A Project report on

Machine Learning Methods for Attack Detection in the Smart Grid

A Dissertation submitted to JNTU Hyderabad in partial fulfillment of the academic requirements for the award of the degree.

Bachelor of Technology

in

Computer Science and Engineering

Submitted by

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CERTIFICATE

This is to certify that the Major Project report entitled **"Machine Learning Methods for Attack Detection in the Smart Grid"** being submitted by MOHAMMED. MOQEED (20H51A05A1), PADAKANTI SHIVA CHARAN (20H51A05J1) in partial fulfillment for the award of **Bachelor of Technology in Computer Science and Engineering** is a record of bonafide work carried out his/her under my guidance and supervision.

The results embodies in this project report have not been submitted to any other University or Institute for the award of any Degree.

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ABSTRACT

Attack detection problems in the smart grid are posed as statistical learning problems for different attack scenarios in which the measurements are observed in batch or online settings. In this approach, machine learning algorithms are used to classify measurements as being either secure or attacked. An attack detection framework is provided to exploit any available prior knowledge about the system and surmount constraints arising from the sparse structure of the problem in the proposed approach. Well-known batch and online learning algorithms (supervised and semisupervised) are employed with decision- and feature-level fusion to model the attack detection problem. The relationships between statistical and geometric properties of attack vectors employed in the attack scenarios and learning algorithms are analyzed to detect unobservable attacks using statistical learning methods. The proposed algorithms are examined on various IEEE test systems. Experimental analyses show that machine learning algorithms can detect attacks with performances higher than attack detection algorithms that employ state vector estimation methods in the proposed attack detection framework.

CHAPTER 1
INTRODUCTION

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1.1.Problem Statement

The smart grid, a modernized electricity distribution system, plays a pivotal role in the reliable and efficient delivery of electrical power to homes, businesses, and critical infrastructure. As it becomes increasingly reliant on advanced technologies and interconnected devices, it becomes more vulnerable to various forms of attacks, including cyberattacks and physical intrusions. Therefore, the primary objective is to develop a robust machine learning system capable of effectively detecting and mitigating these threats[2]. Implementing such a system not only enhances the security of the smart grid but also ensures the continuous and uninterrupted delivery of electricity, safeguards critical infrastructure[1], protects sensitive customer data, and contributes to overall energy sustainability and resilience. In doing so, it strengthens the grid's ability to adapt to emerging challenges and maintain its crucial role in powering modern society[1].

1.2.Research Objective

- Attack Classification: Create a machine learning model that can accurately classify different types of attacks on the smart grid, including but not limited to cyberattacks (e.g., malware, DoS, insider threats) and physical attacks (e.g., tampering with physical components, theft of equipment).
- Real-time Monitoring: Implement a real-time monitoring system that continuously analyzes data from various sensors and devices within the smart grid to promptly identify and respond to threats
- Data Sources Integration: Integrate data from various sources, such as SCADA systems, IoT sensors, network logs, and historical data, to provide a comprehensive view of the grid's state.
- Scalability: Ensure that the machine learning solution is scalable to accommodate the growing complexity of the smart grid and handle large volumes of data efficiently.
- False Positive Reduction: Minimize false positives to prevent unnecessary alarm triggers and reduce the burden on operators.

- Response Mechanism: Develop a response mechanism that can be activated upon the detection of an attack, including alerting, isolation, and recovery procedures.
- Model Training and Adaptation: Implement a system that can continuously learn and adapt to new attack patterns and evolving threats.
- Regulatory Compliance: Ensure that the solution complies with relevant regulations and standards for grid security.
- User-Friendly Interface: Create a user-friendly interface for grid operators and security personnel to interact with the system, investigate alerts, and initiate responses.

1.3.Project Scope

- Real-Time Monitoring: Implementing machine learning models for attack detection allows for continuous and real-time monitoring of smart grid data, enabling the swift identification of anomalies and potential security breaches[3].
- Enhanced Security Measures: Machine learning techniques offer the potential to significantly enhance the security measures within the smart grid, providing proactive defense mechanisms against various cyber-attacks and unauthorized intrusions.
- Adaptive Threat Detection: The application of machine learning facilitates the development of adaptive threat detection systems that can evolve and adapt to emerging attack strategies and patterns, thereby ensuring the resilience of the smart grid infrastructure.
- Improved Anomaly Recognition: Machine learning models can effectively identify subtle patterns and anomalies within large datasets, enabling the detection of sophisticated attacks that may go unnoticed by traditional security measures.

CHAPTER 2
BACKGROUND WORK

CHAPTER 2

BACKGROUND WORK

2.1 False data injection attacks against state estimation in electric power grids

2.1.1. Introduction

A power grid is a complex system connecting electric power generators to consumers through power transmission and distribution networks across a large geographical area. System monitoring is necessary to ensure the reliable operation of power grids, and *state estimation* is used in system monitoring to best estimate the power grid state through analysis of meter measurements and power system models. Various techniques have been developed to detect and identify bad measurements, including *interacting bad measurements* introduced by *arbitrary, nonrandom* [5] causes. At first glance, it seems that these techniques can also defeat malicious measurements injected by attackers[8].

In this article, we expose an unknown vulnerability of existing bad measurement detection algorithms by presenting and analyzing a new class of attacks, called *false data injection attacks*[1], against state estimation in electric power grids. Under the assumption that the attacker can access the current power system configuration information and manipulate the measurements of meters at physically protected locations such as substations, such attacks can introduce *arbitrary* [6] errors into certain state variables without being detected by existing algorithms[4]. Moreover, we look at two scenarios, where the attacker is either constrained to specific meters or limited in the resources required to compromise meters. We show that the attacker can systematically and efficiently construct attack vectors in both scenarios to change the results of state estimation in *arbitrary* ways[3][8]. We also extend these attacks to *generalized false data injection attacks,* which can further increase the impact by exploiting measurement errors typically tolerated in state estimation. We demonstrate the success of these attacks through simulation using IEEE test systems, and also discuss the practicality of these attacks and the real-world constraints that limit their effectiveness[2].

2.1.2 Merits:

- Disruption Potential: False data injection attacks can disrupt the operation of electric power grids, potentially causing blackouts or damage to equipment[1].
- Stealthiness: These attacks can be difficult to detect, especially if the injected data is carefully crafted to mimic legitimate measurements.
- Low Cost: Compared to physical attacks on infrastructure, false data injection attacks can be relatively low-cost and executed remotely.
- Impact: The impact of a successful attack can be significant, affecting not only the operation of the power grid but also potentially causing economic losses and compromising national security[6].

Demerits:

- Risk of Damage: False data injection attacks can cause damage to physical infrastructure and result in widespread power outages, leading to economic losses and potential safety hazards.
- Trust Issues: Successful attacks erode trust in the integrity of data from sensors and other monitoring devices within the power grid[7].
- Regulatory and Legal Ramifications: There may be legal and regulatory consequences for both the attackers and the operators of the power grid in the event of a successful attack.
- Reputation Damage: Utilities and organizations responsible for power grid management may suffer reputational damage in the event of a successful attack, potentially affecting customer trust and investor confidence[2].

Challenges:

- Detection: Developing robust detection mechanisms capable of distinguishing between legitimate and false data is challenging due to the dynamic and complex nature of power grid systems.
- Data Integrity: Ensuring the integrity of data collected from sensors and other devices is crucial but challenging, as attackers may employ sophisticated techniques to evade detection.
- Real-Time Response: Power grid operators must respond to potential threats in real-time to minimize the impact of false data injection attacks, adding to the complexity of defense mechanisms.
- Resource Constraints: Many power grid operators may face resource constraints when implementing comprehensive cybersecurity measures, making it difficult to adequately protect against false data injection attacks.

2.1.3 Implementation

To implement a false data injection attack, an adversary first needs to gain unauthorized access to the communication network or data acquisition systems of the power grid. This can be achieved through various means such as exploiting software vulnerabilities, phishing attacks on system operators, or even physical tampering with devices. Once access is obtained, the attacker aims to inject falsified measurements into the system without being detected.

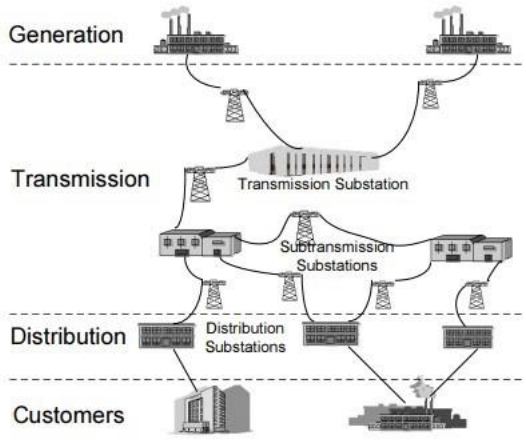
The injected data must be carefully crafted to evade detection by state estimation algorithms while still achieving the attacker's objectives. This involves understanding the structure of the power grid, including its topology, load flow equations, and measurement configurations. The attacker must also consider the constraints imposed by the power grid's physical characteristics and operational limitations.

One common approach to implementing false data injection attacks is to exploit the redundancy present in the power grid's measurement system. By strategically injecting falsified measurements at multiple points in the grid, an attacker can influence the state estimation process in a way that is not immediately apparent to system operators. For example, the attacker may manipulate voltage or phase angle measurements to create the illusion of a stable system while actually causing voltage instability or overloading certain transmission lines.

Another important consideration in implementing false data injection attacks is the timing of the injections. The attacker must carefully synchronize the injection of falsified measurements with the operation of the power grid to maximize the likelihood of success. This may involve coordinating attacks with changes in system operating conditions, such as the switching of generators or the occurrence of contingencies like line outages.

Implementing false data injection attacks also requires careful consideration of the potential impact on the power grid and its operation. The attacker must balance the desire to achieve specific goals, such as causing equipment damage or disrupting service, with the need to avoid detection and attribution. This may involve conducting extensive simulations or experiments to assess the effectiveness of different attack strategies and refine them accordingly.

Overall, implementing false data injection attacks against state estimation in electric power grids is a complex and multifaceted task that requires a deep understanding of power grid operations, measurement systems, and cybersecurity principles. By exploiting vulnerabilities in the system and carefully crafting falsified measurements, an attacker can potentially manipulate the operation of the power grid with significant consequences. As such, robust cybersecurity measures and continuous monitoring are essential to safeguarding the integrity and reliability of electric power systems.



