's ICS calls for an intrusion detection system (IDS) tailored to a specific industrial environment. This research details several attack techniques, including our unique forging assault and penetration strikes. However, we provide a hierarchical IDS that includes both an anomaly detection model and a traffic prediction model. The short-term traffic of the ICS network may be predicted using the autoregressive integrated moving average (ARIMA)-based traffic prediction model, which may accurately detect infiltration assaults in reaction to aberrant changes in traffic patterns. The use of an anomaly detection model was proposed by Raza [5].As power systems get larger and more complicated, there are more factors that may lead to single-phase grounding problems.

To make the most of large data in power systems, we propose an adjusted strategy based on synchronised phasor monitoring. The data-driven technique is utilised to discover and identify singlephase grounding

faults, confirming the relationship between eigenvalues and power system condition that B. Wang et al. [6]proposed. Smart grid monitoring and control are substantially improved by the use of computational and communications intelligence. We are far more vulnerable to damaging assaults due to our dependence on information technology. The supervisory control and data acquisition system is presently at critical risk from the data integrity assault known as false data injection (FDI). In this investigation, we use deep learning methods to recognise the characteristics of FDI assaults from past measurements, as proposed by Y. He et al. [7]. We next use the learned characteristics to the detection of ongoing FDI assaults.

**A. Proposed Scheme**

In order to identify and localise cyber-attacks, the system proposes an adaptive hierarchical structure based on electrical waveforms for active distribution systems with DERs. High-quality models of DER and cyber assaults are constructed to evaluate the impact of cyber attacks on distribution networks, and the effectiveness of the proposed technique is evaluated using quantitative analytics and a large number of trials. Our study shows that the cyber attack may be detected in the proposed system if the monitoring measures deviate from the steady state, which is a challenge for anomaly detection.The plan proposes segmenting the operational distribution networks into smaller zones where cyberattacks are more likely to occur.

- **Service Provider**

To access this section, the Service Provider will need to provide their username and password. The Service Provider's workflow is shown in Figure 1; after he's logged in, he has access to a variety of features including training and testing cyber data sets., Check Out The Cyber Attack Prediction, Check Out The Type Ratio Forecast For Cyber Attacks, See the Accuracy of Cyber Datasets After Training as a Bar Graph, See the Accuracy of Cyber Datasets After Training, Get Ready-to-Use Datasets, Take a look at the breakdown by attack type on all remote users.

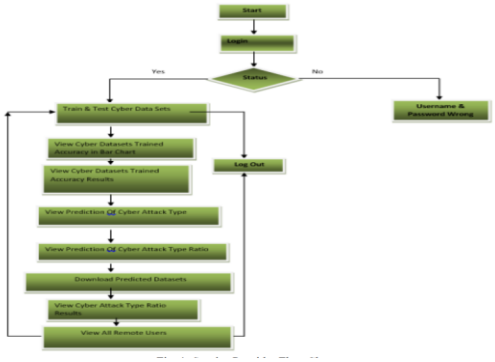



Fig. 1: Diagram of Flow for Service Providers

- **View and authorized user**

Within this module, the administrator has the ability to see a list of users who have registered for the service. The administrator has the ability to look at the user's information, such as the user name, email address, and address, and the administrator also has the ability to approve users.

- **Remote User**

This module currently has a total of n people logged in to it. The flow chart for the Remote User is shown in Figure 2. Users are required to register themselves before they may take any activities. After the user has registered, the database will keep a record of the user's information. After successfully enrolling, he is required to sign in with a valid user name and password in order to use the system. After successfully logging in, users are able to carry out a variety of actions, including REGISTER AND LOGIN, PREDICT CYBER ATTACK TYPE, and SEE YOUR PROFILE.

