### 1. INTRODUCTION

### 1.1 Project Overview

## 1.1.1 Technical Terminology

	Advanced Analytics Software System: A software solution utilizing		
	sophisticated data analysis techniques to identify patterns indicative of fraud.		
	Predictive Framework: An algorithmic model that forecasts potential fraudulent		
	activities by differentiating between normal and anomalous energy usage		
	patterns.		
☐ Technical and Non-Technical Losses: Technical losses refer to			
	during transmission and distribution, while non-technical losses are usually		
	associated with electricity theft or other forms of fraud.		
	Consumption Patterns: The habitual use of electricity by consumers, which can		
	be analysed to detect irregularities.		
	Meter Tampering and Covert Connections: Illegal practices to alter the meter		
	reading or connect directly to the energy supply to avoid billing.		

#### 1.1.2 Problem Statement

In recent years, there has been a substantial increase in fraudulent behaviour and illegal connections within the electricity distribution network, as reported by energy companies. This illicit activity not only compromises the integrity of the distribution system but also poses a considerable challenge to the companies affected by it.

Fraudulent behaviour in the context of electricity distribution refers to a range of actions, such as tampering with meters, bypassing meters altogether, or modifying billing information to reduce or avoid paying for the electricity consumed. These actions may be carried out by individuals, commercial entities, or even organized crime groups looking to profit from the illegal sale of electricity.

Illegal connections, on the other hand, involve unauthorized connections to the electricity grid. These connections can be made by tapping into existing power lines or by creating makeshift connections to the distribution network. Such unauthorized connections not only pose a threat to the safety and stability of the grid but also contribute to the loss of revenue for energy companies. These behaviours often result in a discrepancy between the amount of energy declared by the consumer and the amount actually used. This discrepancy leads to accounting issues, as the energy company is unable to accurately track and bill for the electricity consumed. In turn, this results in significant financial losses for the company, as it is unable to recover the costs of producing and distributing the electricity.

Moreover, these fraudulent practices and illegal connections can lead to other consequences, such as:

- ☐ Increased operational costs: Energy companies must allocate additional resources to identify, investigate, and combat these illegal activities, which further strains their finances.
- Unreliable electricity supply: Illegal connections can overload the distribution network and cause power outages, which affects not only those involved in fraudulent behaviour but also legitimate consumers.
- □ Safety hazards: Tampering with electricity meters and illegal connections can lead to fires, electrocution, or other accidents, posing a danger to the public and utility workers.
- ☐ Environmental impact: The loss of revenue for energy companies may lead to reduced investments in renewable energy sources and energy efficiency initiatives, hampering efforts to combat climate change.

#### 1.1.3 Goal

The goal of the capstone project is to develop an advanced analytics software system that can detect, mitigate, and deter fraudulent behaviour within electricity distribution networks, ensuring integrity and security. This system aims to reduce financial losses due to fraud and increase the operational efficiency of energy companies.

### 1.1.4 Solution

The solution is a predictive software framework that analyses individual customer consumption patterns to distinguish between technical and non-technical losses. The framework involves a tiered approach where:

Tier 1 Engineers: provide a broad analysis of potential fraud hotspots.

Tier 2 Engineers: review detailed consumption histories to pinpoint suspicious activity.

Tier 3 Engineers: conduct on-site inspections to gather physical evidence of fraud.

The system is designed to enhance the precision of fraud detection and enable energy companies to take swift, decisive actions against fraudulent activities, thereby safeguarding the financial interests and operational integrity of the energy distribution infrastructure.

### 1.2 Need Analysis

Energy fraud stands as a formidable challenge that reverberates across governments, utility companies, and consumers, precipitating far-reaching financial and societal consequences. In light of its potential to escalate energy costs, erode revenue streams for utilities, and erode public trust in energy systems, addressing energy fraud emerges as a pressing imperative. The urgency surrounding the detection and prevention of energy fraud necessitates the exploration and implementation of innovative projects aimed at safeguarding the integrity of energy distribution networks.

#### **Economic Implications:**

The economic ramifications of energy fraud are substantial and multifaceted. Consumers find themselves subjected to unjustly inflated energy costs due to fraudulent activities, burdening household budgets and straining individual finances. In parallel, utility companies experience dwindling revenues as a result of underreported or entirely unbilled energy consumption. Consequently, revenue shortfalls hinder vital investments in infrastructure maintenance, network upgrades, and renewable energy integration. Projects that focus on energy fraud detection hold the potential to alleviate this financial strain by enabling swift identification of fraudulent behaviour and primitive measures.

#### Trust and Reliability:

Trust is the cornerstone of any functional energy system, and energy fraud corrodes this trust by casting doubts on the accuracy and transparency of billing practices. The resulting skepticism can erode consumer confidence in the energy system's fairness and accountability. Projects oriented towards energy fraud detection and prevention extend a lifeline to restore this eroded trust. By ensuring accurate billing and transparent consumption tracking, these projects facilitate improved customer relations and engender a renewed sense of credibility in energy providers.

### **Stability and Sustainability:**

Energy fraud has a propensity to disturb the delicate equilibrium of energy distribution networks. Unsanctioned connections and manipulation of consumption data can lead to network instability, resulting in power outages and supply disruptions. This instability has ripple effects on various sectors, impacting industries, healthcare facilities, and households alike. Implementing projects that identify and thwart fraudulent behaviour bolsters the stability of energy systems, mitigates network strain, and contributes to a seamless and dependable energy supply.

#### **Equity and Environmental Concerns:**

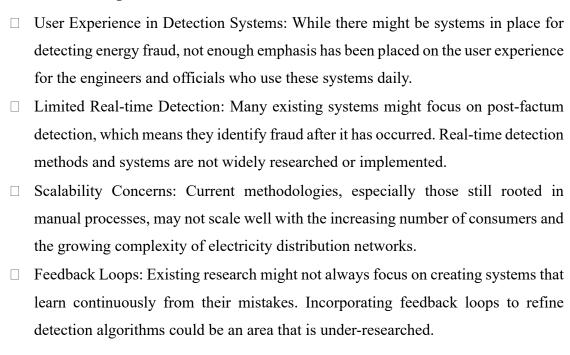
The issue of energy fraud transcends financial matters, touching upon principles of equity and environmental responsibility. Ensuring that every consumer pays their rightful share of energy costs is a matter of fairness, eradicating the exploitation that arises from fraudulent practices. Furthermore, energy fraud often correlates with excessive energy consumption, intensifying greenhouse gas emissions and exacerbating environmental degradation. Projects focusing on energy fraud detection not only promote equitable energy usage but also contribute to the reduction of carbon footprints by curbing energy wastage.

### **Sustainability and Beyond:**

By delving into the realm of energy fraud detection and prevention, these projects address a nexus of critical concerns: economic viability, trust restoration, network stability, equity, and environmental sustainability. The significance of this work reverberates not only within the energy sector but across society as a whole. The outcomes of these projects have the potential to generate substantial cost savings, promote responsible energy consumption habits, foster a sense of community trust, and tangibly contribute to environmental preservation.

In conclusion, the dire need to curb energy fraud is underscored by its pervasive impact on consumers, utility companies, and the broader energy landscape. Projects centred around energy fraud detection and prevention assume a paramount role in rectifying this challenge. Their ability to restore economic equilibrium, bolster trust, fortify network stability, ensure equitable energy consumption, and advance environmental responsibility establishes these projects as critical pillars of a resilient, sustainable, and equitable energy future.

### 1.3 Research Gaps



### 1.4 Problem Definition and Scope

In recent years, there has been a substantial increase in fraudulent behaviour and illegal connections within the electricity distribution network, as reported by energy companies. This illicit activity not only compromises the integrity of the distribution system but also poses a considerable challenge to the companies affected by it.

Fraudulent behaviour in the context of electricity distribution refers to a range of actions, such as tampering with meters, bypassing meters altogether, or modifying billing information to reduce or avoid paying for the electricity consumed. These actions may be carried out by individuals, commercial entities, or even organized crime groups looking to profit from the illegal sale of electricity.

Illegal connections, on the other hand, involve unauthorized connections to the electricity grid. These connections can be made by tapping into existing power lines or by creating makeshift connections to the distribution network. Such unauthorized connections not only pose a threat to the safety and stability of the grid but also contribute to the loss of revenue for energy companies.

These behaviours often result in a discrepancy between the amount of energy declared by the consumer and the amount actually used. This discrepancy leads to accounting issues, as the energy company is unable to accurately track and bill for the electricity consumed. In turn, this results in significant financial losses for the company, as it is unable to recover the costs of producing and distributing the electricity.

Moreover, these fraudulent practices and illegal connections can lead to other consequences, such as:

- Increased operational costs: Energy companies must allocate additional resources to identify, investigate, and combat these illegal activities, which further strains their finances.
- Unreliable electricity supply: Illegal connections can overload the distribution network and cause power outages, which affects not only those involved in fraudulent behaviour but also legitimate consumers.
- Safety hazards: Tampering with electricity meters and illegal connections can lead to fires, electrocution, or other accidents, posing a danger to the public and utility workers.

• Environmental impact: The loss of revenue for energy companies may lead to reduced investments in renewable energy sources and energy efficiency initiatives, hampering efforts to combat climate change.

### 1.5 Assumptions and Constraints

S.No.	Assumptions
1	Smart Meter Integration: The project rests on the premise that each residence is equipped with smart meters capable of capturing real-time and accurate energy consumption data. This foundation enables the model to delve into the nuances of consumption patterns and make informed assessments.
2	Daily Consumption Data: The availability of daily consumption data for each consumer forms a pivotal cornerstone. This data, harnessed for analysis, empowers the model to discern minute variations and anomalies in consumption patterns that might point towards fraudulent activities.

Table 1: Assumptions

S.No.	Constraints
1	Real-Time Adaptation: While the model undergoes initial training on existing datasets, its true efficacy emerges when it is tailored to the unique intricacies of each utility company's real-time data. This transition is paramount to achieve optimal performance and ensure the model's adaptability to the dynamic energy landscape.
2	Household Focus: The model's framework has been meticulously designed to align with residential energy consumption patterns. It is essential to acknowledge that industrial energy consumption patterns, characterized by distinct dynamics, fall beyond the scope of this particular model. As a result, the model's efficacy and accuracy cannot be extended to industrial contexts without further development and tailoring.

Table 2: Constraints

These assumptions and constraints collectively underscore the foundational principles of our capstone project. By leveraging smart meter technology and analysing daily consumption data, the project seeks to forge a cutting-edge solution that identifies fraudulent behaviours. While the model demonstrates promising capabilities, its true potential hinges on the seamless integration of real-time data from utility companies. Additionally, the model's specialized focus on residential energy patterns serves as a reminder that industrial contexts warrant separate consideration and tailored approaches. Through these assumptions and constraints, our project navigates the intricate landscape of energy fraud detection, innovation, and adaptability.

# 1.6 Standards

Data Privacy Standards: Ensure compliance with data privacy regulations such as
GDPR (General Data Protection Regulation) or local equivalents. Implement
rigorous data anonymization and protection measures to safeguard consumers'
sensitive information.
Model Development Standards: Adhere to best practices for machine learning
model development. This includes data preprocessing, feature engineering,
hyperparameter tuning, cross-validation techniques, and model evaluation.
Data Quality Standards: Maintain high standards for data quality and integrity.
Implement data cleansing and validation procedures to address missing values,
outliers, and inconsistencies in the dataset.
Transparency and Explainability: Develop models that are interpretable and provide
insights into how predictions are made. Document the model's decision-making
process and ensure transparency in feature selection and importance.
Model Evaluation Metrics: Define a set of evaluation metrics tailored to fraud
detection, such as Precision, Recall, F1-Score, and AUC-ROC. Establish a
benchmark performance level that the model must meet or exceed.
Bias and Fairness Considerations: Assess and mitigate potential biases in the data
and model predictions to ensure fairness in fraud detection, particularly with respect
to demographic and socioeconomic factors.
Model Validation: Implement robust validation techniques, including cross-
validation and out-of-time validation, to assess the model's generalization
performance and stability over time.
Monitoring and Maintenance: Establish protocols for continuous model monitoring
and maintenance. Periodically retrain the model with updated data to adapt to
evolving fraud patterns.
Documentation Standards: Maintain comprehensive documentation of the entire
project, including data sources, preprocessing steps, model development,
validation, and deployment procedures. This documentation aids in audits and
transparency.
Regulatory Compliance: Ensure compliance with industry-specific regulations and
standards related to fraud detection in the energy sector, if applicable

	Deployment Standards: Follow best practices for deploying machine learning						
	models in a production environment, including version control, containerization,						
	and monitoring of model performance in real-time.						
	Ethical Guidelines: Implement ethical guidelines that guide the project's decision-						
	making process, ensuring ethical considerations in all aspects of the project.						
	Collaboration and Reporting: Establish clear communication and reporting						
standards for collaboration among project team members and stal-							
	Regularly report on model performance, detected fraud cases, and false						
	positives/negatives.						
4 = 1							
1.7 A	Approved Objectives						
	Identifying fraudulent use of resources in order to minimize its effects and reduce						
	the economic impact in terms of both money and time.						
	Optimizing the number of checks using the results from analysis. This way the						
	investment on the service can be redeemed on a short term by avoiding costs						
	incurred by unnecessary checks.						
	Develop a system that can be adapted, enhanced and renewed to several kinds of						
	energy distribution and different geographical areas. Thus, guaranteeing the best						
	model of fraud detection depending on the particular needs of every client.						
1.8 N	Aethodology Used						
	Requirement gathering and analysis.						
	Data Extraction and Preparation						
	Researching and learning the required machine/deep learning techniques.						
	Selection of Input/output Parameters for our model						
	Generation of Training and Validation Datasets						
	Training the model						
	Prediction						
	Researching and learning the required technical frameworks.						
	Designing a user-friendly interface for all tiers involved, i.e., Executive Engineer,						
	Junior Engineer and Inspector.						
	Designing the required database schema.						
	Integrating frontend and backend with our designed ML model.						