Fig(2.1.3) A power grid connecting power plant

2.2 Machine learning for the New York City power grid

2.2.1. Introduction

Power companies can benefit from the use of knowledge discovery methods and statistical machine learning for preventive maintenance. We introduce a general process for transforming historical electrical grid data into models that aim to predict the risk of failures for components and systems. These models can be used directly by power companies to assist with prioritization of maintenance and repair work. Specialized versions of this process are used to produce [1] feeder failure rankings, [2] cable, joint, terminator, and transformer rankings, [3] feeder Mean Time Between Failure (MTBF) estimates, and [4] manhole events vulnerability rankings. The process in its most general form can handle diverse, noisy, sources that are historical (static), semi-real-time, or real-time, incorporates state-of-the-art machine learning algorithms for prioritization (supervised ranking or MTBF), and includes an evaluation of results via cross-validation and blind test. Above and beyond the ranked lists and MTBF estimates are business management interfaces that allow the prediction capability to be integrated directly into corporate planning and decision support; such interfaces rely on several important properties of our general modeling approach: that machine learning features are meaningful to domain experts, that the processing of data is transparent, and that prediction results are accurate enough to support sound decision making. We discuss the challenges in working with historical electrical grid data that were not designed for predictive purposes. The “rawness” of these data contrasts with the accuracy of the statistical models that can be obtained from the process; these models are sufficiently accurate to assist in maintaining New York City's electrical grid.

2.2.2 Merits, Demerits and Challenges

Merits (Advantages):

- Predictive Maintenance: ML algorithms can analyze historical data from the power grid to predict when equipment might fail. This allows for proactive maintenance, reducing downtime and enhancing grid reliability.
- Anomaly Detection: ML techniques can identify abnormal behavior in the power grid, such as sudden load fluctuations or equipment malfunctions, enabling rapid response to potential issues and improving system resilience.
- Optimized Energy Distribution: ML models can optimize energy distribution by predicting demand patterns and adjusting supply accordingly. This helps to minimize waste and optimize the use of resources, leading to cost savings and increased efficiency.
- Grid Optimization: ML algorithms can optimize grid operations by analyzing vast amounts of data to identify inefficiencies and improve grid performance. This includes optimizing the routing of power flows and reducing congestion in the grid.
- Cybersecurity: ML can enhance cybersecurity by identifying and mitigating cyber threats, such as false data injection attacks or unauthorized access attempts. ML algorithms can analyze network traffic and detect patterns indicative of malicious activity, helping to protect the grid from cyber attacks.

Demerits (Disadvantages):

- Data Quality: ML algorithms are highly dependent on the quality of the data they are trained on. Inaccurate or incomplete data can lead to unreliable predictions and suboptimal performance of ML models.
- Interpretability: Many ML models, particularly complex ones like deep neural networks, lack interpretability, making it difficult to understand the rationale behind their predictions. This can be a challenge in critical infrastructure like power grids, where explainability is crucial for decision-making.

- Scalability: Scaling ML algorithms to handle the vast amounts of data generated by the New York City power grid can be challenging. High computational requirements and resource constraints may limit the scalability of ML solutions for grid optimization and analytics.
- Robustness: ML models are susceptible to adversarial attacks and may exhibit poor performance in unanticipated scenarios. Adversarial attacks on ML-based systems could potentially disrupt the operation of the power grid or compromise its security.
- Privacy Concerns: ML algorithms trained on sensitive data from the power grid may raise privacy concerns, particularly regarding the protection of customer data and confidential information about grid operations.

Challenges:

- Data Integration: Integrating data from disparate sources within the power grid, such as sensors, meters, and control systems, poses a significant challenge for ML applications. Data integration is crucial for building accurate and comprehensive ML models.
- Real-Time Processing: Real-time processing of data is essential for applications like grid monitoring, anomaly detection, and control. Achieving low-latency, real-time processing with ML algorithms can be challenging, particularly in large-scale systems like the New York City power grid.
- Regulatory Compliance: Compliance with regulatory requirements and standards is essential when deploying ML solutions in critical infrastructure like the power grid. Ensuring that ML models adhere to regulatory guidelines and safety standards is a significant challenge for grid operators and technology providers.

- Model Robustness: Ensuring the robustness and reliability of ML models in dynamic and uncertain environments, such as the power grid, is a key challenge. ML models must be able to adapt to changing conditions and unforeseen events without compromising performance or safety.
- Human-Machine Collaboration: Effective collaboration between human operators and ML algorithms is essential for leveraging the benefits of ML in the power grid. Developing user-friendly interfaces and decision-support tools that facilitate human-machine collaboration is a significant challenge for grid operators and technology developers.

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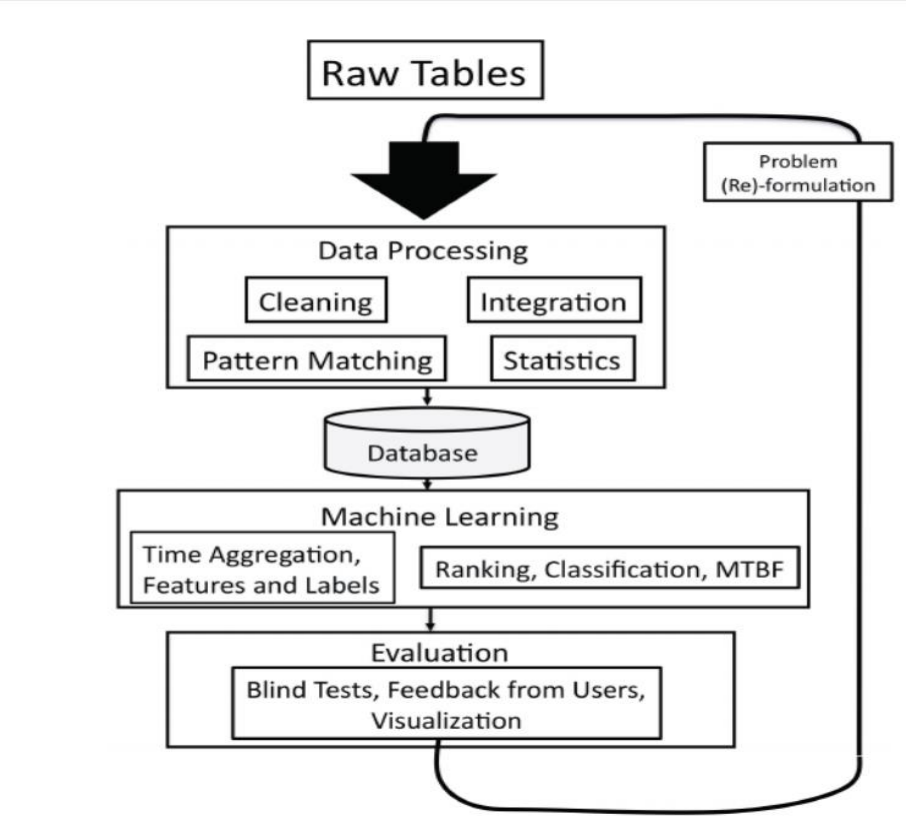


2.3. An early warning system against malicious activities for smart grid communications

2.3.1 Introduction

Smart grid presents the largest growth potential in the machine-to-machine market today. Spurred by the recent advances in M2M technologies, the smart meters/sensors used in smart grid are expected not to require human intervention in characterizing power requirements and energy distribution. These numerous sensors are able to report back information such as power consumption and other monitoring signals. However, SG, as it comprises an energy control and distribution system, requires fast response to malicious events such as distributed denial of service attacks against smart meters. In this article, we model the malicious and/or abnormal events, which may compromise the security and privacy of smart grid users, as a Gaussian process. Based on this model, a novel early warning system is proposed for anticipating malicious events in the SG network. With the warning system, the SG control center can forecast such malicious events, thereby enabling SG to react beforehand and mitigate the possible impact of malicious activity. We verify the effectiveness of the proposed early warning system through computer-based simulations

2.3.2 Merits, Demerits and Challenges

Merits

- Improved Security: An early warning system can enhance the security of smart grid communications by detecting and alerting operators to potential threats in real-time. This allows for prompt action to mitigate the impact of malicious activities, such as cyberattacks or unauthorized access attempts.
- Reduced Downtime: By providing early detection of malicious activities, the system can help minimize downtime and disruptions to grid operations. This is critical for maintaining the reliability and resilience of the smart grid, which is essential for supporting critical infrastructure and services.
- Enhanced Situational Awareness: The system provides operators with increased situational awareness by continuously monitoring communication

networks for suspicious behavior. This allows operators to better understand the threat landscape and respond effectively to emerging threats.

- Adaptive Defense Mechanisms: An early warning system can enable the implementation of adaptive defense mechanisms that automatically respond to detected threats. This may include isolating compromised devices, rerouting traffic, or deploying additional security measures to prevent further attacks.

- Compliance with Regulations: Many regulatory frameworks require utilities to implement measures to protect smart grid communications from cyber threats. An early warning system can help utilities comply with these regulations by providing proactive monitoring and threat detection capabilities.

Demerits (Disadvantages):

- False Positives: One of the challenges of an early warning system is the potential for false positives, where benign activities are mistakenly flagged as malicious. This can lead to alert fatigue and unnecessary disruptions if not properly managed.
- Resource Intensive: Implementing and maintaining an effective early warning system requires significant resources, including investment in technology, personnel, and ongoing monitoring and analysis efforts. This can be challenging for organizations with limited budgets or expertise in cybersecurity.
- Complexity: Smart grid communications involve a complex and dynamic network of devices, protocols, and data flows. Designing an early warning system that can effectively monitor and analyze this complexity while providing actionable insights is a significant challenge.
- Privacy Concerns: Monitoring and analyzing smart grid communications raise privacy concerns, particularly regarding the collection and use of sensitive data about energy consumption patterns and user behavior. Balancing the need for security with privacy considerations is essential but challenging.

- Integration with Existing Systems: Integrating an early warning system with existing smart grid infrastructure, including legacy systems and third-party components, can be challenging. Compatibility issues, interoperability concerns, and technical constraints may arise during the integration process.

Challenges:

- Data Collection and Analysis: An early warning system relies on timely and accurate data collection from various sources within the smart grid communications infrastructure. Ensuring the availability, integrity, and quality of data for analysis is a significant challenge.

- Adaptability: The threat landscape and cybersecurity risks facing smart grid communications are constantly evolving. An effective early warning system must be adaptable and able to detect new and emerging threats, vulnerabilities, and attack techniques.