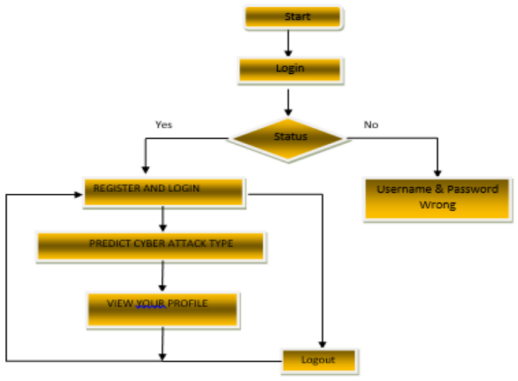



Fig. 2: Distribution Map of Distant Users

## B. ARCHITECTURE

The Adaptive Hierarchical Cyber Attack Detection and Localization in Active Distribution System architecture was designed to learn from new data and adjust to the dynamic nature of the active distribution system. The active distribution system is continually changing, but the suggested design in Figure 3 can adapt to these changes. The service provider, the view, and the authorised user and the remote user are the three components that make up this architecture. Login, train and test cyber data sets, view trained accuracy in bar chart, view trained accuracy results, view prediction of cyber-attack type, view prediction of cyber-attack type ratio, download predicted datasets, view cyber attack type ratio results, view remote users; these are all part of the service provider. The web server is linked to a web database for data retrieval, and it is also linked to a service provider for data collection and storage.Data from several service providers is stored in a web-based database and retrieved as needed. Users from afar need to sign up, log in, and make cyberattack predictions before they can access your profile.

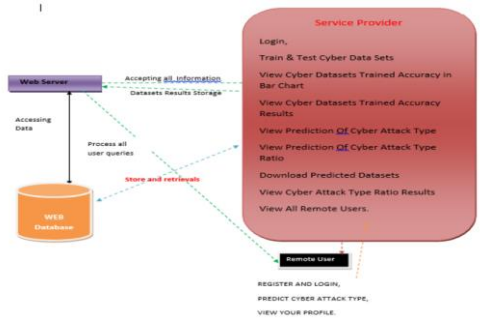



Fig. 3: Conceptual Design

# III. METHODOLOGIES

## A. GRADIENT BOOSTING

Gradient boosting machine learning methods are utilised for regression and classification analyses. It works by building a series of weak decision trees that have been trained on different subsets of the data. The final result is obtained by adding the predictions from all the decision trees.

Multiple layers of hierarchically organised detection techniques are used in the adaptive hierarchical approach with gradient boosting. Gradient boosting classifiers are employed at each layer to categorise system data and spot possible cyber-attacks. The broad-based detection technique at the top tier of the hierarchy utilises a gradient boosting classifier to recognise well-known assault patterns and deviations from typical system activity. The classifier can recognise typical attack characteristics and abnormalities since it has been trained on past data.

Gradient boosting classifiers are used in the intermediate tier of the hierarchy's detection techniques to find assaults that have gotten past the top-level ones. These classifiers may identify assaults that are exclusive to certain system components or activities since they were trained on more specialised data. After an assault has been discovered, reaction mechanisms are initiated in the hierarchy's bottom layer. Automated reactions including traffic snarling, quarantining infected systems, and warning security personnel are examples of these techniques.Flowchart for the gradient boosting machine learning technique (Fig. 4). The ensemble classifiers

are made up of a number of weak classifiers. The weights of the incorrectly predicted points are raised in the next classifier. The ultimate determination is made using the weighted average of each forecast.

Adaptive hierarchical cyber-attack detection and localization in active distribution systems employing gradient boosting contains localization techniques that may identify the attack's location in addition to detection and response methods. These mechanisms use methods like network topology analysis and geo-location to pinpoint the attack's origin and the system components that were harmed.

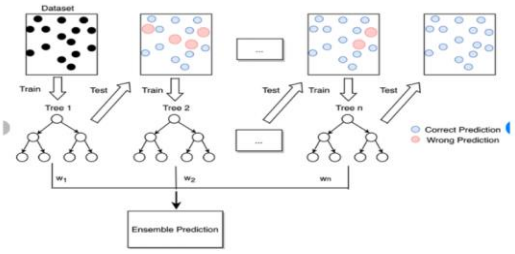



Fig. 4: Boosting Gradients

**B. K-NEAREST NEIGHBORS (KNN)**

This simple but very efficient classification system categorises objects based on a similarity measure. Non-parametric lazy learning technique that postpones "learning" until the test example is shown. Every time we have fresh data to categorise, we find the K-nearest neighbours of the new data using the training data. Figure 5 depicts the data points before and after using K-Nearest Neighbours (KNN).

- **Example:**

Learning that is based on instances also functions in a lazy manner. This is due to the fact that examples that are geographically close to the input vector for the test or prediction may take some time to emerge in the training dataset.