Containerizing the application using Docker.
 Deploying the application.
 Stress testing the deployed portal.
 Adding additional features as and when required.

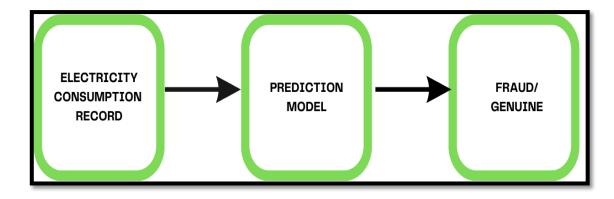


Fig 1: Methodology

## 1.9 Project Outcomes and Deliverables

The designed portal will streamline the process by leveraging the expertise of three types of engineers and utilizing data analysis to identify potential fraud sites.

### Tier 1 Engineers-City-wide View and Site Selection

- ☐ Utilize the software system to obtain a city-wide view of potential fraud
- ☐ Manually select or deselect sites based on the software's analysis and their expertise

#### **Tier 2 Engineers-Electricity Consumption Analysis**

- □ Receive detailed electricity consumption history of homes in areas with potential fraud
   □ Selectively choose homes to inspect based on their analysis of consumption data and
  - patterns

#### **Tier 3 Engineers - On-site Inspection and Evidence Collection**

- ☐ Visit selected homes to inspect for signs of fraud
- Document findings, take pictures, and submit comprehensive reports
- ☐ If sufficient evidence is gathered, initiate an official raid to hold perpetrators accountable

By detecting instances of fraudulent energy use, it is possible to take corrective action to prevent further wastage of energy and ensure that resources are being used in a responsible and sustainable manner. This can result in significant cost savings, improved efficiency, and reduced environmental impact, making it a valuable investment for businesses and individuals alike.

### 1.10 Novelty of Work

The energy fraud detection capstone project stands as a pioneering endeavour, introducing novel approaches and contributions to the field of energy distribution security. What sets this project apart is its innovative amalgamation of advanced analytics, machine learning, and real-time adaptability to combat fraudulent activities within electricity distribution networks.

At the heart of its novelty lies the integration of real-time data adaptation into the fraud detection model. While existing research has predominantly focused on training models on historical data, our project takes a dynamic leap forward by acknowledging the inherent complexities of real-time data. This novel approach addresses the challenges of data drift, shifting patterns, and evolving fraud tactics that emerge when models encounter dynamic and live data streams. This adaptation showcases the project's proactive stance towards addressing contemporary challenges that impact the efficacy of fraud detection systems.

Furthermore, the project's extension into the industrial realm presents an additional layer of innovation. While fraud detection has primarily targeted residential energy consumption, our project acknowledges the distinct energy consumption patterns of industrial sectors. This extension showcases the project's versatility and the foresight to account for nuances in diverse sectors, thereby contributing to a comprehensive and inclusive energy security framework.

The incorporation of explainable AI techniques adds another layer of ingenuity to the project. By offering transparency into the decision-making processes of the model, the project cultivates a sense of trust and accountability, ensuring that outcomes are understandable and justifiable. This emphasis on explainability aligns with the evolving discourse on ethical AI deployment, especially in high-stakes domains such as energy distribution.

Lastly, the project's exploration of legal and ethical implications demonstrates its comprehensive approach towards responsible technology deployment. The nuanced understanding of potential false positives and their consequences underscores the project's commitment to safeguarding the rights and interests of both consumers and utility companies.

In summation, the novelty of the energy fraud detection capstone project rests upon its convergence of real-time adaptation, industrial sector inclusion, explainable AI integration, and comprehensive ethical considerations. This unique synthesis positions the project as a trailblazer in the realm of energy security, contributing substantively to the advancement of knowledge and practice in the field.

## 2. REQUIREMENT ANALYSIS

### 2.1. Literature Survey

### 2.1.1. Theory Associated With Problem Area

In recent years, there has been a notable surge in fraudulent activities and illicit connections within the electricity distribution network, as reported by energy companies. These activities encompass meter tampering, meter bypassing, and manipulation of billing information, all with the intent to evade payment for electricity. These actions can be perpetrated by individuals, businesses, or organized crime syndicates seeking to profit from the unlawful sale of electricity. Illegal connections pertain to unauthorized links to the electricity grid, which can involve tapping into existing power lines or creating makeshift connections. These connections not only jeopardize the safety and stability of the grid but also lead to revenue losses for energy companies. They create disparities between the declared and actual energy consumption, resulting in accounting challenges and significant financial setbacks for energy providers, who are unable to recoup the costs associated with electricity production and distribution.

## 2.1.2. Existing Systems and Solutions

Historically, the domain of energy fraud detection was heavily reliant on traditional methods. These methods, which included:

☐ manual meter readings

- physical inspections
- □ sporadic spot checks

were the primary tools employed by utility providers. While these techniques offered a certain degree of success, they were not without their limitations. The most significant challenges were their labour intensive nature, limited scalability, and their inability to detect sophisticated frauds. The technological revolution heralded a new age of automated, data-driven solutions.

## 2.1.3. Research Gaps of Existing Literature

Following are the observations in our Research Findings:

S.No	Paper Title	Tools/Techno	ology	Findings	Citations
1.	Theft detection dataset for benchmarking and machine learning based classification in a smart grid environment	KNN, DT, Bagging, ANN.	RF, and	This paper introduces a novel theft detection dataset for assessing various automatic classification methods in categorizing theft instances. The study also reports initial experiments with machine learning algorithms, including KNN, DT, RF, Bagging, and ANN. The results indicate that these machine learning approaches effectively identify different theft types in smart meter data. While the paper doesn't elaborate on the data labelling process, it mentions that various theft scenarios, like meter tampering, bypassing, and replacement, were randomly and fairly applied to create the dataset. Confusion matrices derived from these scenarios were used to compute True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) for performance assessment.	[1]

2.	Review of the Data- Driven Methods for Electricity Fraud Detection in Smart Metering Systems	Python	The paper's key findings include the effectiveness of data-driven methods, particularly deep learning, in detecting electricity fraud within smart grid systems. It also discusses strategies for preserving consumer privacy while ensuring accurate fraud detection, along with the importance of building robust detection systems to resist adversarial attacks. The paper conducts a comprehensive comparison of existing research and provides insightful recommendations for future directions in electricity fraud detection.	[2]
3.	An Energy-Fraud Detection-System Capable of Distinguishing Frauds from Other Energy Flow Anomalies in an Urban Environment	Automation	The paper presents a novel algorithm that utilizes specialized knowledge and AI to improve fraud detection accuracy and reduce false positives in urban energy systems.  Additionally, the paper presents a mathematical foundation for energy fraud detection and identifies major phenomena that can disguise or affect it.  Overall, the research provides valuable insights and tools for improving energy fraud detection in urban environments.	[3]

Table 3: Research Gaps

### 2.1.4. Problem Identified

The surge in fraudulent activities and unauthorized connections within electricity distribution networks has emerged as a pressing concern for energy companies. These illicit activities, which range from meter tampering to outright bypassing of meters, undermine the very integrity of the distribution system. Furthermore, they not only result in significant financial implications for companies but also destabilize the network, putting both legitimate consumers and the grid at risk.

This burgeoning issue is further complicated by the discrepancies observed between declared and actual energy consumption. Such discrepancies skew accounting, making accurate billing a challenge, and thus, exacerbating the financial losses incurred by energy companies. The ramifications of these fraudulent activities are multifaceted, encompassing:

- Economic Strain: Energy companies face heightened operational costs as they grapple with the need to allocate more resources towards identifying, investigating, and mitigating these fraudulent actions.
   Network Instability: Unauthorized connections have the potential to overload the system, leading to power disruptions that affect a wider consumer base, beyond just those involved in fraudulent activities.
   Safety Concerns: The direct tampering of electricity infrastructure, be it meters or connections, poses severe safety hazards, including the risks of fires, electrocution, and other potential accidents that endanger public safety and the well-being of utility workers.
   Environmental Impact: The financial strain on energy companies might lead to a decreased emphasis on renewable energy investments and energy.
- Environmental Impact: The financial strain on energy companies might lead to a decreased emphasis on renewable energy investments and energy conservation initiatives, thereby hindering global efforts to address climate change.

Given this backdrop, it becomes evident that the current solutions, particularly those that predominantly rely on manual interventions, are woefully inadequate. There is an urgent need for a comprehensive, technologically advanced approach to bridge the evident gaps in real-time fraud detection, ensuring both accuracy and operational efficiency.

### 2.1.5. Survey of Tools and Technologies Used

- ☐ Machine Learning Algorithms: These algorithms, built on intricate computational models, are adept at analysing complex energy consumption behaviours, offering rapid and precise anomaly detection.
- □ **Data Mining Techniques:** Rooted in robust algorithms, data mining techniques dive deep into extensive datasets, revealing crucial patterns and insights related to energy consumption.
- □ Portal/Software Interface: An ergonomically designed digital platform, tailored to accommodate the multi-layered operational structure of utility providers. This platform facilitates everything from deep data analytics to the submission of evidence pointing towards fraud, ensuring a streamlined workflow.

### 2.2. Software Requirement Specification

#### 2.2.1. Introduction

#### **2.2.1.1.** Purpose

The Energy Fraud Detection Portal, at its core, is conceived as an avant-garde solution, meticulously designed to revolutionize the fraud detection paradigm. By harnessing the computational prowess of machine learning algorithms coupled with data mining techniques, the portal is envisioned to serve as the vanguard in the battle against energy fraud, streamlining processes and elevating operational efficiency.

### 2.2.1.2. Intended Audience and Reading Suggestions

This document is intended for:

- 1. Developers who will design and implement the system it sets the roadmap for future development.
- 2. Project testers can make use of this document to design the testing strategy, as some bugs can be found easily by conforming to a requirements document. This way, the testing process becomes much more organized.
- 3. Anyone who wishes to read about the project and its functions.

Further sections contain a comprehensive description of the project, its functionality and the requirements.

### 2.2.1.3. Project Scope

The project is designed to identify electricity theft and deceptive practices by examining the power consumption trends of users. This analysis will incorporate various vital aspects such as billing records, reading comments, and the specific regions of the load being studied. With the aid of machine learning, the system will pinpoint irregularities that hint at fraudulent activities. By recognizing dishonest consumers, the project will mitigate the substantial economic repercussions stemming from illicit electricity consumption. This will, in turn, elevate the service quality provided by electric utility companies. Moreover, the insights derived from this project can be instrumental for power providers, particularly in emerging nations. They can strategize their smart meter deployment initiatives in fraud-prone zones, streamlining their transition both operationally and financially.

## 2.2.2. Overall Description

## 2.2.2.1. Product Perspective

The "Energy Fraud Detection" system is a user-friendly web-based portal designed to tackle the issue of fraudulent activities in electricity distribution networks. It offers different access levels for Tier 1, Tier 2, and Tier 3 engineers, as well as an administrative interface for employee management.

For Tier 1 engineers, the portal provides a city-wide view and analytics tools to monitor system performance. They can assign priority to regions, view potential fraud sites, and access comprehensive reports. Tier 2 engineers analyse electricity consumption history, compile a list of potential defaulters, and select homes for inspection. Tier 3 engineers conduct on-site inspections, capturing photographs and submitting remarks through the portal.

Administrators manage employee registration and details to ensure smooth operations. The ML Model uses advanced algorithms to detect fraudulent consumption patterns, leveraging historical and real-time data.