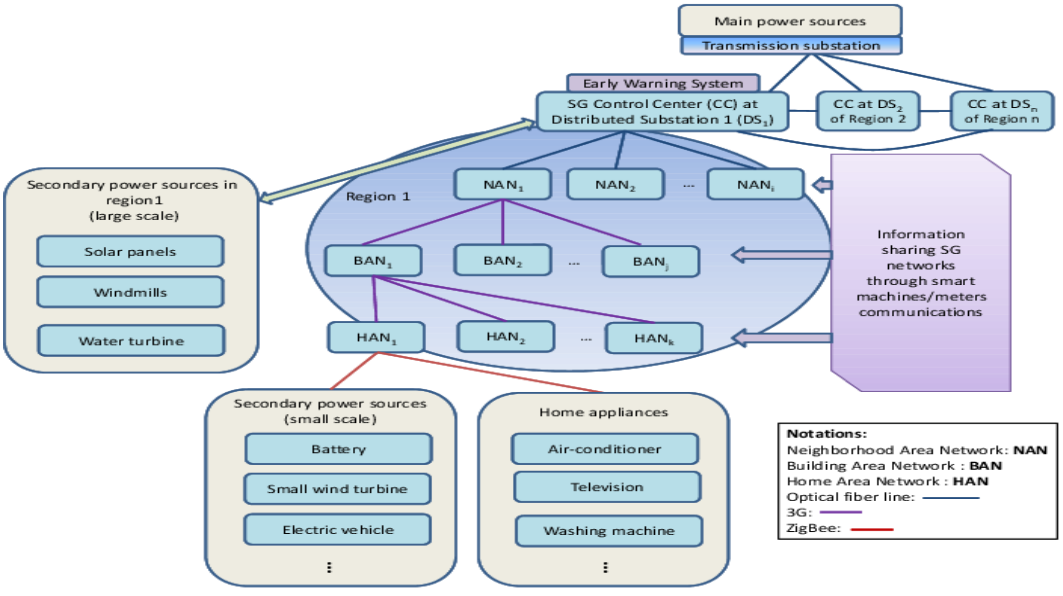
- Scalability: As the smart grid continues to grow and evolve, an early warning system must be able to scale to accommodate increasing volumes of data and traffic while maintaining performance and effectiveness.

- Human Factors: Human factors such as user awareness, training, and response procedures play a crucial role in the effectiveness of an early warning system. Ensuring that operators are adequately trained and prepared to respond to security alerts and incidents is essential.

- Regulatory Compliance: Compliance with regulatory requirements and standards related to cybersecurity is a key challenge for organizations operating in the smart grid space. An early warning system must support compliance efforts by providing evidence of adherence to relevant regulations and guidelines.

2.3.3 Implementation

An early warning system against malicious activities for smart grid communications involves the development and implementation of sophisticated monitoring and detection mechanisms. Firstly, the system collects and analyzes data from various sources within the smart grid communication network, including communication traffic, network topology, and device behavior. Machine learning algorithms are then employed to detect patterns indicative of malicious activities, such as unauthorized access attempts, data tampering, or denial-of-service attacks. Once suspicious activity is identified, the system generates alerts and triggers appropriate responses, such as isolating compromised devices or blocking malicious traffic. Additionally, the system continuously learns from new data and adapts its detection capabilities to evolving threats. Key components of the implementation include robust data collection infrastructure, advanced analytics algorithms, and seamless integration with existing smart grid communication systems. Ultimately, an effective early warning system enhances the security posture of the smart grid by enabling proactive detection and mitigation of potential cyber threats.



Fig(2.3.3) Smart grid hierarchical Network

CHAPTER 3
PROPOSED SYSTEM

CHAPTER 3

PROPOSED SYSTEM

3.1. Objective of Proposed Model

When it comes to keeping an eye on and managing electricity grids, several articles in the smart grid literature have suggested using machine learning techniques. A smart framework for the system design is proposed by Rudin et al., in which machine learning methods are used to foresee component failures. For the purpose of managing loads and sources of energy in smart grid networks, Anderson et al. utilise machine learning techniques. At the network layer of smart grid communication systems, machine learning approaches have been explored to anticipate malicious activities and identify intrusions. In this work, we examine the challenge of detecting physical-layer attacks on the smart grid that involve fraudulent data injection. Using the paradigm of distributed sparse assaults introduced in, we attack a network in which the measurements are hierarchically structured by injecting erroneous data into the local measurements recorded by local network operators or smart phasor measurement units (PMUs). Statistics-based attack detection requires knowledge of the network topology, cluster-level measurements, and the measurement matrix, all of which are known to network operators.

Advantages of Proposed System:

- High Accuracy
- Quick response

3.1.1.Modules Information:

To implement this project author has used 4 different types of machine learning algorithms such as Perceptron, KNN, SVM and Logistic Regression. This project consists of following modules

1) Upload Dataset: Using this module we will upload smart grid dataset to application
2) Preprocess Dataset: Dataset often contains missing and null values and non-numeric values and using this module we will replace all such values with 0. This module will split dataset into train and test part where 80% dataset used to train machine learning algorithms and 20% dataset used to test machine learning algorithms prediction accuracy.

3) Run Algorithms: using above dataset we will train all 4 machine learning algorithms and then calculate various metrics such as Accuracy, Precision, Recall and FSCORE.

4)Upload Test Data & Predict Attack: Using this module we will upload test data and then application will predict whether that test smart grid data is normal or contains attack.

5)Performance Graph: Using this module we will plot performance graph between all algorithms.

3.1.2 System Configuration:-

Software Reqirements:

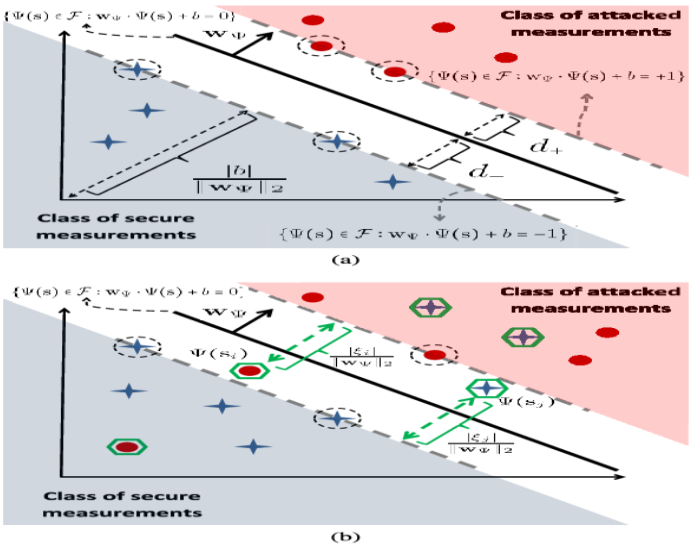
System Attributes:

1. filename
2. X, Y
3. dataset
4. classifier
5. X_train, X_test, y_train, y_test

Data base Requirements:

No need

3.1.3 Workdown Structure:-



Fig(3.1.3) Workdown Structure

3.1.4 SYSTEM REQUIREMENT:

HARDWARE REQUIREMENTS:

- Processor - Intel i3(min)
- Speed - 1.1 GHz
- RAM - 4GB(min)
- Hard Disk - 500 GB
- Key Board - Standard Windows Keyboard
- Mouse - Two or Three Button Mouse
- Monitor - SVGA

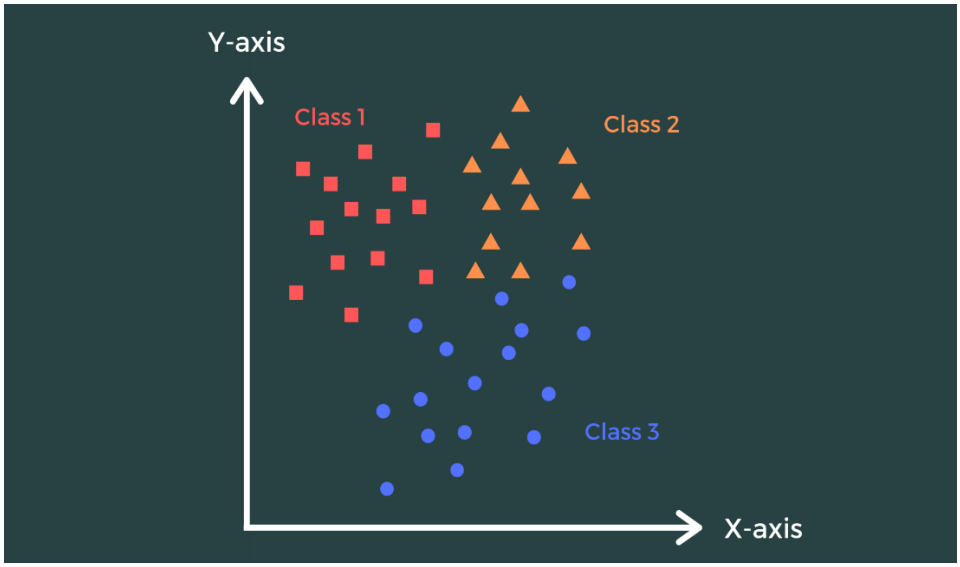
SOFTWARE REQUIREMENTS:

- Operating System - Windows10(min)
- Programming Language - Python

3.2 Algorithms used

- **K Nearest Neighbour (KNN)**

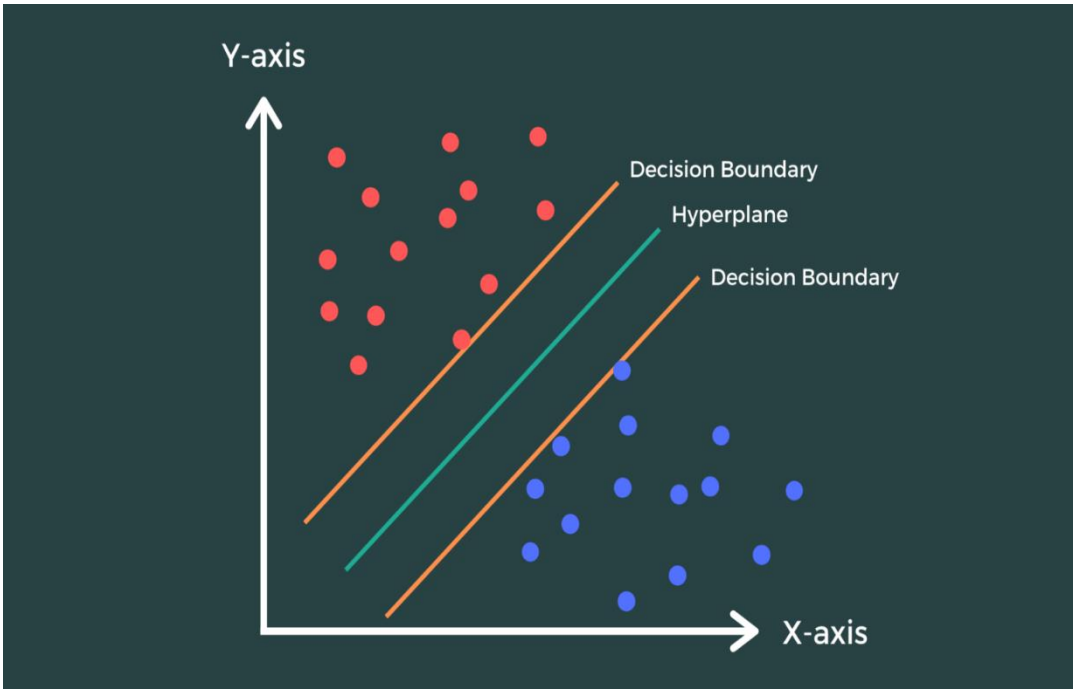
The K-Nearest Neighbors (KNN) algorithm plays a vital role in machine learning projects for smart grids by facilitating anomaly detection and predictive maintenance. In smart grids, KNN can analyze historical data to identify patterns in energy consumption, grid performance, or equipment behavior. It aids in predicting potential failures or anomalies in grid components based on similarities with past occurrences. By leveraging KNN, smart grid systems can proactively address issues, optimize energy distribution, and enhance overall grid reliability and efficiency, leading to improved performance and cost savings.