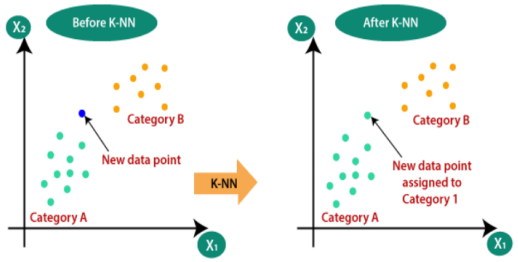



Fig. 5: K-Nearest Neighbors (KNN)

**C. LOGISTIC REGRESSION CLASSIFIERS**

Logistic regression technique probes the association between a set of independent (explanatory) factors and a categorical dependent (outcome) variable. When the dependant variable may only take on the values 0 and 1, as in "Yes" and "No," the term "logistic regression" is employed. Multinomial logistic regression is often used when the dependent variable has three or more unique values, such as Married, Single, Divorced, or Widowed.Different data are used for the dependent variable, but the approach serves a similar purpose to that of multiple regression.

For both numeric and categorical independent variables, this programme can calculate binary logistic regression and multinomial logistic regression. The regression equation and information on odds ratios, confidence intervals, probabilities, and standard deviations are included. A thorough residual analysis is carried out, and diagnostic residual charts and reports are generated. It searches for the optimal regression model with the fewest number of independent variables by doing an independent variable subset selection. It provides ROC curves and confidence intervals on anticipated values to aid in selecting the optimal cut-off point for classification. Verifying your findings is made easier by the programmatic detection of rows that were skipped over throughout the analysis.

The regression classifiers are shown in fig. 6.The naïve bays approach is a supervised

learning method that makes the basic assumption that the presence or absence of a feature in a class has no bearing on any other feature. Still, it seems potent and efficient. Comparable to other supervised learning methods in terms of efficacy. The literature provides a plethora of explanations for this. In this lesson, we focus on an explanation based on representation bias. Linear classifiers (support vector machines) include the naive Bayes classifier, linear discriminant analysis, logistic regression, and linear support vector machines. This discrepancy (the learning bias) is taken into consideration by the method used to estimate the classifier's parameters.

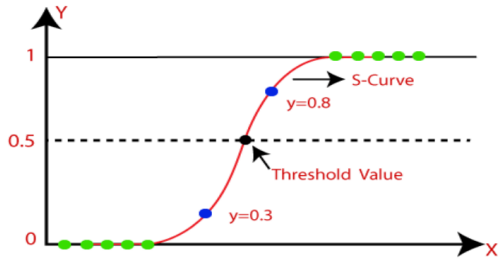



Fig. 6: Classes Determined Using Logistic Regression

## D. RANDOM FOREST

One method developed to achieve just that is called "Adaptive Hierarchical Cyber Attack Detection and Localization in Active Distribution System using Random Forest."The method employs machine learning methods, most notably the Random Forest algorithm, to classify and localise the kind of cyber-attack that has occurred in the system.

Hierarchical organisation is used to improve the precision of the detection and localization procedure. The ruleset upon which the hierarchy rests is used to categorise the nature of the cyberattack that has taken place. The regulations are structured in a hierarchical fashion, with the most serious cyber-attacks categorised first.

Random Forest is used to train the algorithm using a dataset containing examples of cyberattacks. The programme generates a decision tree using attack characteristics to determine the attack type. The characteristics may include the origin of the assault, the time of the assault, the nature of the assault, and any other pertinent details.

Cyberattacks on the active distribution system may be categorised and localised with the help of the trained model. By giving more priority to the categorization of severe assaults, the hierarchical structure helps to enhance the precision of the detection and localization process. The training set and test set that will be used to inform the random forest's prediction are shown in Figure 7 below.

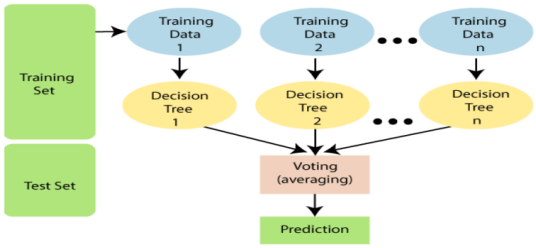



Fig. 7: Random Forest

## E. SVM

A discriminant machine learning approach for classification problems uses a iid training dataset to find a discriminant function that accurately predicts labels for newly acquired instances. A discriminant classification function takes a data point x and assigns it to one of the several classes that make up the classification job, as opposed to generative machine learning approaches that involve the generation of conditional probability distributions. Because discriminant procedures are less reliable when outlier identification is included in the prediction process, generative methods are often used. This is particularly true when just posterior probabilities are required, as is the case with multi-dimensional feature spaces. Finding the equation for a multidimensional surface that optimally separates the different classes in the feature space is the geometrical equivalent of learning a classifier.