The system integrates with external systems and facilitates communication for streamlined processes. It optimizes resources, minimizes financial losses, and promotes responsible energy usage.

In summary, the "Energy Fraud Detection" system is an intelligent and user-friendly solution for electricity distribution companies. It empowers engineers, enhances fraud detection, inspection processes, and reporting capabilities, and enables efficient resource utilization.

#### 2.2.2.2. Product Features

Some possible features include:

- 1. **User Authentication and Role-based Access:** Secure user login with authentication to ensure authorized access, and role-based access control to provide different levels of functionality based on user roles.
- 2. **Dashboard and Analytics:** A comprehensive dashboard with visualizations and analytics tools to monitor and analyse system performance, track potential fraud sites, view region-wise reports, and detect anomalies in electricity consumption patterns.
- 3. **Real-time Data Integration:** Integration with smart meters and other data sources to collect real-time electricity consumption data for immediate detection and response to fraudulent activities.

- 4. **Machine Learning Algorithms:** Implementation of advanced machine learning algorithms to analyse consumption data, identify patterns, and detect anomalies that indicate potential fraud.
- 5. **Fraud Risk Assessment:** Assessing the risk level of each customer based on their consumption patterns and historical data to prioritize inspection and investigation efforts.
- 6. **Inspection Management:** A system for managing inspections, assigning tasks to Tier 3 engineers, and tracking the progress and outcomes of inspections.
- 7. Evidence Collection and Documentation: Capture and store site photographs, inspection remarks, and other relevant evidence securely within the system for record-keeping and further analysis.
- 8. **Reporting and Alerts:** Generate comprehensive reports on detected fraud cases, inspection outcomes, and system performance. Automated alerts and notifications to relevant stakeholders regarding potential fraud sites, inspection assignments, and updates.
- 9. **Integration with External Systems:** Integration with existing electricity distribution, billing, and customer management systems to facilitate seamless data exchange and enhance operational efficiency.
- 10. **Scalability and Customizability:** The ability to scale the system to handle large amounts of data and adapt to specific requirements of different electricity distribution companies.
- 11. **Data Privacy and Security:** Robust data privacy measures to protect sensitive customer information and ensure compliance with data protection regulations

### 2.2.3. External Interface Requirements

#### 2.2.3.1. User Interfaces

The "Energy Fraud Detection" system has a tiered interface:

- ☐ Tier 1 Engineers: They receive a broad city-wide view, highlighting potential fraud areas for quick decision-making.
- ☐ Tier 2 Engineers: The interface offers detailed consumption histories of homes in suspect zones, aiding in targeted inspections.
- ☐ Tier 3 Engineers: Equipped with a simple reporting tool for on-site findings and photo uploads, ensuring swift and accurate reporting.

#### 2.2.3.2. Hardware Interfaces

To address issues like meter tampering and unauthorized connections, our project easily connects with the latest hardware like smart meters. These meters give real-time electricity use details. Additionally, we are set up to work with other devices in the future that will help watch over the power network. This ensures our system always has the latest and most accurate data, helping us spot fraud quickly.

#### 2.2.3.3. Software Interfaces

To ensure the system's robustness and adaptability, the "Energy Fraud Detection" platform is designed to integrate smoothly with existing energy consumption databases, a feature paramount given the discrepancies observed between declared and actual energy consumption. Furthermore, considering the rapidly advancing landscape of energy distribution and fraud detection methodologies, the system's modular design allows for integration with future software tools, platforms, and analytical solutions. This guarantees that the system remains scalable and adaptable to future challenges and innovations in the realm of energy fraud detection.

### 2.2.4. Other Non-functional Requirements

### 2.2.4.1. Performance Requirements

- **Real-time Data Processing:** The system should process and analyse electricity consumption data in near real-time to enable timely fraud detection.
- **Response Time:** The system should provide quick responses to user queries and interactions.

### 2.2.4.2. Safety Requirements

- User Data Protection: The system should ensure the privacy and protection of user data, adhering to relevant data protection regulations.
- Audit Trail: The system should maintain an audit trail of user activities, inspections, and data modifications for accountability and traceability.

### 2.2.4.3. Security Requirements

- The system should enforce secure access control mechanisms and authentication protocols to prevent unauthorized access.
- Sensitive data, such as user credentials and inspection evidence, should be encrypted to protect against unauthorized access.
- The system should implement monitoring mechanisms to detect and mitigate security threats and vulnerabilities.

### 2.3. Cost Analysis

S.No.	Services Name	Total Price
1.	Web-Hosting	₹8000
2.	Model Training and Deployment	₹3000
3.	Domain Name Registration	₹2000
4.	SSL Certificate	₹1000

Table 4: Cost Analysis

## 2.4. Risk Analysis

The following risks are associated with our project:

### **□** Data Integrity:

- ➤ Risk of receiving inaccurate or manipulated data from meters, which could compromise detection accuracy.
- ➤ Potential discrepancies between real-time data and stored historical data.

#### ☐ Hardware Failures:

- > Smart meters or other IoT devices malfunctioning or becoming offline, leading to gaps in data collection.
- Risks associated with unauthorized tampering or physical damage to the meters.

#### **☐** Software Glitches:

- > Bugs or vulnerabilities in the software could compromise data analysis.
- > Issues with software integration, especially when interfacing with legacy systems.

### ☐ Cybersecurity Threats:

- ➤ Potential hacking attempts to manipulate consumption data or system functionalities.
- ➤ Unauthorized access to the system, leading to data breaches or false detections.

#### **☐** Scalability Concerns:

- As the number of connected devices grows, the system might face challenges in processing vast amounts of data in real-time.
- ➤ Integrating newer technologies or methods might require substantial system overhauls.

#### ☐ Resistance to Adoption:

- > Stakeholders, especially consumers, might be resistant to adopting new monitoring systems due to privacy or trust concerns.
- ➤ Utility providers might be hesitant to transition from traditional methods due to costs or training requirements.

### 3. METHODOLOGY ADOPTED

### 3.1. Investigative Techniques

Pattern Analysis: Look at how electricity is used over time. If there's a sudden drop or change without a clear reason, it might be a sign of fraud.

Area Comparison: Check if a house or building uses a lot more or less electricity than others nearby. Big differences can be suspicious.

Historical Data Review: Compare current electricity use to past months or years. Big changes might need a closer look.

Alerts: Set up the system to send warnings when unusual electricity use happens, like very high use late at night.

Feedback from Field Engineers: When Tier 3 engineers visit homes or buildings, their feedback can help understand if the system's fraud predictions were right.

Database Cross-checks: Look at billing history, payment patterns, and previous fraud reports. If a customer has a history of late payments or suspected fraud, they might need more attention.

Consumer Behaviour Analysis: See how electricity is used. For example, if a house uses a lot of power when no one's home, that's odd.

Peer Review: Sometimes, it's good to have another expert look at the data. They might see something that was missed the first time.

### 3.2. Proposed Solution

#### Introduction

In response to the growing concerns surrounding electricity fraud, we present a robust solution that combines cutting-edge machine-learning techniques with an intuitive application architecture. This proposal outlines our comprehensive approach to detect, prevent, and mitigate electricity fraud by leveraging advanced data analysis, powerful machine learning models, and an innovative application framework.

#### **Data Collection and Preprocessing**

The foundation of our solution lies in the meticulous collection and preprocessing of data. We utilized the dataset graciously provided by STEG, encompassing both client-specific information and detailed billing histories. Through an exploratory data analysis, we unearthed hidden insights that informed our subsequent steps.

Our data preprocessing pipeline was carefully designed to ensure data quality and relevancy. We addressed label imbalance effectively, a common concern in fraud detection scenarios within the context of our model selection and training.

### **Dataset Description**

The dataset provided by STEG consists of two key files. The first file captures essential client details, including client ID, district, category, region, creation date, and a target label indicating fraud (1) or non-fraud (0). The second file contains detailed invoice information, such as invoice date, tariff type, counter details, consumption levels, index values, and counter type. This dataset forms the bedrock of our solution, enabling us to develop a robust model for fraud detection.

#### **Feature Engineering**

Feature engineering emerged as a pivotal step in molding our dataset for optimal model utilization. This strategic process adeptly captures the underlying dynamics of energy consumption behaviours. By incorporating a suite of statistical aggregates including mean, median, min, max, and standard deviation, we skillfully distilled the fundamental characteristics of energy usage patterns. Through this process, we managed to encapsulate the intrinsic nuances of energy consumption trends, effectively neutralizing the influence of customer tenure variations.

#### **Model Exploration and Selection**

Our model development journey encompassed a wide array of machine-learning models. To address the imbalanced nature of the data, we considered models known for their prowess in handling such scenarios. Following rigorous experimentation, LightGBM emerged as the frontrunner due to its ability to excel with imbalanced data. This model demonstrated exceptional accuracy, exceeding 96%.

To refine the model further, we employed Optuna for fine-tuning, a process that hones the model's parameters for enhanced accuracy. We remain committed to continuous improvement, with plans to explore additional models and finetune their parameters to ensure the model's effectiveness against evolving fraud tactics.

#### **Application Architecture**

Our solution extends beyond the machine learning model to a sophisticated application architecture that streamlines the entire fraud detection process. The architecture is composed of three tiers, each tailored to different aspects of fraud detection.

#### Tier 1: Strategic Oversight

At the highest tier, Tier 1 engineers are empowered with a panoramic overview of potential fraud hotspots across the region. This strategic insight enables them to strategically allocate resources for further investigation.

#### Tier 2: Detailed Analysis

Tier 2 engineers delve deeper into electricity consumption histories within regions exhibiting signs of potential fraudulent activities. Armed with comprehensive data insights, they can perform meticulous analyses to identify homes warranting closer inspection.

#### **Tier 3: On-Ground Verification**

The final tier involves the deployment of engineers to physically inspect shortlisted premises. They meticulously document their findings using photographic evidence, providing essential validation for official actions if fraudulent activities are confirmed.

### **Deployment**

As we advance, our focus extends beyond model refinement. We envision the completion of our application development process, encompassing user-friendly dashboards and intuitive interfaces. The impending stages will witness rigorous adherence to software development practices and DevOps principles, resulting in a seamlessly deployable application that minimizes downtime and optimizes user experience.

#### 3.3. Work Breakdown Structure

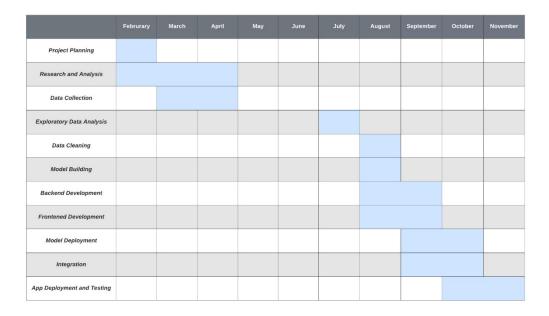


Fig 2: Gantt Chart

### 3.4. Tools and Technology

10	ools				
	Google Colab				
	VS Code				
	Amazon AWS				
	Github				
	Docker				
	Kubernetes				
Te	Technology				
	Django				
	Django Rest Framework				
	React				
	Node JS				
	Postgre SQL				
	Machine Learning Libraries(E.g.: LightGBM, XgBoost)				

### 4. DESIGN SPECIFICATIONS

### 4.1. System Architecture

The system architecture for the "Energy Fraud Detection" project revolves around a block diagram that encompasses various components and their interactions. At the core of the system is the User block, which allows users to log in, recover forgotten passwords, and update personal information.

The Tier 1 block plays a crucial role in overseeing the system's performance, tracking the effectiveness of officers at lower tiers, assigning priority to regions based on fraud likelihood, and accessing region-wise reports. This information helps in strategic decision-making and resource allocation.

The Tier 2 block focuses on consumption analysis, leveraging data from the database containing electricity consumption history. Through data analysis techniques, it compiles a tentative list of potential defaulters and assigns inspections to Tier 3 officers for further investigation.

The Tier 3 block involves on-site inspections conducted by officers who capture site photographs and submit remarks regarding potentially fraudulent activities. This information is crucial in building comprehensive reports and initiating further actions if necessary.

The admin block handles employee management, allowing for the registration of new employees and the modification of employee details as required. This ensures the smooth operation and scalability of the system.

The ML Model, a pivotal component, utilizes the data from the database and the smart meter to employ advanced machine learning algorithms for fraud detection and analysis. By training on historical data, it can identify patterns, anomalies, and potential instances of fraudulent energy consumption.

The system's architecture relies on a database to store and manage electricity consumption history, which serves as a valuable resource for analysis and detection. Additionally, the smart meter plays a critical role in collecting real-time data, providing accurate and up-to-date information for fraud detection and prevention.