Fig(3.2.1) KNN Algorithm implementation

- **Support Vector Machine (SVM)**

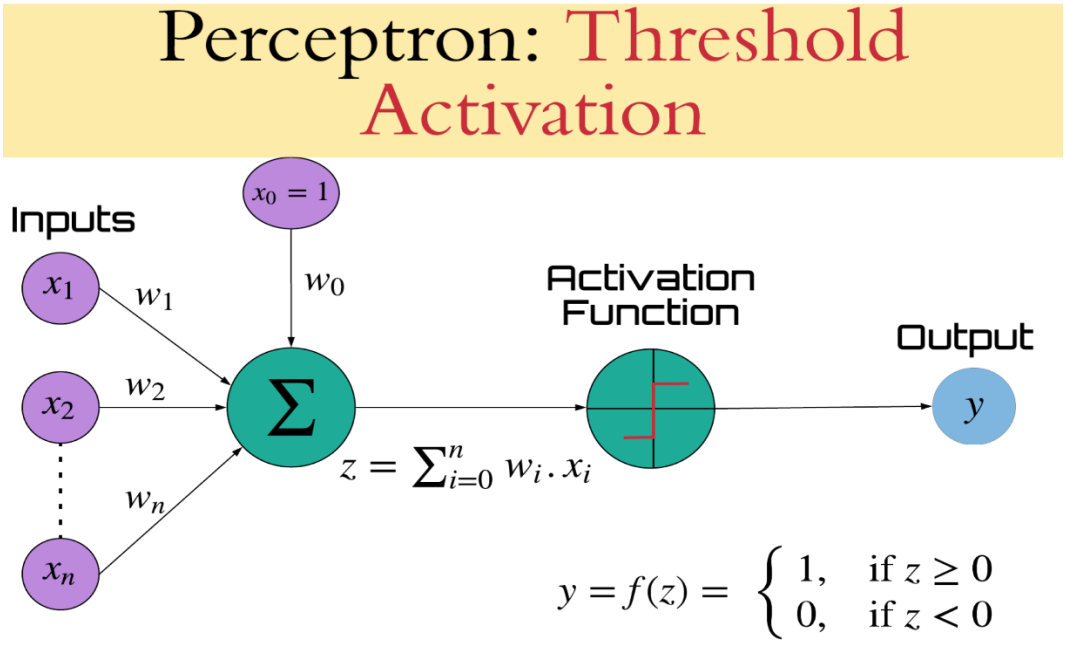
Support Vector Machine (SVM) algorithms play a crucial role in smart grid machine learning projects by classifying data points to detect anomalies, predict equipment failures, and optimize energy distribution. SVMs excel in handling high-dimensional data and are effective in identifying patterns in smart grid data, such as voltage fluctuations or abnormal consumption patterns. They contribute to enhancing grid reliability, reducing downtime, and optimizing energy usage.



Fig(3.2.2) Support Vector Machine Algorithm implementation

- **Perceptron:**

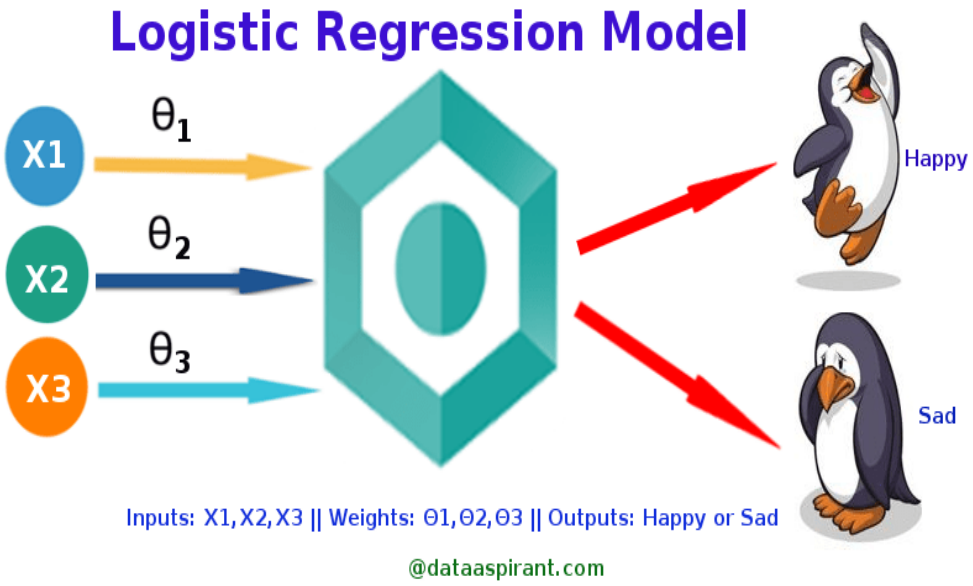
The perceptron algorithm plays a crucial role in machine learning projects within smart grid applications by enabling pattern recognition and classification tasks. In the context of smart grids, perceptrons can be utilized for fault detection, load forecasting, and anomaly detection. By analyzing data from various sensors and meters, perceptrons can identify abnormal patterns in power consumption or grid behavior, helping to improve system reliability and efficiency. Additionally, perceptrons can aid in optimizing energy distribution and demand response strategies, contributing to the overall resilience and sustainability of smart grid infrastructures.



Fig(3.2.3) Perceptron Algoritlun implementation

- **Logistic Regression :**

Logistic regression plays a crucial role in machine learning projects for smart grids by aiding in predictive analytics and anomaly detection. It helps forecast energy demand, identify potential grid failures, and detect anomalies in power consumption patterns. By analyzing historical data, logistic regression models can predict future events, such as load forecasting or equipment failures, enabling proactive maintenance and efficient resource allocation. Its simplicity, interpretability, and scalability make logistic regression a valuable tool for optimizing grid operations and enhancing reliability in smart grid environments.



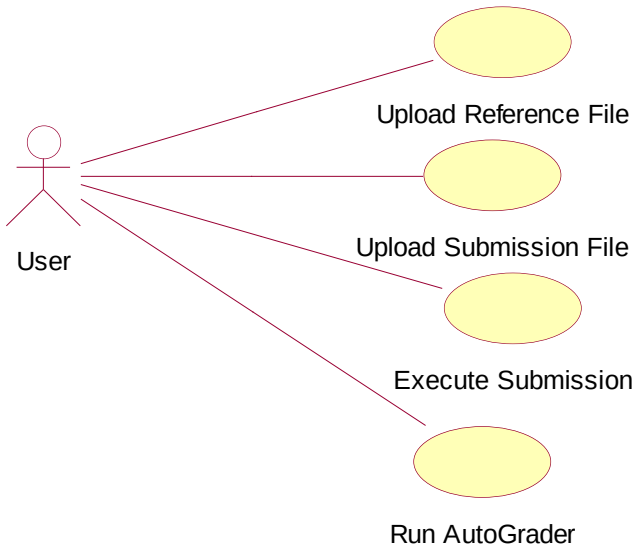
Fig(3.2.4) Logistic regression Algorithm implementation

3.3 Designing

3.3.1 UML Diagram

- **USECASE DIAGRAM:**

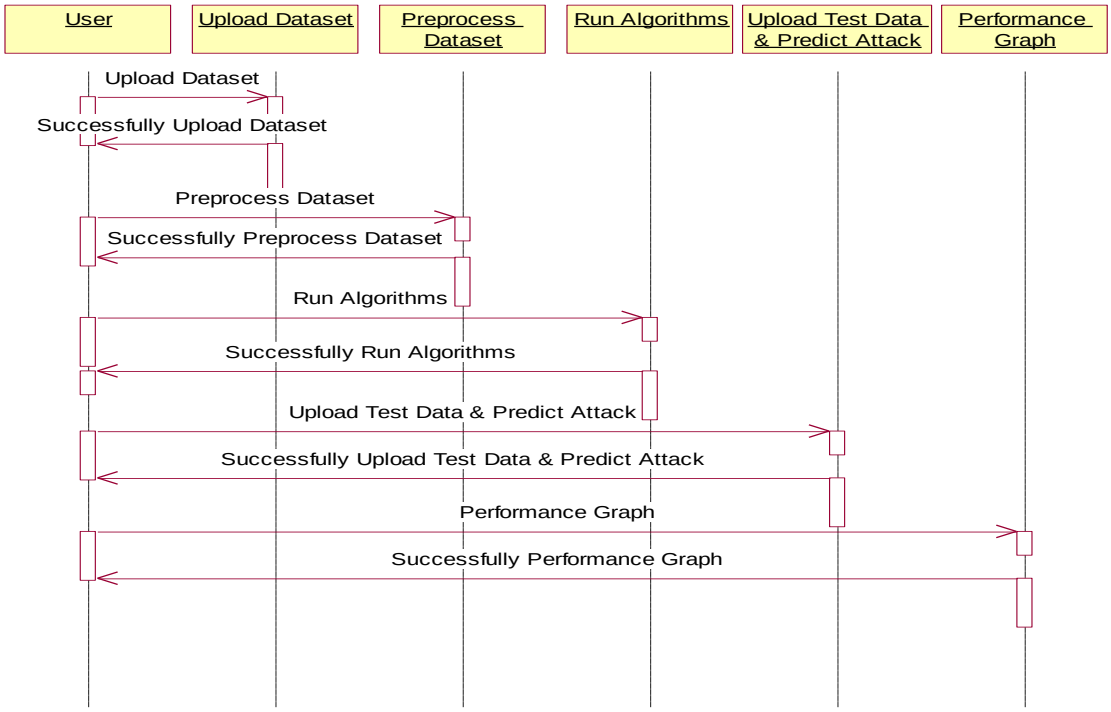
A use case diagram at its simplest is a representation of a user's interaction with the system and depicting the specifications of a use case. A use case diagram can portray the different types of users of a system and the various ways that they interact with the system. This type of diagram is typically used in conjunction with the textual use case and will often be accompanied by other types of diagrams as we