Figure 8 shows SVM, a discriminant approach that, in contrast to the GAs and

perceptrons that are also commonly used for classification in machine learning, provides the same optimal hyperplane value every time because it solves the convex optimisation issue analytically. Perceptron solutions are heavily influenced by the requisite start and stop times. The parameters of a support vector machine (SVM) model for a given training set and a particular kernel that transforms the data from the input space to the feature space are different every time training is started, but the models of a perceptron and a generalised additive classifier (GA) are not.Many hyperplanes will meet this criterion since Gas and perceptrons only care about minimising error during training.

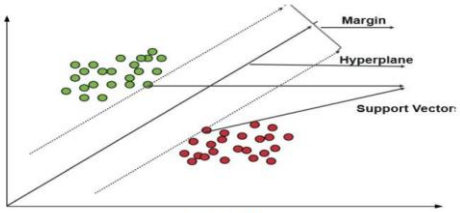



FIG 8: SVM

## IV. RESULT ANALYSIS

- The proposed approach functions as described below. Accessing • Training and Testing Cyber Data Sets
- Download predicted datasets
- View results for cyber attack type prediction
- View bar charts of trained accuracy on cyber datasets
- View results for cyber attack type ratio View all remote users.

### A. Login Page

Below Fig. 9 are the User Registration and User Login sections. Users may sign up for an account and enter their credentials here.

Fig. 9: Sign In Screen

### B. View Cyber Datasets Trained Accuracy Results

A bar chart showing the precision of several datasets is shown in fig10.Accuracy of SVM, random forest, KNN - neighbours classifiers, and gradient boosting algorithms are shown as bars in this bar chart. Various charts (bar, line, and pie) display the reliability findings.

- **View Cyber Datasets Trained Accuracy in Bar Chart**

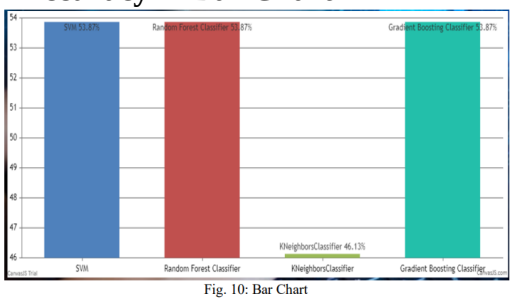
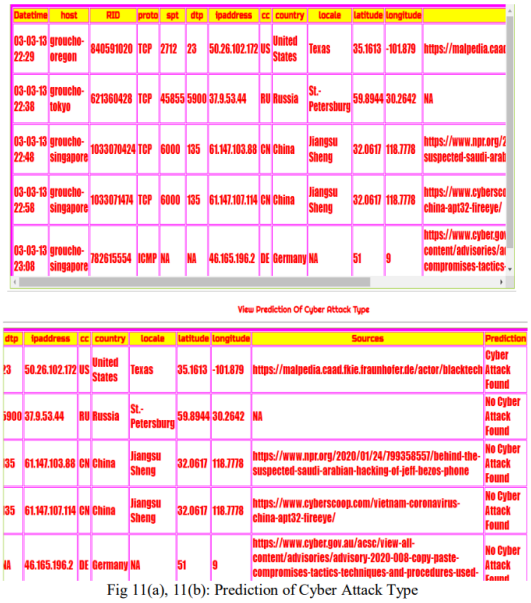