Through the interaction of these components, the system aims to streamline the process of identifying and preventing fraudulent activities in electricity distribution networks. It empowers different tiers of engineers to collaborate effectively, leveraging data analysis and machine learning techniques to detect potential fraud, conduct inspections, and generate comprehensive reports. Ultimately, this architecture enables energy companies to minimize financial losses, enhance operational efficiency, and ensure responsible and sustainable resource usage

System architecture includes the following diagrams:

#### **Block Diagram**

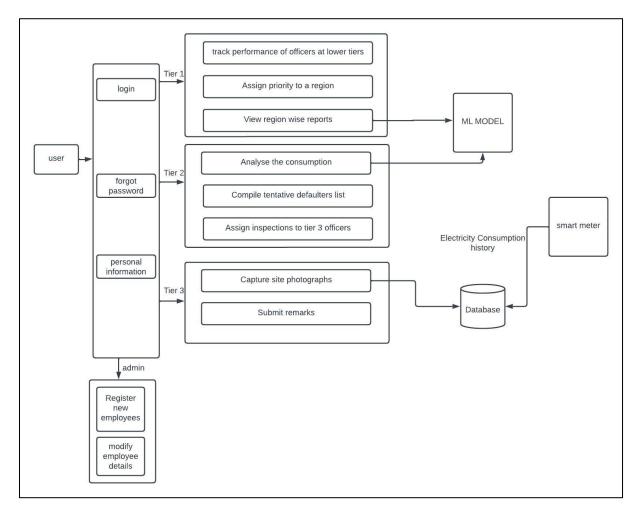


Fig 3: Block Diagram

The Energy Fraud Detection System, is structured across three primary tiers. Tier 1 focuses on administrative oversight, enabling tracking of officer performance at lower tiers, assigning priority to different regions, and offering a holistic view of region-specific reports. Tier 2 integrates user interfaces for personal information management and password recovery, but its core functionality lies in its machine learning model. This model is designed to meticulously analyse energy consumption data, identify potential defaulters, and subsequently delegate inspection tasks to Tier 3 officers. Tier 3 officers play a crucial onground role, capturing site photographs, accessing historical electricity consumption records, and submitting remarks post-inspection. The system is further enhanced with an employee management segment that allows for registration and modification of employee details. All this data, combined with real-time readings from smart meters, is stored and managed in a centralized database, ensuring a seamless and efficient fraud detection process.

## 4.2. Design Level Diagrams

### 4.2.1. Swimlane/Activity Diagram

Activity diagrams are behavioural diagrams. In other words, it indicates the behaviour of the system. An activity diagram represents the flow of control from a start point to an end point, showing the various decision paths that exist during the execution of an activity.

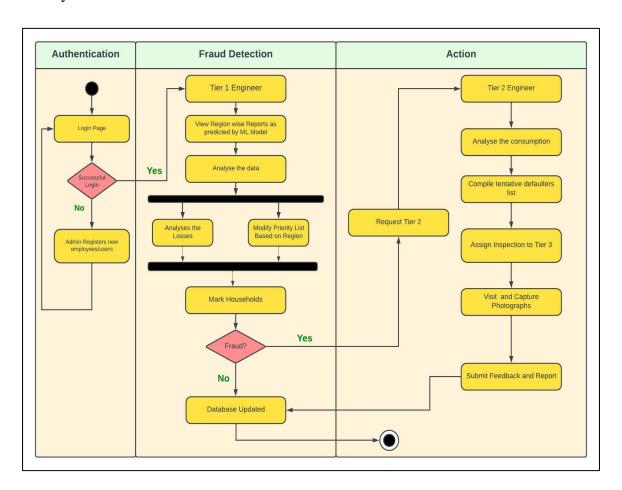


Fig 4: Swimlane Diagram

In the Energy Fraud Detection System swim lane diagram, the process is stratified into three distinct lanes, ensuring a structured and sequential approach to fraud detection and management. The Authentication lane is pivotal in safeguarding the system, focusing primarily on user or device identity verification. This might encompass user login procedures, token generation, and rigorous validation, ensuring that only authorized users or entities gain access. The heart of the system is the Fraud Detection lane, which is dedicated to identifying potential energy fraud scenarios. This lane intricately processes data, possibly leveraging sophisticated algorithms, to pinpoint anomalies or suspicious activities. Upon detecting any discrepancies, the system transitions to the Action lane.

Here, definitive measures are initiated, ranging from alerting the concerned stakeholders to flagging the implicated account for closer scrutiny, ensuring that fraudulent activities are swiftly addressed.

### 4.2.2. Class Diagram

A Class diagram is a static diagram. A class diagram describes the attributes and operations of a class and the constraints imposed on the system. Class diagrams show collections of classes, interfaces, associations, collaborations, and constraints.

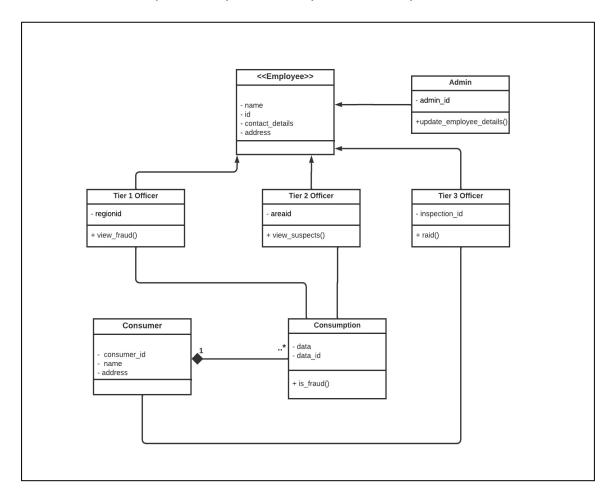


Fig 5: Class Diagram

Within the Energy Fraud Detection System, as portrayed in Figure 3's class diagram, several classes collaborate to ensure a methodical approach to fraud detection. Employee class, encapsulates core attributes like 'name', 'id', 'contact\_details', and 'address'. This class offers the foundational method 'update\_employee\_details()', which likely allows modification or updating of an employee's core details.

The hierarchy within the organization is further delineated through subclasses such as the Tier 1 Officer, and Tier 2 Officer, Tier3 Officer. These subclasses, derived from the primary Employee class, embody the different officer roles or tiers within the organization, with each tier potentially having specific duties or permissions.

On the consumer front, the Consumer class represents the end-users. It houses attributes like 'consumer id', 'name' and 'Address', capturing comprehensive details about each consumer's identity and consumption patterns. Paired closely with this is the Consumption class, likely serves as the repository for individual consumption data, forming the basis for fraud analysis. A pivotal method, 'is\_fraud()', signals the system when a particular consumer's behaviour hints at potential fraudulent activity.

## 4.2.3. Data Flow Diagrams

A Data Flow Diagram (DFD) is a traditional visual representation of the information flows within a system.

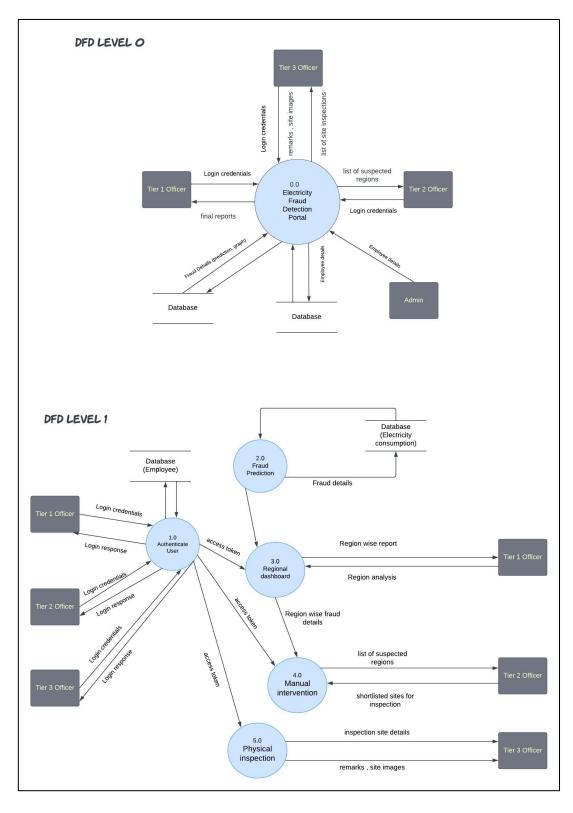


Fig 6: DFD 0 and DFD 1 Diagram

Within the broader framework of the Energy Fraud Detection System, the DFD provides a systematic representation of data flow and functional processes across two levels: DFD LEVEL 0 and DFD LEVEL 1.

DFD LEVEL 0 serves as the top-tier abstraction, offering a bird's eye view of the system's primary functionalities. From this perspective, the system is shown to handle a series of data elements, including 'remarks', 'site images', a 'list of site inspections', and a 'list of suspected regions'. These elements collectively provide a high-level understanding of the system's operation, emphasizing region-based inspections and the collation of relevant data.

Delving deeper, DFD LEVEL 1 presents a more granular view, elucidating specific interactions with a central entity labelled 'Database'. One of the critical data flows includes 'electricity consumption', indicating that the system actively monitors and records energy usage metrics. Another vital data stream is the 'Region wise report', suggesting the system's capability to generate detailed reports based on geographical or administrative regions. Additionally, data elements such as 'remarks' and 'site images' reiterate the system's emphasis on collecting on-site inspection data for thorough analysis.

### 4.2.4. State Chart Diagram

State diagrams are used to model the dynamic nature of a system. They define different states during the lifetime of an object.

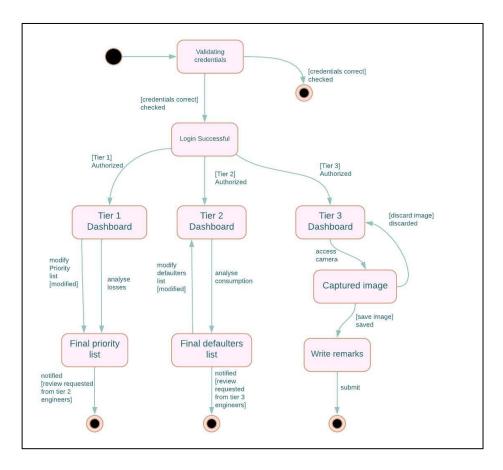


Fig 7: State Chart Diagram

The diagram commences with "Validating credentials", a crucial step to ensure that only authorized individuals gain access. Upon successful validation, where the credentials are confirmed as correct, the system transitions to the "Login Successful" state. The subsequent state or dashboard accessed is contingent upon the tier or role of the user, with distinct dashboards for Tier 1, Tier 2, and Tier 3 officers.

For Tier 3 officers, they possess the privilege to capture images, evident from the "Captured image" state. Post-capture, a decision arises: the image can either be saved, transitioning the state to "Saved", or discarded, leading to the "Discarded" state. This suggests a quality control or review mechanism in place for the images captured during inspections.

In parallel, Tier 3 officers can also access and potentially modify consumption data, as indicated by the "Access" and "Modify" states. The system further facilitates the analysis of this data, moving through states like "Data Analysed", "Final Defaulters List", and culminating in the "Final Priority List". This sequence underscores the system's rigorous approach to identifying potential defaulters based on consumption patterns.

## 4.2.5. ER Diagram

The purpose of an ER diagram is to provide a clear and concise overview of the entities, attributes, and relationships within a database. It aids in database design, communication between stakeholders, and understanding the structure and flow of data.

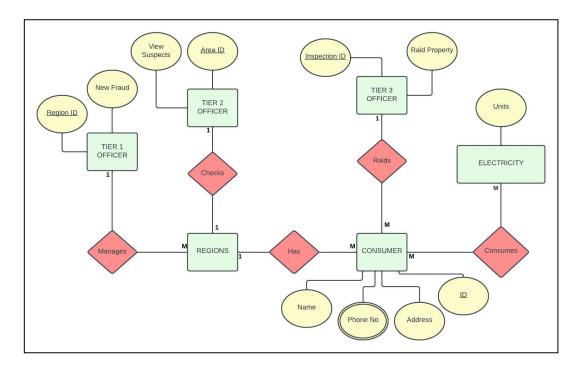


Fig 8: ER Diagram

The ER diagram intricately maps out the core components of the Energy Fraud Detection System. It highlights the system's multi-tiered approach, the importance of regional analysis, and the pivotal role of consumers in the fraud detection process.

The "Tier 1 Officer" entity, likely representing administrative or high-level officers, indicates the hierarchical structure within the system. Similarly, the "Tier 3 Officer" entity represents another level of officers, possibly those on the ground handling inspections, as further emphasized by the "Inspection" entity. This hints at a multi-tiered approach to fraud detection, with different officer levels handling various responsibilities.