Fig(3.3.1) USECASE Diagram

- **SEQUENCE DIAGRAM**

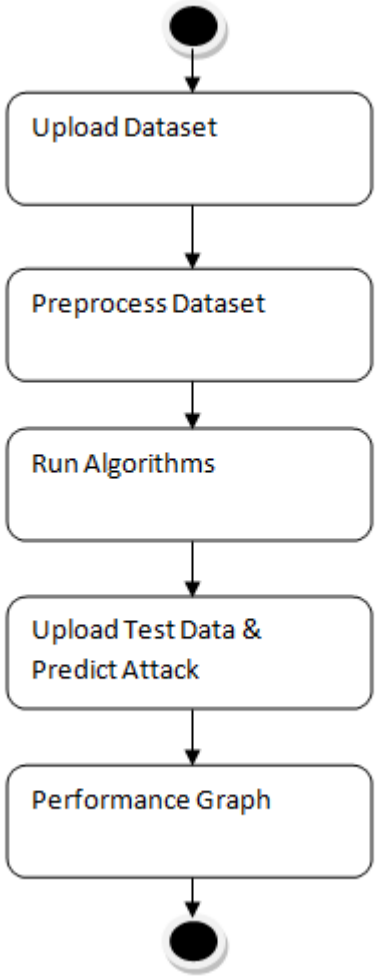
  A sequence diagram is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. A sequence diagram shows object interactions arranged in time sequence. It depicts the objects and classes involved in the scenario and the sequence of messages exchanged between the objects needed to carry out the functionality of the scenario. Sequence diagrams are typically associated with use case realizations in the Logical View of the system under development. Sequence diagrams are sometimes called **event diagrams**, **event scenarios**, and timing diagrams.



Fig(3.3.2) SEQUENCE Diagram

- **ACTIVITY DIAGRAM:**

Activity diagram is another important diagram in UML to describe dynamic aspects of the system. It is basically a flow chart to represent the flow form one activity to another activity. The activity can be described as an operation of the system. So the control flow is drawn from one operation to another. This flow can be sequential, branched or concurrent



Fig(3.3.3) Activity Diagram

3.4 Stepwise Implementation and Code

To implement this project author has used 4 different types of machine learning algorithms such as Perceptron, KNN, SVM and Logistic Regression. This project consists of following modules

1) Upload Dataset: Using this module we will upload smart grid dataset to application
2) Preprocess Dataset: Dataset often contains missing and null values and non-numeric values and using this module we will replace all such values with 0. This module will split dataset into train and test part where 80% dataset used to train machine learning algorithms and 20% dataset used to test machine learning algorithms prediction accuracy.
3) Run Algorithms: using above dataset we will train all 4 machine learning algorithms and then calculate various metrics such as Accuracy, Precision, Recall and FSCORE.
4) Upload Test Data & Predict Attack: Using this module we will upload test data and then application will predict whether that test smart grid data is normal or contains attack.
5) Performance Graph: Using this module we will plot performance graph between all algorithms.

3.4.1 Source Code :

```
from tkinter import messagebox
from tkinter import *
from tkinter import simpledialog
import tkinter
from tkinter import filedialog
import matplotlib.pyplot as plt
import numpy as np
from tkinter.filedialog import askopenfilename
import os
import numpy as np
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
import pandas as pd
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
from sklearn import svm
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import normalize
from sklearn.linear_model import Perceptron
import pandas as pd

main = tkinter.Tk()
main.title("Machine Learning Methods for Attack Detection in the Smart Grid")
main.geometry("1300x1200")
```

```
global filename

global X, Y
global dataset
global classifier
global X_train, X_test, y_train, y_test
le = LabelEncoder()
accuracy = []
precision = []
recall = []
fscore = []

def upload():
    global filename
    global dataset
    filename = filedialog.askopenfilename(initialdir="Dataset")
    pathlabel.config(text=filename)
    text.delete('1.0', END)
    text.insert(END,filename+" loaded\n\n")

    dataset = pd.read_csv(filename)
    dataset.fillna(0, inplace = True)
    dataset = dataset.replace(np.nan, 0)
    text.insert(END,str(dataset)+"\n")

def processDataset():
    global X, Y
    global dataset
    text.delete('1.0', END)
```

```
global X_train, X_test, y_train, y_test
    dataset['marker'] = pd.Series(le.fit_transform(dataset['marker']))
    dataset = dataset.fillna(dataset.mean())
    temp = dataset

dataset.replace([np.inf, -np.inf], np.nan, inplace=True)
    dataset = dataset.values
    print(np.isnan(dataset.any()))
    X = dataset[:,0:dataset.shape[1]-1]
    Y = dataset[:,dataset.shape[1]-1]
    X = X.round(decimals=4)
    X = normalize(X)
    indices = np.arange(X.shape[0])
    np.random.shuffle(indices)
    X = X[indices]
    Y = Y[indices]
    print(Y)
    X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.1)
    print(y_test)
    print(y_train)
    text.insert(END,"Total records found in dataset are : "+str(X.shape[0])+"\n")
    text.insert(END,"Total records used to train machine learning algorithms are :
"+str(X_train.shape[0])+"\n")
    text.insert(END,"Total records used to test machine learning algorithms are :
"+str(X_test.shape[0])+"\n\n")
    text.insert(END,str(temp)+"\n\n")

def runPerceptron():
    global X_train, X_test, y_train, y_test
```

```
text.delete('1.0', END)
    accuracy.clear()
    precision.clear()
    recall.clear()
    fscore.clear()
cls = Perceptron(class_weight='balanced')
cls.fit(X_train,y_train)
    predict = cls.predict(X_test)
    a = accuracy_score(y_test,predict) * 100
    p = precision_score(y_test, predict,average='macro') * 100
    r = recall_score(y_test, predict,average='macro') * 100
    f = f1_score(y_test, predict,average='macro') * 100
    text.insert(END,"Perceptron Precision : "+str(p)+"\n")
    text.insert(END,"Perceptron Recall : "+str(r)+"\n")
    text.insert(END,"Perceptron FScore : "+str(f)+"\n")
    text.insert(END,"Perceptron Accuracy : "+str(a)+"\n\n")
    accuracy.append(a)
    precision.append(p)
    recall.append(r)
    fscore.append(f)

def runKNN():
    global classifier
    global X_train, X_test, y_train, y_test
    cls = KNeighborsClassifier(n_neighbors = 3)
    cls.fit(X_train,y_train)
    predict = cls.predict(X_test)
    a = accuracy_score(y_test,predict) * 100
    p = precision_score(y_test, predict,average='macro') * 100
```

```
    r = recall_score(y_test, predict,average='macro') * 100
    f = f1_score(y_test, predict,average='macro') * 100
    text.insert(END,"KNN Precision : "+str(p)+"\n")
    text.insert(END,"KNN Recall : "+str(r)+"\n")
    text.insert(END,"KNN FScore : "+str(f)+"\n")
    text.insert(END,"KNN Accuracy : "+str(a)+"\n\n")

    accuracy.append(a)
    precision.append(p)
    recall.append(r)
    fscore.append(f)
    classifier = cls

def runSVM():
    global X_train, X_test, y_train, y_test
    cls = svm.SVC(class_weight='balanced')
    cls.fit(X_train,y_train)
    predict = cls.predict(X_test)
    a = accuracy_score(y_test,predict) * 100
    p = precision_score(y_test, predict,average='macro') * 100
    r = recall_score(y_test, predict,average='macro') * 100
    f = f1_score(y_test, predict,average='macro') * 100
    text.insert(END,"SVM Precision : "+str(p)+"\n")
    text.insert(END,"SVM Recall : "+str(r)+"\n")
    text.insert(END,"SVM FScore : "+str(f)+"\n")
    text.insert(END,"SVM Accuracy : "+str(a)+"\n\n")
    accuracy.append(a)
    precision.append(p)
    recall.append(r)
```

```
    fscore.append(f)

def logisticRegression():
    global X_train, X_test, y_train, y_test
    cls = LogisticRegression(class_weight='balanced')
    cls.fit(X_train,y_train)
    predict = cls.predict(X_test)
    a = accuracy_score(y_test,predict) * 100

  p = precision_score(y_test, predict,average='macro') * 100
    r = recall_score(y_test, predict,average='macro') * 100
    f = f1_score(y_test, predict,average='macro') * 100

    text.insert(END,"Logistic Regression Precision : "+str(p)+"\n")
    text.insert(END,"Logistic Regression Recall : "+str(r)+"\n")
    text.insert(END,"Logistic Regression FScore : "+str(f)+"\n")
    text.insert(END,"Logistic Regression Accuracy : "+str(a)+"\n\n")
    accuracy.append(a)
    precision.append(p)
    recall.append(r)
    fscore.append(f)


def detectAttack():
    text.delete('1.0', END)
    filename = filedialog.askopenfilename(initialdir="Dataset")
    test = pd.read_csv(filename)
    test.fillna(0, inplace = True)
    rawValues = test:
```

```
    rawValues = rawValues.values
    test = test.values
    test = normalize(test)
    predict = classifier.predict(test)
    print(predict)
    for i in range(len(test)):
        if predict[i] == 0:
            text.insert(END,"X=%s, Predicted = %s" % (rawValues[i], ' Attack Observation Detected : ')+"\n\n")
        if predict[i] == 1   text.insert(END,"X=%s, Predicted = %s" % (rawValues[i], '   No Attack Observation Detected : ')+"\n\n")


def graph():

    df = pd.DataFrame([['Perceptron','Precision',precision[0]],['Perceptron','Recall',recall[0]],['Perceptron','F1 Score',fscore[0]],['Perceptron','Accuracy',accuracy[0]],
                       ['KNN','Precision',precision[1]],['KNN','Recall',recall[1]],['KNN','F1 Score',fscore[1]],['KNN','Accuracy',accuracy[1]],
                       ['SVM','Precision',precision[2]],['SVM','Recall',recall[2]],['SVM','F1 Score',fscore[2]],['SVM','Accuracy',accuracy[2]],
                       ['Logistic Regression','Precision',precision[3]],['Logistic Regression','Recall',recall[3]],['Logistic Regression','F1 Score',fscore[3]],['Logistic Regression','Accuracy',accuracy[3]],
                      ],columns=['Parameters','Algorithms','Value'])
    df.pivot("Parameters", "Algorithms", "Value").plot(kind='bar')
    plt.show()
```

```
font = ('times', 14, 'bold')
title = Label(main, text='Machine Learning Methods for Attack Detection in the Smart Grid')
title.config(bg='yellow3', fg='white')
title.config(font=font)
title.config(height=3, width=120)
title.place(x=0,y=5)
,
font1 = ('times', 13, 'bold')
uploadButton = Button(main, text="Upload Smart Grid Dataset", command=upload)
uploadButton.place(x=50,y=100)
uploadButton.config(font=font1)
pathlabel = Label(main)
pathlabel.config(bg='brown', fg='white')
pathlabel.config(font=font1)
pathlabel.place(x=460,y=100)

processButton = Button(main, text="Preprocess Data", command=processDataset)
processButton.place(x=50,y=150)
processButton.config(font=font1)

perceptronButton = Button(main, text="Run Perceptron Algorithm", command=runPerceptron)
perceptronButton.place(x=280,y=150)
perceptronButton.config(font=font1)

knnButton = Button(main, text="Run KNN Algorithm", command=runKNN)
knnButton.place(x=530,y=150)
knnButton.config(font=font1)
svmbutton = Button(main, text="Run Support Vector Machine", command=runSVM)
```

```
svmbutton.place(x=730,y=150)
svmbutton.config(font=font1)

lrButton = Button(main, text="Run Logistic Regression", command=logisticRegression)
lrButton.place(x=50,y=200)
lrButton.config(font=font1)

detectButton = Button(main, text="Detect Attack from Test Data", command=detectAttack)
detectButton.place(x=280,y=200)
detectButton.config(font=font1)

graphButton = Button(main, text="All Algorithms Performance Graph", command=graph)
graphButton.place(x=530,y=200)
graphButton.config(font=font1)


font1 = ('times', 12, 'bold')
text=Text(main,height=20,width=150)
scroll=Scrollbar(text)
text.configure(yscrollcommand=scroll.set)
text.place(x=10,y=250)
text.config(font=font1)


main.config(bg='burlywood2')
main.mainloop()
```