Fig. 10: Bar Chart

C. View Prediction of Cyber Attack Type Fig 11(a) and fig11(b) tells about the prediction of cyber-attack type



| Datetime | host | RID | proto | spt | dtp | Ipaddress | cc | country | locale | latitude | longitude | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 03-03-13 22:29 | groucho-oregen | 840591020 | TCP | 2712 | 23 | 50.26.102.172 | US | United States | Texas | 35.1613 | -101.879 | https://malpedia.caad |
| 03-03-13 22:38 | groucho-tokyo | 621360428 | TCP | 45855 | 5900 | 37.9.53.44 | RU | Russia | St.-Petersburg | 59.8944 | 30.2642 | NA |
| 03-03-13 22:48 | groucho-singapore | 1033070424 | TCP | 6000 | 135 | 61.147.103.88 | CN | China | Jiangsu Sheng | 32.0617 | 118.7778 | https://www.npr.org/2 suspected-saudi-arab |
| 03-03-13 22:58 | groucho-singapore | 1033071474 | TCP | 6000 | 135 | 61.147.107.114 | CN | China | Jiangsu Sheng | 32.0617 | 118.7778 | https://www.cybersca china-apt32-fireeye/ |
| 03-03-13 23:08 | groucho-singapore | 782615554 | ICMP | NA | NA | 46.165.196.2 | DE | Germany | NA | 51 | 9 | https://www.cyber.go content/advisories/a compromises-tactics |

View Prediction Of Cyber Attack Type

| dtp | Ipaddress | cc | country | locale | latitude | longitude | Sources | Prediction |
|---|---|---|---|---|---|---|---|---|
| 23 | 50.26.102.172 | US | United States | Texas | 35.1613 | -101.879 | https://malpedia.caad.fkie.fraunhofer.de/actor/blacktech | Cyber Attack Found |
| 5900 | 37.9.53.44 | RU | Russia | St.-Petersburg | 59.8944 | 30.2642 | NA | No Cyber Attack Found |
| 135 | 61.147.103.88 | CN | China | Jiangsu Sheng | 32.0617 | 118.7778 | https://www.npr.org/2020/01/24/799358557/behind-the-suspected-saudi-arabian-hacking-of-jeff-bezos-phone | No Cyber Attack Found |
| 135 | 61.147.107.114 | CN | China | Jiangsu Sheng | 32.0617 | 118.7778 | https://www.cyberscoop.com/vietnam-coronavirus-china-apt32-fireeye/ | No Cyber Attack Found |
| NA | 46.165.196.2 | DE | Germany | NA | 51 | 9 | https://www.cyber.gov.au/acsc/view-all-content/advisories/advisory-2020-008-copy-paste-compromises-tactics-techniques-and-procedures-used- | No Cyber Attack Found |

Fig 11(a), 11(b): Prediction of Cyber Attack Type

### D. View Cyber Attack Type Ratio Results

The percentages of successful cyberattacks are shown in a pie chart format in figures 12 and 13 below.

View Prediction Of Cyber Attack Type Ratio Details

| Cyber Attack Type | Ratio |
|---|---|
| No Cyber Attack Found | 80.0 |
| Cyber Attack Found | 20.0 |

Fig. 12: Forms of Cyber-Attacks

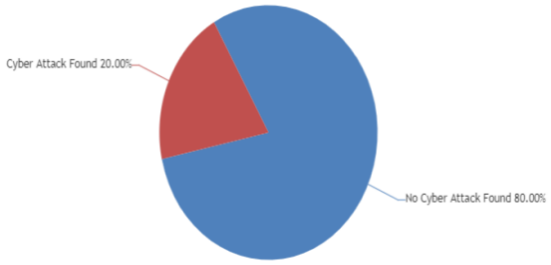



Fig. 13: Venn Diagram

**E. View All Remote Users**

The Remote Users List is shown on this page.

VIEW ALL REMOTE USERS !!!

| USER NAME | EMAIL | Gender | Address | Mob No | Country | State | City |
|---|---|---|---|---|---|---|---|
| Rajesh | Rajesh123@gmail.com | Male | #8928,4th Cross,Vijayanagar | 9535866270 | India | Karnataka | Bangalore |
| Manjunath | tmksmanju13@gmail.com | Male | #892,4th Cross,Rajajinagar | 9535866270 | India | Karnataka | Bangalore |

Fig 14: Table of Users

## V. CONCLUSION

Based on these findings, we propose an adaptable hierarchical cyber attack localization strategy for active distribution systems. Electric waveform data from WMU sensors is used to record the anomalous characteristics, which would otherwise be ignored. We propose a modified version of spectral clustering to first divide the whole massive network into manageable "coarse" chunks. The specific location of the 'fine' cyber-attack may then be determined by calculating and analysing the effect score of each sensor in the prospective sub-region. We also compare our method to others in terms of localisation, subgraph clustering, and the detection of cyber-attacks. The results from two sample distribution networks show how effective our method may be.

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