The "Regions" entity suggests that the system categorizes or manages data based on geographical or administrative segments, allowing for region-specific fraud detection and management. The "Consumer" entity represents the end-users or the households and businesses consuming electricity. Their relationship with the "Electricity" entity might indicate the consumption patterns, history, or specific metrics related to each consumer.

### 4.2.6. Component Diagram

The purpose of a Component diagram is to illustrate the high-level structure of a software system by representing its individual components or modules, their dependencies, and interfaces.

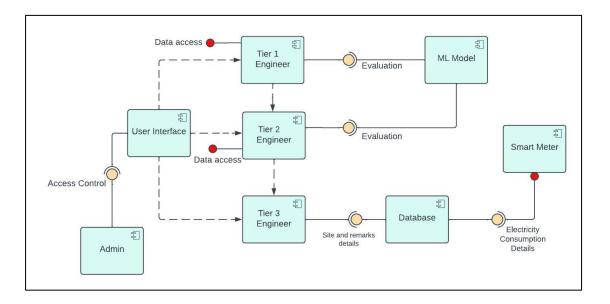


Fig 9: Component Diagram

The main component depicted by the diagram is the "ML Model", which likely processes "Electricity Consumption Details" sourced from "Smart Meters". The "Access Control" component ensures secure data access, seamlessly interfacing with both "Tier" roles and "Engineer" roles. The "Evaluation" component signifies the system's analytical capabilities, possibly in tandem with "Engineer Evaluation" for technical insights. Additionally, the "Site and Remarks Details" component captures on-ground observations, further enhancing the system's analytical depth.

# 4.2.7. Use Case Diagram

The purpose of a use case diagram in UML is to demonstrate the different ways that a user might interact with a system.

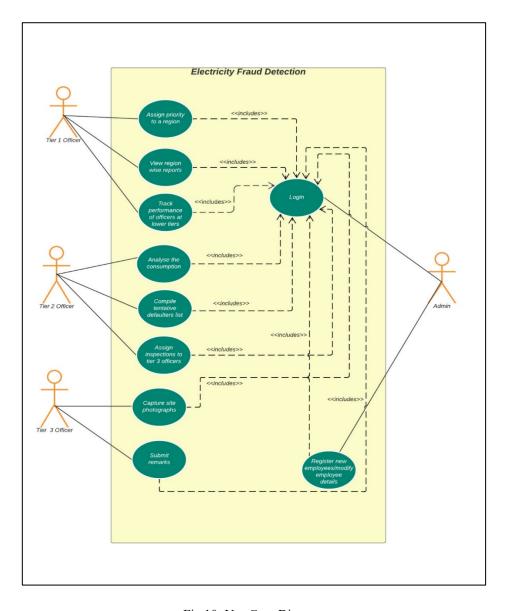


Fig 10: Use Case Diagram

At the heart of the system is the primary use case, "Electricity Fraud Detection". Various operations, represented by the "<<includes>>" relationships, branch out from this central use case, suggesting a multifaceted approach to fraud detection. The "Tier 3 Officer" stands as a primary actor, interacting directly with these operations. This underscores the officer's pivotal role in executing, overseeing, and perhaps refining the fraud detection process. Collectively, the diagram emphasizes a user-centric design, where system functionalities are aligned with user roles and responsibilities.

# 4.2.8. Use Case Templates

Use Case ID	1
Use Case Name	Assign priority to a region
Actor(s)	Tier 1 Officer
Purpose	To set priority to a region where electricity fraud is possible
Pre-Conditions	User should be logged in
Post Conditions	A notification is sent to tier 2 officers
Success Scenario	Tier 2 officers are informed about the regions.

Use Case ID	2
Use Case Name	View region wise reports
Actor(s)	Tier 1 Officer
Purpose	To view the reports of electricity theft
Pre-Conditions	User should be logged in
Post Conditions	Theft/loss data will be shown to the user
Success Scenario	Tier 1 officer have a detailed information about losses in every area.

Use Case ID	3
Use Case Name	Track performance of officers at lower tiers
Actor(s)	Tier 1 Officer
Purpose	To track the performance of lower tier officers.
Pre-Conditions	User should be logged in
Post Conditions	Lower tier officer's performance data will be visible to the user
Success Scenario	Tier 1 officer have a detailed information about the performance data of every lower tier officer.

Use Case ID	4
Use Case Name	Analyse the consumption
Actor(s)	Tier 2 Officer
Purpose	To analyse the consumption of the area set as priority by tier 1 officer
Pre-Conditions	User should be logged in.  An area must be selected by tier 1 officer.
Post Conditions	User is able to view the data of electricity consumption of a particular area.
Success Scenario	Tier 2 officers are able to view the electricity data of the area marked by tier 1 officer.

Use Case ID	5
Use Case Name	Compile tentative defaulters list
Actor(s)	Tier 2 Officer
Purpose	To prepare the list of households where fraud is possible.
Pre-Conditions	User Should be logged in.  The area must be marked by tier 1 officer in which the household exists.
Post Conditions	A list of households possible of doing fraud is saved in database .
Success Scenario	The household list is successfully saved in the database.

Use Case ID	6
Use Case Name	Assign inspections to tier 3 officers
Actor(s)	Tier 2 Officer
Purpose	To assign duty to tier 3 officers
Pre-Conditions	User should be logged in.  The household list must be prepared
Post Conditions	Inspection assignment is given to various tier 3 officers of different households.
Success Scenario	Tier 3 officers receive the assigned inspections.

Use Case ID	7
Use Case Name	Capture site photographs
Actor(s)	Tier 3 Officer
Purpose	To capture the proof of site inspected.
Pre-Conditions	Site must have been assigned by tier 2 officer where inspection is taking place.
Post Conditions	-
Success Scenario	Photos are captured and saved.

Use Case ID	8
Use Case Name	Submit remarks
Actor(s)	Tier 3 Officer
Purpose	To submit remarks of all the sites inspected
Pre-Conditions	User should be logged in.  Sites assigned ,must have been inspected.
Post Conditions	The photos captured are sent to higher tier officers
Success Scenario	Higher tier officers receive the remarks.

Use Case ID	9	
Use Case Name	Login	
Actor(s)	Tier 1 Officer, Tier 2 officer, Tier 3 officer, Admin	
Purpose	To login into the system	
Pre-Conditions	Must have valid credentials	
Post Conditions	If internet connection is available. User will be logged in. If internet connection is not available. The backup screen will be displayed.	
Success Scenario	Logged in successfully	

Use Case ID	10
Use Case Name	Register new employees/modify employee details
Actor(s)	Admin
Purpose	To set credentials of newly appointed employees or update their information when necessary
Pre-Conditions	-
Post Conditions	Information is valid. Saved in database Invalid Information. Error message displayed.
Success Scenario	-

## 4.3. User Interface Diagrams

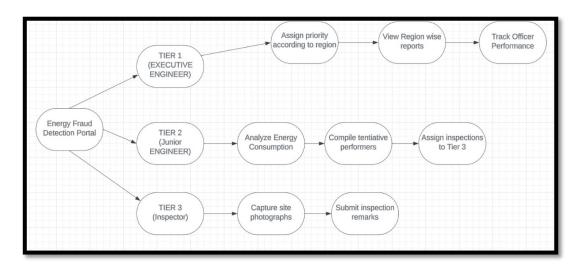


Fig 11: User Interface Diagram

The user interface diagram for the "Energy Fraud Detection Portal" showcases a well-defined separation of responsibilities across three tiers: Tier 1, Tier 2, and Tier 3. Starting at the central node, the portal branches into these tiers, ensuring distinct roles and tasks. Tier 1 engineers access the portal to assign priority to regions, view reports, and track officer performance. Tier 2 engineers analyse energy consumption, compile tentative defaulter's lists, and assign inspections to Tier 3. Within the Tier 3 interface, engineers capture site photographs and submit inspection remarks. This organized branching ensures that responsibilities are distributed efficiently across the tiers, enhancing collaboration while maintaining a structured workflow. The design prevents these paths from converging, ensuring each tier's tasks remain independent and focused, ultimately contributing to a more effective energy fraud detection process.

### 5. IMPLEMENTATION AND EXPERIMENTAL RESULTS

### 5.1. Experimental Setup

The experimental setup consists of following components:

 Machine Learning Model: This backend component uses algorithms to analyze data and detect unusual patterns indicative of energy fraud. It processes input from smart meters and other data sources to identify irregularities.

- 2. User Interface: The web-based interface includes login functionality, along with signin and sign-up capabilities. After authentication, users can navigate through different pages tailored to various user tiers (tier1, tier2, tier3), each providing specific information and analytical tools relevant to their role in fraud detection.
- **3. PostgreSQL Server:** This robust database server stores and manages the vast amounts of data required for real-time analytics and machine learning processes. It ensures data is consistently available for querying and analysis.
- **4. Backend Server:** The backend infrastructure, developed using Django REST Framework handles the application logic. It receives data from the user interface and the database, performing necessary operations and sending back the results.

### 5.2. Experimental Analysis

#### 5.2.1. Data

The Energy Fraud Detection project, specifically utilizes the residential electricity load profile data from the "Commercial and Residential Hourly Load Profiles for all TMY3 Locations in the United States" dataset. This section of the analysis focuses solely on the residential aspect, specifically on the electrical energy consumption patterns.

The dataset comprises hourly electricity load profiles for single-family detached homes. These homes are modelled to reflect the 2009 International Energy Conservation Code (IECC) construction standards and are distributed across five distinct climate regions in the TMY3 locations. The data is crucial in understanding residential electricity usage patterns and identifying anomalies that may indicate fraudulent activities.

However, it is important to note that this dataset, initially created around 2012 as a byproduct of solar photovoltaics and solar water heating analyses, has certain limitations. Notably, it applies specific algorithms from a single city to entire climate zones. For instance, the heating season defined for Tampa, FL, is erroneously applied to all locations in the Hot-Humid zone, potentially leading to inaccuracies in energy usage profiles. Additionally, the dataset includes "HIGH" and "LOW" building load profiles, intended to represent a range of older and newer home vintages, but their actual representativeness of the housing stock's energy use range is uncertain.

Furthermore, this dataset has been superseded by the "End-Use Load Profiles for the U.S. Building Stock" dataset, which provides a more comprehensive and validated representation of hourly load profiles for the U.S. commercial and residential building stock. While the newer dataset is recommended for enhanced accuracy and reliability, the archived residential load data from the original dataset, prior to its update on July 2nd, 2013, has been used for this project. This decision was made due to the specific requirements of the project in analysing residential electricity data, despite the known limitations of the original dataset.

#### **5.2.2.** Performance Parameters

The following performance parameters have been considered:

- 1. Accuracy: Measures the percentage of total predictions that the model correctly identifies as fraudulent or non-fraudulent. High accuracy is pivotal for system credibility.
- 2. Precision: Indicates the proportion of identified cases that were correctly predicted as fraud, minimizing the time and resources spent on investigating false positives.
- 3. Recall: Measures the model's ability to detect all actual fraud cases from the dataset, which is crucial for preventing revenue loss due to undetected fraud.
- 4. F1 Score: Harmonic mean of precision and recall, providing a single metric for cases where the balance between false positives and false negatives is important.
- 5. Response Time: The speed with which the system processes data and flags potential fraud. For real-time applications, low response time is essential for timely fraud prevention.
- 6. Throughput: The volume of data the system can handle in a given time frame. It reflects the system's efficiency and is key for scalability.

### **5.3.** Working of the project

This section of the report discusses the implementation of the proposed project, in terms of its workflow and deployment.