CHAPTER 4
RESULTS AND DISCUSSION

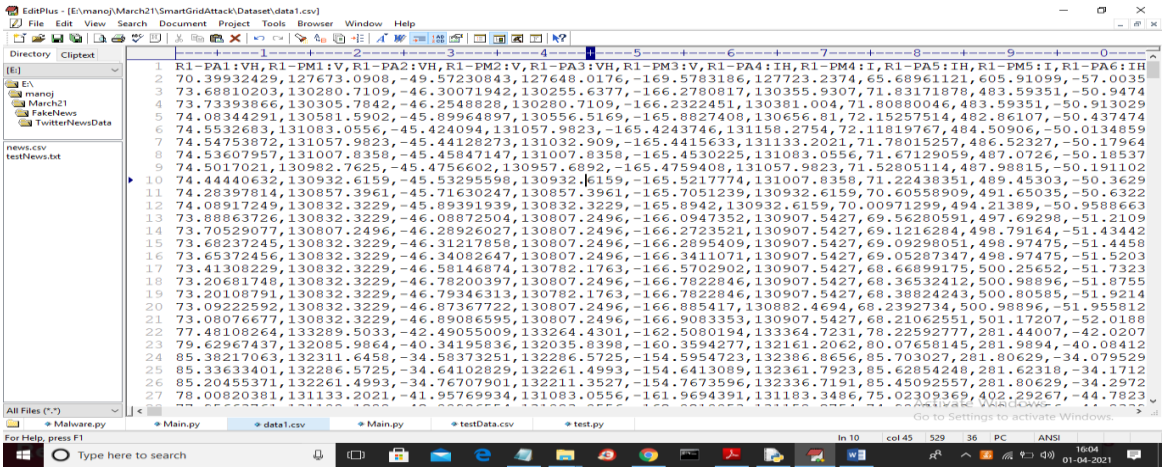
RESULTS AND DISCUSSION

3.1 Performance metrics

Using KNN, SVM, Perceptron, and Logistic Regression algorithms, the results and discussions for machine learning methods in attack detection within the smart grid emphasize unique performances and trade-offs. KNN is easy to use and effective at identifying assaults; it performs well, especially in situations where the normal and anomalous data points are well-defined clusters. However, the curse of dimensionality may cause its performance to deteriorate in high-dimensional spaces. SVM exhibits significant generalization capabilities and is robust when handling non-linear decision boundaries. However, proper kernel tuning and selection are critical to its efficacy, which presents difficulties in intricate and dynamic smart grid contexts. Perceptrons are known for their agility in online learning and their capacity to adapt to shifting attack patterns. However, they can have performance concerns with convergence and become susceptible to noisy input. The best is Logistic Regression.

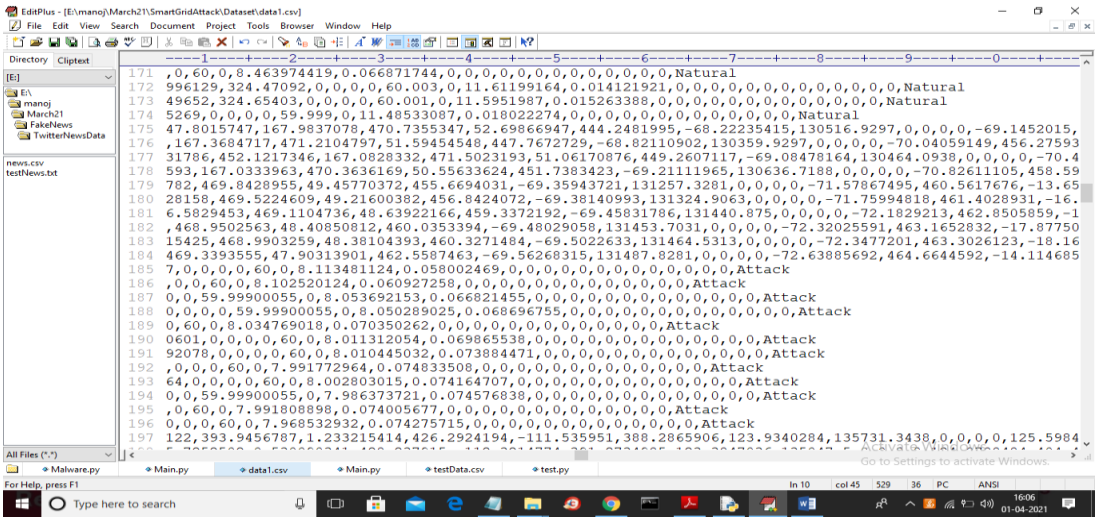
4.1 Output Screens :

1) To implement this project we are using dataset shown in below screen



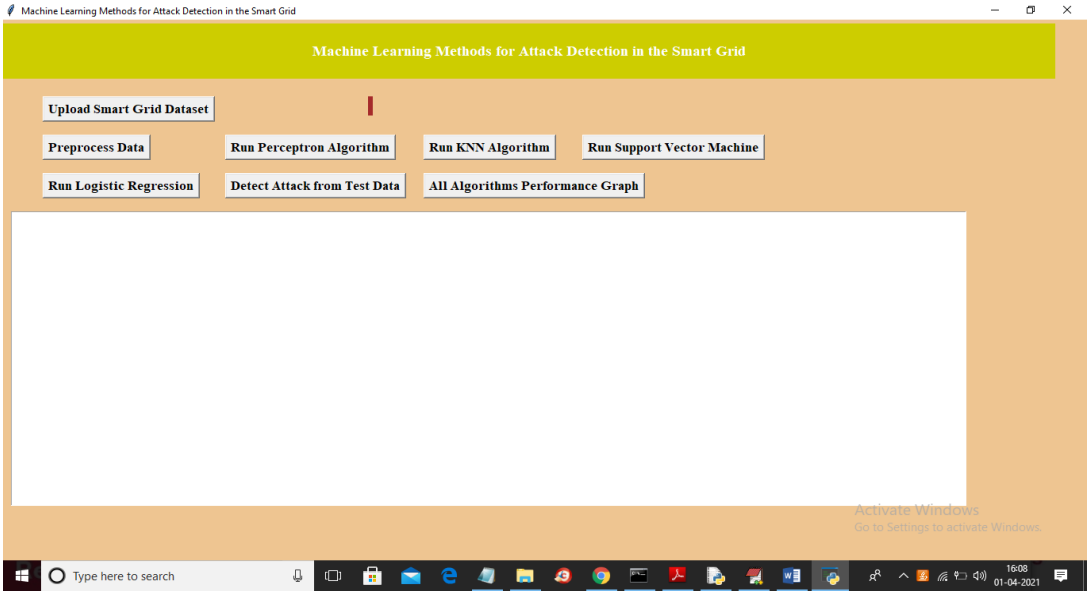
In above dataset screen first record contains column names and other records contains columns values and all those values are called as power vector generated from smart grid system and each record is associated with 2 labels called ‘ATTACK’ or ‘NATURAL’ where attack means record contains attack vector or natural means normal vector.

2)

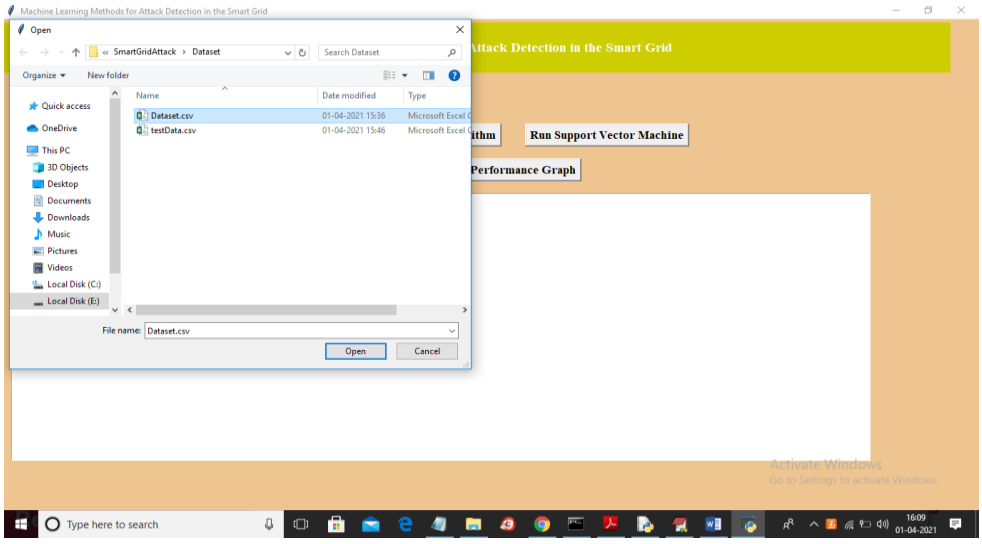


In above screen each record contains 192 column values and in last column we have values as Natural or Attack and we will use above dataset to train all 4 machine learning algorithms.

3) To run project double click on 'run.bat' file to get below screen

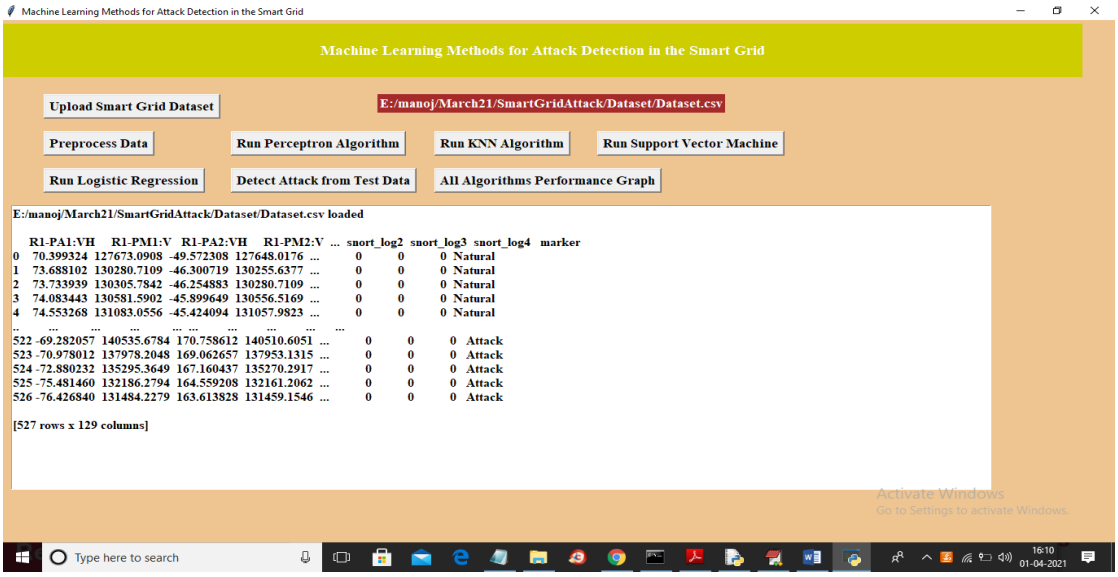


4) In above screen click on 'Upload Smart Grid Dataset' button and upload dataset



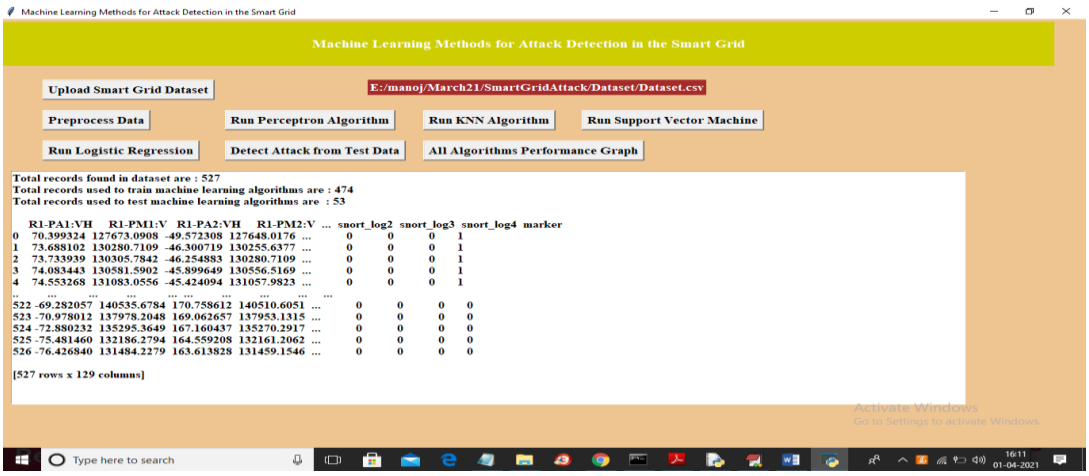
In above screen we are selecting and uploading 'Dataset.csv' file and then click on 'Open' button to load dataset and to get below screen

5)



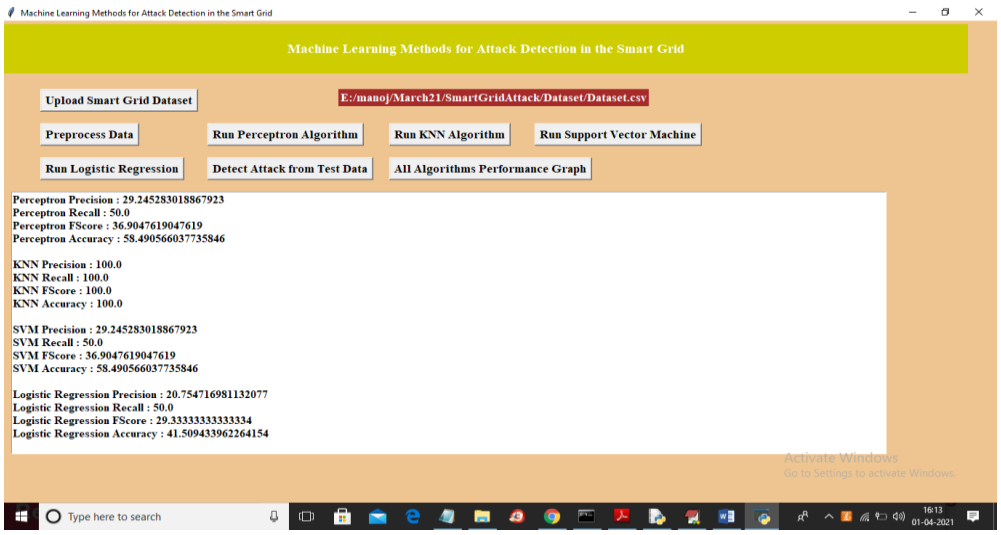
In above screen dataset loaded and we can see above dataset showing non-numeric values and to replace them click on 'Preprocess Data' to replace with numeric values.

6)



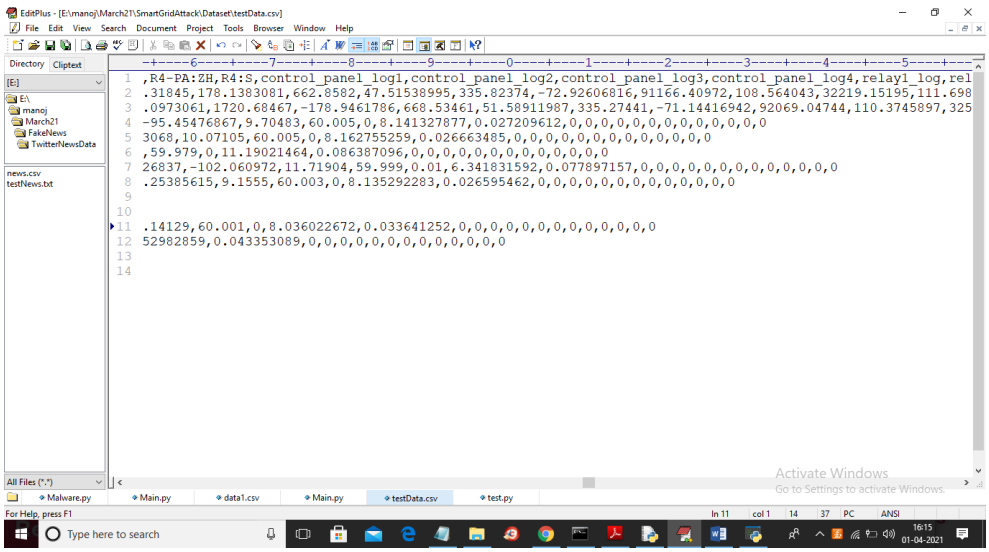
In above screen all string values and missing values are replace with numeric values and in above screen in first 3 lines we can see dataset contains total 527 records and application using 474 records to train ML and 53 records to test ML accuracy. Now dataset is ready with train and test parts and now click on 'Run Perceptron Algorithm' button to train perceptron algorithm on above dataset and to get its accuracy

7)



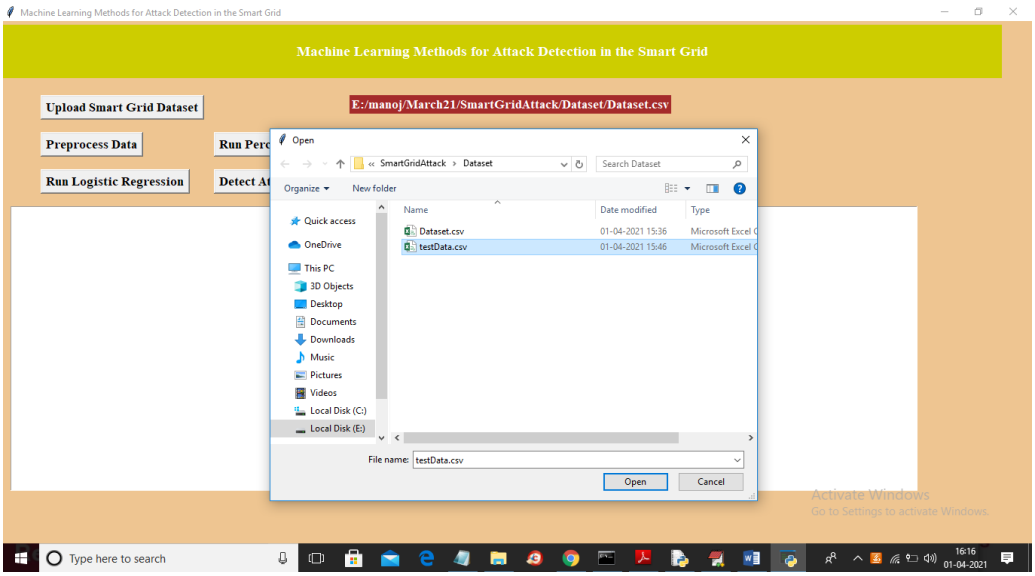
In above screen I clicked on all 4 algorithms button and then we got accuracy, precision, recall and FSCORE of each algorithm and in all algorithm KNN is giving better performance result. Now we can upload test data and then ML algorithm will predict class label as normal or attack. In below test data we can see we have vector values but we don't have class label and this class label will be predicted by ML.