# 5.3.1. Procedural Workflow

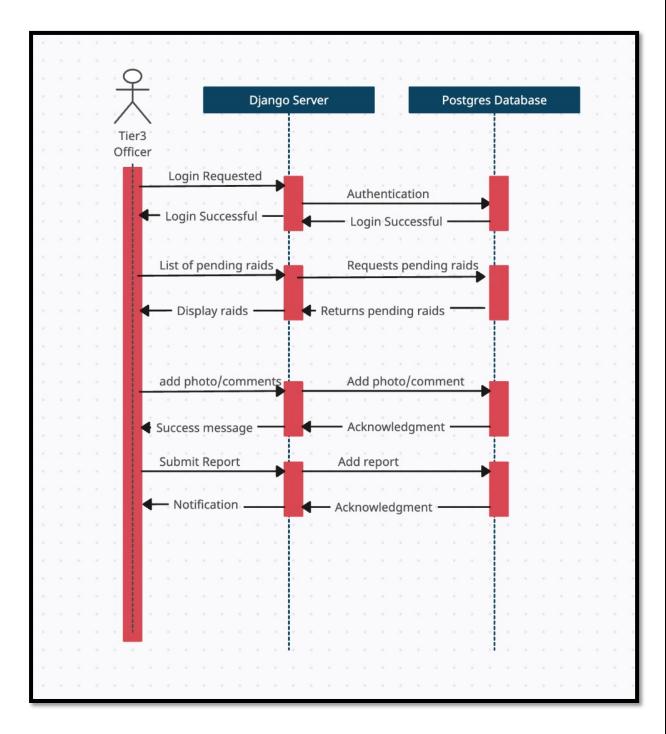


Fig 12: Sequence Diagram

The sequence diagram illustrates the interactions between a Tier 3 Officer and the system, consisting of a Django Server and a Postgres Database, during a typical workflow session. Here's a step-by-step explanation of the processes depicted:

1. Log	in Process:
	The Tier 3 Officer initiates a "Login Requested" action.
	The Django Server handles the request and performs "Authentication" against the
	Postgres Database.
	Upon successful verification, the Postgres Database responds with a "Login
	Successful" message to the Django Server.
	The Django Server then sends a "Login Successful" message back to the Tier 3
	Officer.
2. Viev	w Pending Raids:
	The Tier 3 Officer sends a request for a "List of pending raids."
	The Django Server processes this request and asks the Postgres Database for
	"Requests pending raids."
	The Postgres Database retrieves the information and returns "Pending raids" to the
	Django Server.
	The Django Server then "Displays raids" to the Tier 3 Officer.
3. Add	ing Photo/Comments:
	The Tier 3 Officer decides to "Add photo/comments" to a particular raid.
	The Django Server takes this information and adds the "Photo/comment" to the
	Postgres Database.
	The Postgres Database acknowledges the addition and sends an "Acknowledgment"
	back to the Django Server.
	The Django Server then sends a "Success message" to the Tier 3 Officer.
4. Sub	mitting a Report:
	The Tier 3 Officer then "Submits Report" on the raid.

The Django Server forwards this report and instructs the Postgres Database to "Add
report."
Once the report is successfully added, the Postgres Database sends another"
Acknowledgment" to the Django Server.
The Django Server notifies the Tier 3 Officer that the report submission was
successful with a "Notification "

### 5.3.2. Algorithmic Approaches Used

The algorithmic approaches for the Energy Fraud Detection project involve two main algorithms: the Labelling algorithm and the Anomaly Detection using the Isolation Forest method. Here's a description of each:

### ☐ Labelling Algorithm:

This algorithm is employed to label consumers as potential defaulters based on their electricity consumption patterns. Using Python's Pandas and NumPy libraries, it begins by loading the consumption data from a CSV file. It then iterates through each consumer's data to calculate a 'day level score' which is a measure of deviation from their typical consumption pattern. This score is determined by first calculating the mean (\(\(\mu\_h \\)) and standard deviation (\(\sigma\_h \\)) of each consumer's historical data. The Z-score (\((z\_{h\_d} \\))) for each day's consumption is then calculated, which measures how many standard deviations a point is from the mean. Days where the Z-score falls below a negative threshold (indicative of underconsumption, potentially due to energy theft) are flagged. These flags are summed up to produce the 'day level score' for each consumer.

The scores are used to rank the consumers, with those having higher scores being more likely to have engaged in fraudulent activities. A predetermined percentage (e.g., top 10%) of consumers with the highest scores are then marked as potential defaulters. Their 'consumer\_number' is used to update the original dataset with a 'fraud\_status' label, which is then saved as a new CSV file for further analysis or investigation.

☐ Anomaly Detection (Isolation Forest):

For Anomaly Detection, the Isolation Forest algorithm is utilized, which is particularly effective for high-dimensional datasets. This unsupervised learning algorithm works on the principle of isolating anomalies instead of profiling normal data points. The assumption is that anomalies are few and different, which makes them more susceptible to isolation.

In the context of the Energy Fraud Detection project, the Isolation Forest algorithm would be applied to the consumer electricity consumption data to identify outliers. These outliers represent consumption patterns that significantly deviate from the norm and could indicate fraudulent activity, such as energy theft or meter tampering. The algorithm randomly selects a feature and a split value between the maximum and minimum values of the selected feature to isolate observations. The number of splittings required to isolate a sample is equal to the path length from the root node to the terminating node. This path length, averaged over a forest of such random trees, is a measure of normality and our decision function. Anomaly scores are then computed based on the path lengths, with shorter paths indicating anomalies.

By implementing these algorithmic approaches, the project aims to systematically identify and label potential fraudulent activities within the electricity distribution network, thereby providing a means to protect the revenue and integrity of the utility providers.

#### ☐ Recurrent Neural Network (RNN):

An RNN is a class of artificial neural networks where connections between nodes form a directed graph along a temporal sequence. This allows it to exhibit temporal dynamic behavior and utilize internal state memory to process sequences of inputs. This feature makes RNNs particularly suitable for applications like energy fraud detection, where consumption patterns over time are crucial for identifying anomalies.

In the context of the Energy Fraud Detection project, an RNN can be trained on sequences of electricity usage data to learn and predict normal consumption patterns. The RNN would be able to identify potential fraud by detecting deviations from these learned patterns. Unlike traditional machine learning algorithms that treat data points as independent, an RNN can understand the context and temporal dependencies of electricity usage across different time periods, which can significantly improve the accuracy of fraud detection.

### 5.3.3. Project Deployment

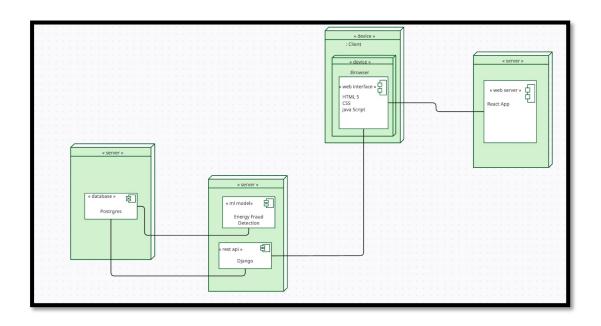


Fig 13: Deployment Diagram

The deployment diagram illustrates the setup for an Energy Fraud Detection system, structured into distinct layers for optimal functionality. The client-side employs a browser with a web interface crafted using HTML5, CSS, and JavaScript, providing users with interactive access. On the server-side, a Postgres database server is responsible for storing and managing the data. The core analytical engine is a machine learning model dedicated to identifying patterns indicative of fraud, interfaced with a Django REST API for efficient data exchange. The front end is powered by a React application hosted on a web server, which interacts with the Django API, serving as the system's user interface and presenting the analysis results from the machine learning model. This multi-tiered architecture enables a robust and scalable system for real-time energy fraud detection and monitoring.

# **5.3.4.** System Screenshots

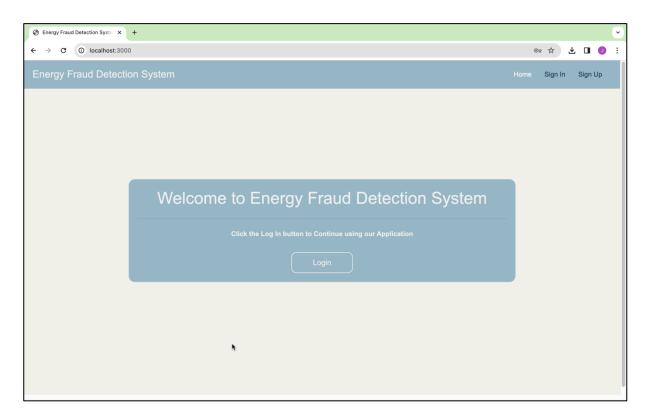


Fig 14: Login Page

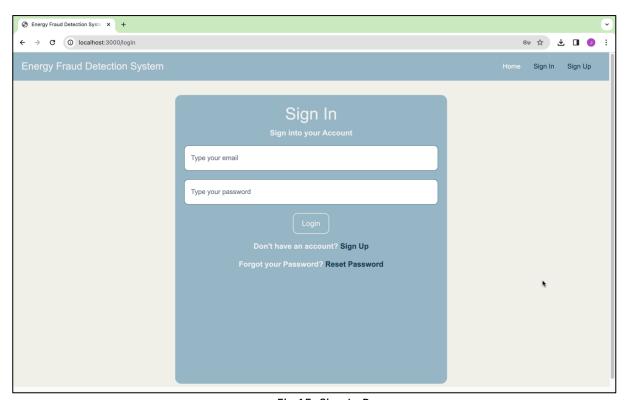


Fig 15: Sign In Page

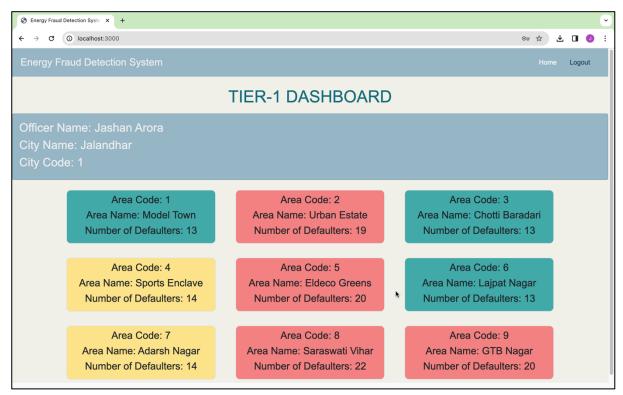


Fig 16: Tier-1 Dashboard

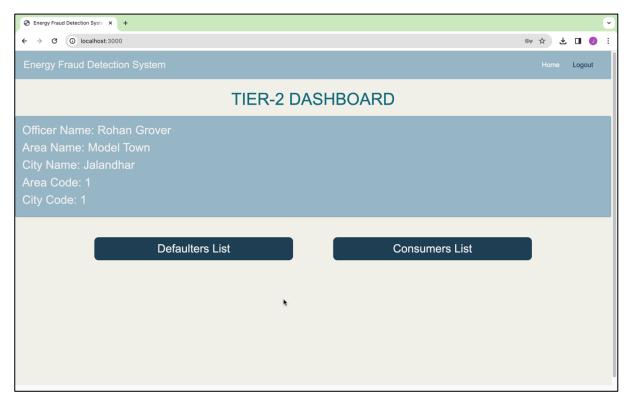


Fig 17: Tier-2 Dashboard

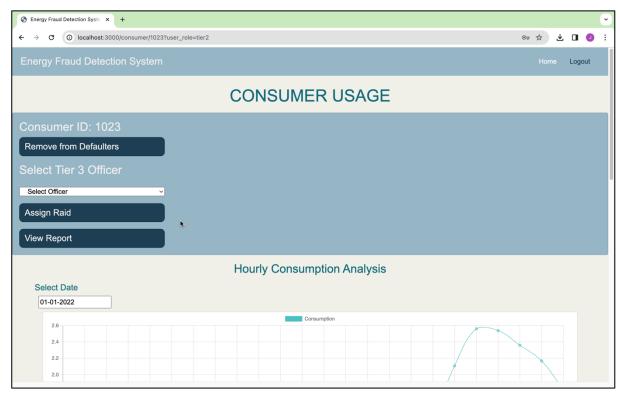


Fig 18: Consumer Usage



Fig 19: Field Report

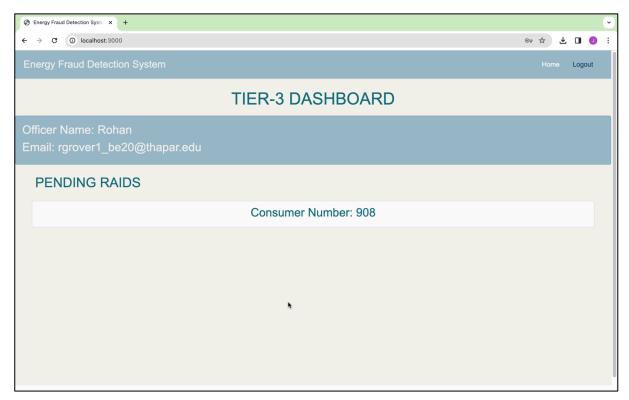


Fig 20: Tier-3 Dashboard

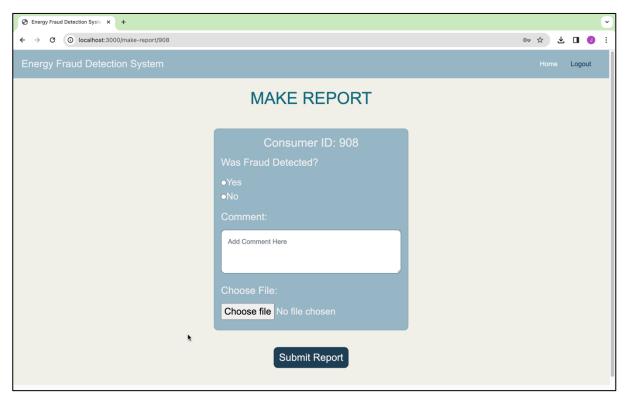


Fig 21: Make Report

### **5.4.** Testing Process

### 5.4.1. Test Plan

This section of the document discusses the features to be tested, the testing strategy, and the testing techniques used.

The Test Plan for the Energy Fraud Detection project is designed to comprehensively assess the system's functionality, performance, and security. It encompasses both automated and manual testing methodologies to ensure thorough coverage of all system components. This includes detailed testing of user authentication processes, API functionalities, dashboard operations, database integrations, machine learning model effectiveness, overall system performance, and security protocols. The plan specifies the tools and resources necessary for testing, outlines the testing schedule, and incorporates risk management strategies. Quality assurance measures are integrated throughout the testing process to maintain high standards and ensure the system meets all specified requirements.

#### **5.4.2.** Features to be tested

S.No.	Item Being Tested	Scenario Being Tested
1	User Authentication	Login, Registration, Password Recovery
2	Admin Access	Access control to admin features
3	Authentication Token	Token generation and validation
4	Area Codes Retrieval	Correct retrieval of area codes for a city
5	User Details Retrieval	Fetching user-specific details
6	Consumer List Retrieval	Listing consumers for specific city and area codes

7	Defaulter Identification	Identifying defaulters in specific areas
8	Consumption History Access	Accessibility of consumption history data
9	Dashboard Functionality	Data visualization, updates, user access levels
10	Database Integration	Query performance, data backup, integrity checks
11	ML Models	Fraud detection accuracy, prediction timing
12	System Performance	Load capacity, response time, browser compatibility
13	Security Features	Data encryption, vulnerability protection, access control
14	Load Testing	System's behaviour under peak load and stress conditions

Table 5: Features to be tested

# 5.4.3. Test Strategy

The Energy Fraud Detection project integrates a sophisticated blend of APIs and a web application, necessitating a comprehensive test strategy. To ensure the system functions flawlessly in real-world scenarios, our testing process is meticulously designed. We employ a variety of environments that simulate different stages of development and deployment, from initial coding and unit testing to final release and user acceptance. This approach guarantees that the web application and APIs are thoroughly vetted for performance, security, and reliability across different network settings.

Sr No.	Environment Name	Description	Network	Usage
1	Development	Initial testing environment for developers	Internal	Unit Testing
2	Testing/Staging	Environment mirroring production settings	VPN/Protected	System Integration
3	Production Clone	Exact replica of the production environment	Secure Network	Pre-release testing, Beta Testing
4	Production	Live environment accessible by endusers.	Public	Real-world usage monitoring, Live Testing

Table 6: Test Strategy

## **5.4.4.** Test Techniques

Mentioned below are the techniques used for the testing of this project:

Unit Testing: Focused on testing individual units or components of the web application and APIs to ensure each part functions correctly in isolation.
 Integration Testing: Aimed at combining and testing the units as a group to ensure smooth interactions within the system.
 System Integration Testing: Involved testing the complete integrated system to evaluate the system's compliance with its specified requirements.
 Beta Testing: A live application test with real users to validate the usability and functionality of the application in a production-similar environment.
 Live Testing: Monitored the real-world operation of the system to ensure it performs as intended under normal usage conditions.

#### 5.4.5. Test Cases

Test Case No.	Test Case	Steps	Expected Output
1	Tests successful login with valid user credentials.	<ol> <li>Enter valid credentials.</li> <li>Submit login request.</li> </ol>	Successful login and access to the user dashboard.
2	Validates system response to invalid login attempts.	Enter invalid credentials.      Submit login request.	Error message and no access to the dashboard.
3	Checks the new user registration process for correctness.	<ol> <li>Fill registration form with new user details.</li> <li>Submit the form.</li> </ol>	Confirmation of successful registration.

4	Ensures the system detects and alerts for duplicate user registration.	<ol> <li>Fill registration form with existing user details.</li> <li>Submit the form.</li> </ol>	Error indicating user already exists
5	Verifies admin access and its exclusive functionalities.	Login as admin.      Access admin- specific features.	Access to admin functionalities.
6	Confirms the generation and receipt of authentication tokens.	Request authentication token.      Verify token receipt.	Receipt of a valid JWT token for session management.
7	Assesses the retrieval of area codes based on a given city code.	Provide a valid city code.      Request area codes.	List of area codes corresponding to the city code.

Table 7: Unit Testing

Test Case No.	Test Case	Steps	Expected Output
1	Validates the accuracy of user details retrieval.	Access user details page.      Request specific user details.	Display of accurate user-specific information.
2	Checks the listing of consumers in specified areas.	Enter valid city and area codes.	List of consumers in the specified area.

		2. Request consumer list.	
3	Tests the system's ability to correctly identify defaulters.	Enter valid city and area codes.      Request defaulter list.	List of defaulters in the specified area.
4	Assesses the accessibility and accuracy of consumption history data.	Provide a valid consumer number.      Request consumption history	Detailed consumption history for the specified consumer.
5	Evaluates dashboard data display and functionality for different user tiers.	Access different tier dashboards.      Review displayed data and functionalities.	Correct data display and functionality as per user tier.
6	Measures the performance of database queries under typical conditions.	Perform typical database queries.     Monitor response time.	Queries return results within an acceptable time frame.
7	Tests system stability and responsiveness under peak load conditions.	Simulate peak user load.      Monitor system performance.	System remains stable and responsive under high load.

Table 8: Beta Testing

# 5.4.6. Test Results

Test Case No.	Test Case	Expected Output	Actual Output	Verdict
1	Tests successful login with valid user credentials.	Successful login and access to the user dashboard.	As Expected	Pass
2	Validates system response to invalid login attempts.	Error message and no access to the dashboard.	As Expected	Pass
3	Checks the new user registration process for correctness.	Confirmation of successful registration.	As Expected	Pass
4	Ensures the system detects and alerts for duplicate user registration.	Error indicating user already exists	As Expected	Pass
5	Verifies admin access and its exclusive functionalities.	Access to admin functionalities.	As Expected	Pass

6	Confirms the generation and receipt of authentication tokens.	Receipt of a valid JWT token for session management.	As Expected	Pass
7	Assesses the retrieval of area codes based on a given city code.	List of area codes corresponding to the city code.	As Expected	Pass

Table 9: Unit Testing Results

Test Case No.	Test Case	Expected Output	Actual Output	Verdict
1	Validates the accuracy of user details retrieval.	Display of accurate user-specific information.	As Expected	Pass
2	Checks the listing of consumers in specified areas.	List of consumers in the specified area.	As Expected	Pass
3	Tests the system's ability to correctly identify defaulters.	List of defaulters in the specified area.	As Expected	Pass
4	Assesses the accessibility and accuracy of	Detailed consumption history for the	As Expected	Pass

	consumption	specified		
	history data.	consumer.		
5	Evaluates	Correct data	As Expected	Pass
	dashboard data	display and		
	display and	functionality as		
	functionality for	per user tier.		
	different user			
	tiers.			
6	Measures the	Queries return	As Expected	Pass
	performance of	results within an		
	database queries	acceptable time		
	under typical	frame.		
	conditions.			
7	Tests system	System remains	As Expected	Pass
	stability and	stable and		
	responsiveness	responsive under		
	under peak load	high load.		
	conditions.			

Table 10: Beta Testing Results

### 5.5. Results and Discussions

For the Energy Fraud Detection project, several factors were pivotal for accurate predictions: consumer number, time, and consumption.

The effectiveness of these factors was evaluated using different machine learning models:

Ш	Recurrent Neural Network (RNN): Applied due to its ability to nandle sequence
	data, making it ideal for time-based consumption analysis.
	Long Short-Term Memory (LSTM): Chosen for its proficiency in recognizing long-
	term patterns in time-series data, essential for the nuanced detection of fraudulent

☐ Anomaly Detection: Utilized for pinpointing outliers in consumption, thus identifying instances of fraud that deviate from established patterns.

Each model underwent rigorous testing to validate its predictive capabilities, ensuring the accuracy and reliability of the system's fraud detection measures.

### 5.6. Inferences Drawn

activities.

From the Energy Fraud Detection project that utilizes the labelling algorithm and anomaly detection, several inferences can be drawn:

- 1. Efficacy in Identifying Irregular Patterns: The project successfully implements a system that can identify irregular consumption patterns that deviate significantly from a customer's historical data, suggesting that it's effective in pinpointing potential fraudulent activities.
- Prioritization of Inspection Resources: By ranking consumers based on their deviation scores, the project allows for the efficient allocation of inspection resources to those consumers most likely to be defaulters, thus optimizing operational efficiency.
- 3. Adaptability to Different Consumer Profiles: The system's adaptability to different consumer profiles is inferred by its use of individualized mean and standard deviation calculations, implying that it can be tailored to various regions and consumer behaviours.

- 4. Unsupervised Learning Advantage: The utilization of an unsupervised learning algorithm, such as Isolation Forest, underscores the advantage of being able to detect anomalies without the need for a labelled training dataset, which is often not available in real-world scenarios.
- 5. Proactive Fraud Mitigation: The project's ability to detect potential fraud proactively, rather than reactively, infers a shift towards preventive measures in energy fraud management, potentially reducing financial losses.
- 6. Potential for Real-Time Application: Given the algorithms used, there is an implication that the system could be adapted for real-time fraud detection, providing immediate alerts and enabling quick response to potential fraud.
- 7. Scalability of the Solution: The system demonstrates the potential for scalability, as the algorithms can handle large datasets, which is essential for utility companies that manage vast networks with numerous consumers.

### 5.7. Validation of Objectives

SNo.	Objectives	Status
1	Identifying fraudulent use of resources in order to minimize its effects and reduce the economic impact in terms of both money and time.	Successful
2	Optimizing the number of checks using the results from analysis.  This way the investment on the service can be redeemed on a short term by avoiding costs incurred by unnecessary checks.	Successful
3	Develop a system that can be adapted, enhanced and renewed to several kinds of energy distribution and different geographical areas. Thus,	Successful

guaranteeing the best model of	
fraud detection depending on the	
particular needs of every client.	

Table 11: Validation of objectives

### 6. CONCLUSIONS AND FUTURE DIRECTIONS

#### 6.1. Conclusions

The proposed solution represents a pivotal advancement in combatting electricity fraud. By synergizing the potential of data-driven insights and innovative machine learning techniques, harmonized within an adaptable application architecture, our endeavor promises to revolutionize the domain of fraud detection. This solution addresses a critical need in the energy sector – safeguarding its integrity against fraudulent activities that can not only incur financial losses but also erode trust within communities.

The tiered approach, catering to different levels of engineers, ensures that potential fraud sites are identified, scrutinized, and acted upon promptly. The system's seamless integration with both hardware and software interfaces guarantees real-time detection, making it a robust and adaptable solution for the challenges posed by energy fraud.

The infusion of data analytics and advanced models is not only a strategic approach but also a proactive one, allowing us to anticipate and counteract new tactics employed by fraudulent actors. In embracing this paradigm shift, we forge a path towards a future where electricity fraud detection is not only robust but also agile, capable of swiftly adapting to evolving threats. Our solution envisions a world where data-driven precision meets intuitive application, effectively preserving the sanctity of the energy sector while empowering stakeholders with actionable intelligence.

### 6.2. Environmental, Economic and Social Benefits

Developing a project on energy fraud detection can yield several significant economic benefits, which include:

Revenue Protection: Detecting and preventing energy fraud ensures that energy
companies are accurately billing customers for the electricity they consume. This
leads to increased revenue collection, reducing revenue losses due to fraudulent
activities.

Operational Efficiency: Improved fraud detection can streamline operational processes within energy companies. It reduces the need for extensive investigations and legal actions against fraudulent customers, saving both time and resources.

- □ Reduced Operational Costs: By minimizing the need for physical inspections and manual meter reading, energy companies can lower operational costs. Automation through fraud detection technology can lead to substantial savings over time.
- ☐ Fair Pricing for Customers: Energy fraud often results in higher prices for honest customers to compensate for the losses. Detecting and mitigating fraud helps ensure fair pricing for all customers, promoting customer loyalty and satisfaction.
- ☐ Energy Conservation: Fraud detection can also identify instances of energy wastage or inefficiency, contributing to energy conservation efforts. This aligns with global trends toward sustainability and can lead to positive branding for the company.