8)



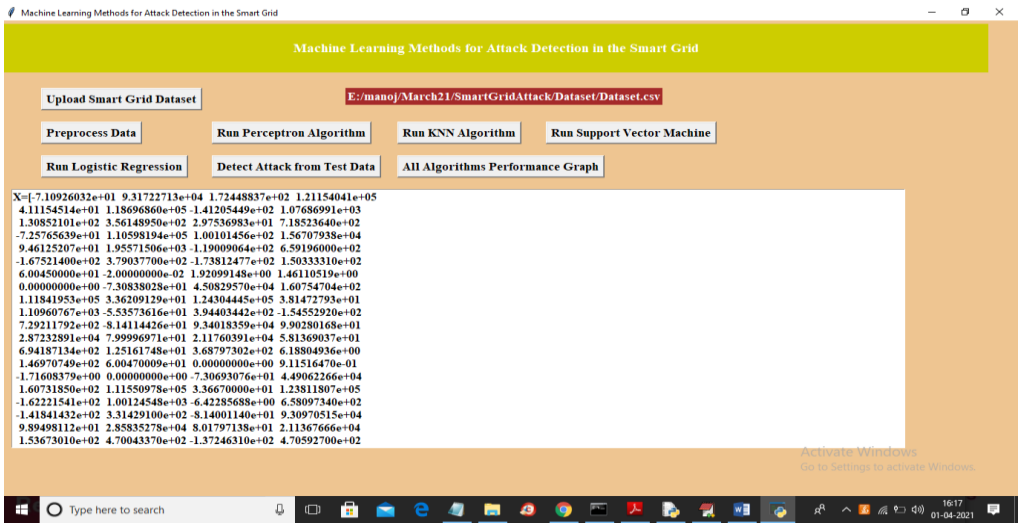
In above test dataset screen we don't have class label as natural or attack and now we will upload above dataset to application and then ML predict class label for each record. Now click on 'Detect Attack from Test Data' button to get below screen

9)



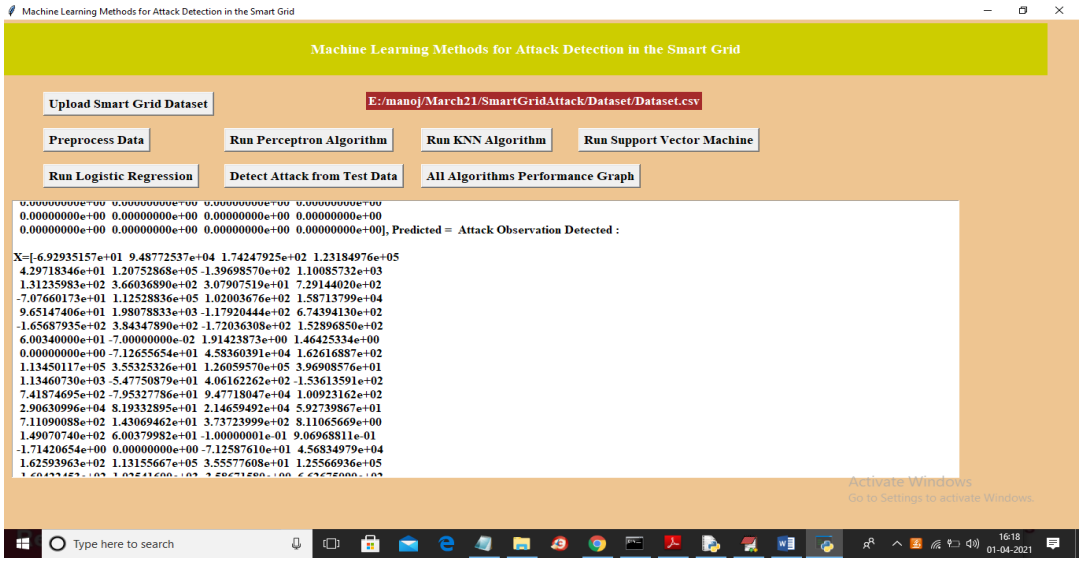
In above screen selecting and uploading 'testData.csv' file and then click on 'Open' button to get below result

10)



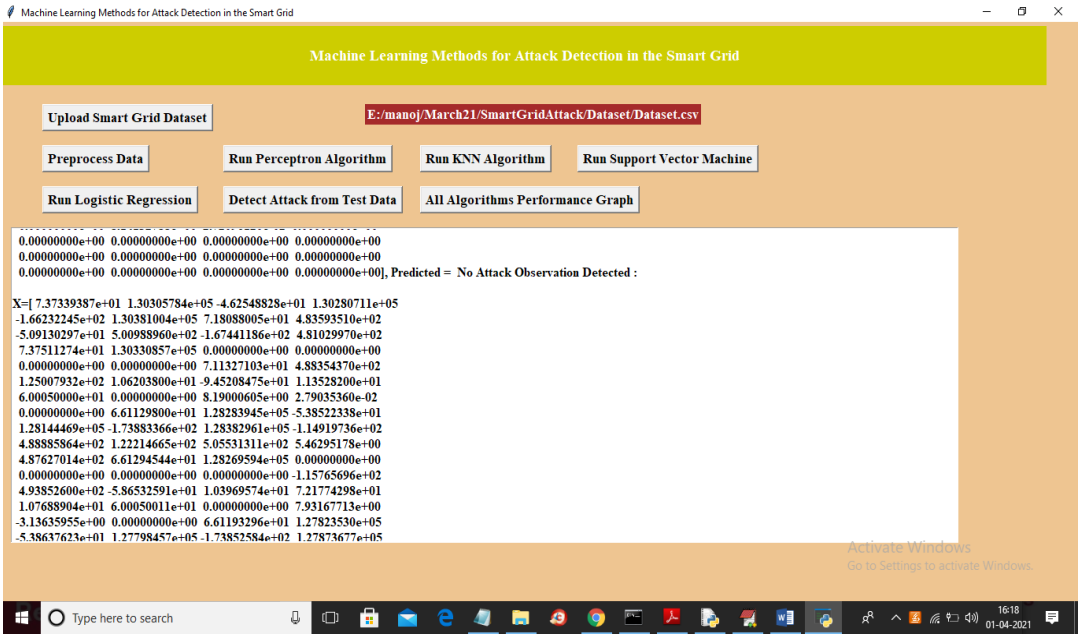
In above screen in square bracket we have grid vector values and after square bracket we can see predicted result as below screen and to see predicted result just scroll down above screen textarea.

11)



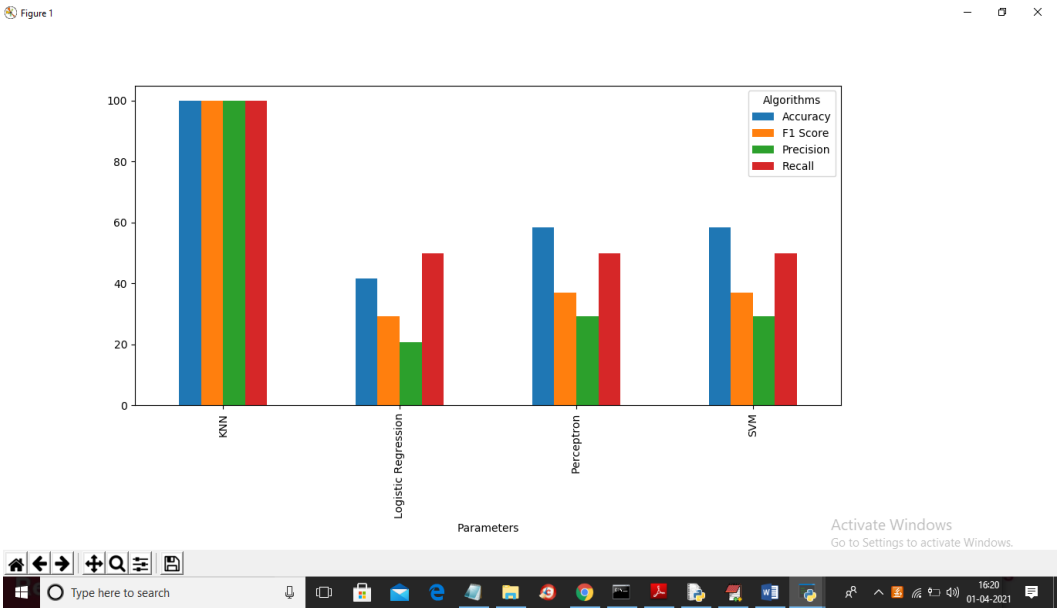
In above screen we can see predicted result as ATTACK observation values detected

12)



In above screen we can see NO attack detected for 4th records and similarly scroll down to see each record prediction result. Now click on 'All Algorithms Performance Graph' button to get below graph

4.2 Performance Metrics :



Fig(4.2) Performance Metric

In above graph x-axis represents algorithm name and y-axis represents accuracy, precision, recall and FSCORE for each algorithm and from above graph we can say KNN is giving better result.

CHAPTER 4
CONCLUSION

CHAPTER 4

CONCLUSION

The study addresses the attack detection problem in smart grid systems, redefined as a machine learning challenge, where various algorithms are evaluated across different scenarios. Results indicate that state-of-the-art machine learning approaches outperform traditional SVE-based detection methods. Notably, perceptron exhibits lower sensitivity, while k-NN's performance varies with system size and data imbalance. SVM outperforms other algorithms in large-scale systems, with a notable phase transition at $\kappa*$, the threshold of accessible measurements for constructing unobservable attacks. However, SVM's performance is affected by kernel selection and system sparsity. Semisupervised methods, Adaboost, and MKL fusion techniques offer robustness against system changes and sparsity, albeit with higher computational complexity. Online learning algorithms show comparable performance to batch methods. Future research aims to extend these methods to attack classification, explore noise and bias-variance relationships, and consider nonstationary distributions, such as concept drift and dataset shift, for enhanced detection in smart grid systems.

REFERENCES

REFERENCES

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GITHUB LINK :

https://github.com/ShivaCharan12/ShivaCharan-Major-Project-Machine-Learning-Methods-for-Attack-Detection-in-the-Smart-Grid