#### 6.3. Reflections

Reflecting on the Energy Fraud Detection project, several insights and learnings come to the forefront:

- 1. Importance of Data: The project underscored the critical role of high-quality data in building effective predictive models. It brought into focus the meticulous attention needed for data collection, cleaning, and preprocessing to ensure that the inputs to the model are as accurate and reliable as possible.
- 2. Challenges of Real-World Applications: Translating a theoretical model into a real-world application revealed the complexities of operationalizing analytics solutions. It emphasized the need for scalability, performance optimization, and the ability to process data in real-time to deliver actionable insights.
- 3. Interdisciplinary Synergy: The project illustrated the value of interdisciplinary collaboration, combining expertise in data science, energy management, software engineering, and user experience design. This collaboration was essential to creating a solution that was not only technically sound but also user-friendly and aligned with business objectives.
- 4. Ethical Responsibility: Engaging with the ethical dimensions of automated fraud detection was enlightening. It highlighted the responsibility of data scientists to consider the consequences of false positives and negatives and the importance of incorporating ethical considerations into the design and implementation of such systems.

- 5. Learning from Limitations: The challenges encountered, such as data limitations and the need for continuous model refinement, were valuable learning opportunities. They provided insights into the iterative nature of developing advanced analytics systems and the importance of maintaining flexibility to incorporate new data and adapt to emerging fraud patterns.
- 6. Security Imperatives: The project brought to light the critical importance of cybersecurity. As the system handles sensitive consumer data, it became clear that robust security measures are essential to protect against potential breaches and maintain the integrity of the fraud detection process.
- 7. Impact on Stakeholders: Reflecting on the project's broader impact, it became evident that the benefits extend beyond the immediate financial gains for the energy companies. There is a potential for positive social and environmental impacts by ensuring fair billing practices and contributing to the efficient use of energy resources.

#### **6.4. Future Work**

The future development of the Energy Fraud Detection project could significantly advance its capabilities by focusing on key areas of improvement. Firstly, continuous refinement of predictive models is essential, achieved through the incorporation of additional data sources and advanced machine learning algorithms. Regular model retraining will ensure adaptability to evolving consumption patterns and fraud tactics. Second, integrating realtime data analysis, particularly from smart meters, will enable immediate detection and response to fraudulent activities. Third, expanding the model to include industrial and commercial profiles necessitates customization for diverse energy consumption patterns. Improving user interface and experience, implementing dashboards for real-time analytics, and exploring advanced anomaly detection techniques, such as deep learning, will enhance usability and accuracy. Geographic and demographic analyses, involving GIS and demographic data, can uncover spatial patterns and correlations. Establishing a legal and ethical framework, verifying suspected fraud activities, ensuring system scalability and performance, interdisciplinary collaboration, and robust cybersecurity measures are crucial aspects. Finally, an economic impact assessment, including cost-benefit analyses, will justify investments in this technology.

### 7. PROJECT METRICS

### 7.1. Challenges Faced

- 1. Data Quality and Integrity: The accuracy of predictive models is highly dependent on the quality and integrity of the input data. Any inaccuracies or inconsistencies in the data can lead to incorrect predictions and misidentification of fraudulent activities.
- 2. Algorithmic Complexity: Developing algorithms that can accurately differentiate between legitimate consumption patterns and fraudulent activities can be complex, especially when dealing with diverse and evolving tactics used by individuals engaging in energy theft.
- 3. Real-Time Data Processing: The ability to process and analyze data in real-time is crucial for immediate fraud detection. Implementing such a system requires significant computational resources and sophisticated data handling capabilities.
- 4. Scalability Concerns: As the utility network grows, the system must scale to handle an increasing volume of data without compromising performance. Scalability is essential to maintain efficiency and accuracy in larger, more complex networks.
- 5. False Positives and Negatives: Like all predictive systems, there is a risk of false positives (flagging honest consumers as fraudulent) and false negatives (failing to detect actual fraud). Minimizing these errors is crucial to maintain trust in the system.
- 6. Adaptability to New Fraud Tactics: Fraud tactics evolve, and the system must be adaptable to identify new patterns of fraudulent behaviour as they emerge. Continuous learning and adaptation are key to staying ahead of such tactics.
- 7. Integration with Existing Systems: Integrating the new fraud detection system with existing infrastructure and systems can be challenging, requiring careful planning and execution.
- 8. User Acceptance and Trust: Building trust among consumers and within the organization is essential. Users need to have confidence in the system's predictions and the actions taken as a result.

# 7.2. Relevant Subjects

Subjects Code	Subject Name	Description
UML501	Machine Learning	Concepts of the subjects were used to select the correct Machine learning model, and the optimised parameters.
UCS310	Database Management System	This subject was instrumental in designing the robust database architecture required for the energy fraud detection system. The course provided a comprehensive understanding of

		relational database management systems (RDBMS), data normalization, SQL querying, and transaction management. These concepts were applied to create efficient and scalable databases capable of handling real-time data ingestion from smart meters and IoT devices, optimizing data retrieval for machine learning processing, and ensuring data integrity and security.
UCS503	Software Engineering	The documentation of the report and SRS is learned in this subject and the documentation is done as per the IEEE format. The software development cycle is also learned and is used throughout the development of this project.

Table 12: Relevant Subjects

#### 7.3. Interdisciplinary Knowledge Sharing

For the complete development of this project in-depth knowledge of various courses was required. The members of the team are pursuing B.E. in computer engineering so we thought of dividing the learning task amongst the team members. Each member of the team learns a new technology or concept and share it with other team members. All the team members were eager to learn new technologies that helped in the development of this project. Some of the concepts and technologies which were required to develop this project are briefly explained below:

- 1. DJANGO REST FRAMEWORK: This is a tool we used to build the part of our energy fraud detection app that runs on servers. It helps our app's user interface talk to our server smoothly, allowing users to see and interact with energy use and fraud alerts as they happen.
- 2. MICROSOFT AZURE: We used Microsoft Azure to put our databases online in a way that is safe and works well. It runs our fraud detection software and can handle analysing energy use data quickly to spot possible fraud.
- 3. POSTGRESQL: This is a powerful database system we chose for keeping all our data organized and safe. It can handle lots of information coming in all the time, like the data from smart meters and other devices that track energy use.
- 4. REACT: We picked React to make the parts of our app that people see and use. It lets us make a dashboard that is easy to use and looks good, where users can check on energy patterns and get warnings if the system finds something wrong.
- 5. PYCARET: PyCaret is a set of tools that made it easier for us to create and use machine learning models, which are like the app's brain. It helps us choose the best model to find fraud by trying out different ones and seeing which one works best.

### 7.4. Peer Assessment Matrix

		Evaluation	n of			
		Rohan Grover	Mritunjay Dubey	Saksham Khetarpal	Jashan Arora	Simardeep Singh
<b>Evaluation</b> by	Rohan Grover	5	4	5	4	5
	Mritunjay Dubey	5	4	4	5	5
	Saksham Khetarpal	5	4	5	4	5
	Jashan Arora	4	5	5	5	4
	Simardeep Singh	5	5	5	4	4

Table 13: Peer Assessment Matrix

### 7.5. Role Playing and Work Schedule

Members/Modules	Rohan Grover	Mritunjay Dubey	Saksham Khetarpal	Jashan Arora	Simardeep Singh
Dataset selection and analysing	✓	✓	✓	✓	<b>√</b>
Generating ground truth data	<b>√</b>			<b>√</b>	
ML Model Selection	<b>√</b>			<b>√</b>	✓

Performance Analysis	✓	✓	<b>√</b>	✓	<b>√</b>
Database Design and Prototyping	✓			✓	
Backend API Development	<b>√</b>			<b>√</b>	
Frontend Development	<b>√</b>	<b>√</b>	<b>√</b>		<b>√</b>
Integration of Frontend and Backend	<b>√</b>	✓	✓	✓	<b>√</b>
Testing of the project	<b>√</b>	<b>√</b>	<b>√</b>	<b>√</b>	<b>√</b>
Report	<b>√</b>	<b>√</b>	<b>√</b>	<b>√</b>	✓

Table 14: Role Playing and Work Schedule

# 7.6. Student Outcomes Description and Performance Indicators (A-K Mapping)

SO	SO Description	Outcome
1.1	Ability to identify and formulate problems related to	We developed an advanced analytics
	computational domain	and machine learning-based system for
		real-time detection of electricity fraud.
1.2	Apply engineering, science, and mathematics body	To assess whether the analytics
	of knowledge to obtain analytical, numerical, and	software system is capable of
	statistical solutions to solve engineering problems.	effectively processing and analysing the
		real-time data from smart meters across
		the electricity distribution network for
		accurate detection of fraudulent
		activities

2.1	Design computing system(s) to address needs in different problem domains and build prototypes, simulations, proof of concepts, wherever necessary, that meet design and implementation specifications.	We developed a real-time electricity fraud detection system, effectively addressing issues like meter tampering and unauthorized connections.
2.2	Ability to analyze the economic trade-offs in	While there were more cost-effective
	computing systems.	options available, we chose a sophisticated analytics platform for our electricity fraud detection system. This decision was made to accommodate
		potential future expansions in data complexity and to ensure robust processing capabilities, crucial for accurately identifying and mitigating
		sophisticated fraudulent activities in the energy sector.
3.1	Prepare and present variety of documents such as project or laboratory reports according to computing standards and protocols	Our team diligently prepared and submitted comprehensive reports on the electricity fraud detection project, adhering to computing standards. The documents were meticulously crafted, ensuring accuracy, proper formatting,
3.2	Able to communicate effectively with peers in well	and adherence to technical protocols.  The project team demonstrated
3.2	organized and logical manner using adequate technical knowledge to solve computational domain	The project team demonstrated effective communication and collaboration, utilizing technical
	problems and issues.	expertise to address and resolve complex issues in the electricity fraud detection domain, leading to a cohesive and successful project outcome.

4.1	Aware of ethical and professional responsibilities	In developing the electricity fraud
	while designing and implementing computing	detection system, we consulted with
	solutions and innovations.	energy sector professionals to
		incorporate domain-specific knowledge
		and requirements, ensuring our
		approach was ethically sound and
		professionally responsible.
4.2	Evaluate computational engineering solutions	While our electricity fraud detection
	considering environmental, societal, and economic	system is technologically advanced, we
	contexts.	acknowledged potential societal and
		economic challenges, understanding its
		broader impact on environmental
		sustainability and ethical considerations
		in the energy sector.
5.1	Participate in the development and selection of ideas	Our team actively engaged in
	to meet established objective and goals.	brainstorming and refining ideas,
		leading to the selection of the most
		viable solution for electricity fraud
		detection that aligned with our
		established objectives and goals.
5.2	Able to plan, share and execute task responsibilities	Task responsibilities were equitably
	to function effectively by creating collaborative and	distributed among the team members,
	inclusive environment in a team.	fostering a collaborative environment
		that enhanced the effectiveness and
		coordination in developing the
		electricity fraud detection system.
6.1	Ability to perform experimentations and further	We conducted various tests on our
	analyse the obtained results.	electricity fraud detection system,
		analyzing the results to refine and
		improve the prototypes, culminating in
		the development of an effective final
		product.

Ability to analyse and interpret data, make necessary	In the electricity fraud detection project,
judgement(s) and draw conclusion(s).	various machine learning models were
	rigorously tested with our dataset. After
	thorough analysis and interpretation,
	the model demonstrating the highest
	accuracy in detecting fraudulent
	activities was selected, ensuring the
	most effective and reliable fraud
	prediction.
Able to explore and utilize resources to enhance self-	Throughout the development of the
learning.	electricity fraud detection system, the
	team proactively engaged in self-
	learning by researching the latest
	technological advances and studying
	relevant research papers. This
	continuous learning approach was
	instrumental in incorporating cutting-
	edge methodologies into our system,
	enhancing its effectiveness and
	adaptability.
SO Description	Outcome
Ability to identify and formulate problems related to	We developed an advanced analytics and
computational domain	machine learning-based system for real-time
	detection of electricity fraud.
Apply engineering, science, and mathematics body of	To assess whether the analytics software system
knowledge to obtain analytical, numerical, and statistical	is capable of effectively processing and
solutions to solve engineering problems.	analysing the real-time data from smart meters
solutions to solve engineering problems.	
solutions to solve engineering problems.	across the electricity distribution network for accurate detection of fraudulent activities
	Able to explore and utilize resources to enhance self-learning.  SO Description  Ability to identify and formulate problems related to computational domain  Apply engineering, science, and mathematics body of knowledge to obtain analytical, numerical, and statistical

2.1	Design computing system(s) to address needs in different problem domains and build prototypes, simulations, proof of concepts, wherever necessary, that meet design and implementation specifications.	We developed a real-time electricity fraud detection system, effectively addressing issues like meter tampering and unauthorized connections.
2.2	Ability to analyze the economic trade-offs in computing systems.	While there were more cost-effective options available, we chose a sophisticated analytics platform for our electricity fraud detection system. This decision was made to accommodate potential future expansions in data complexity and to ensure robust processing capabilities, crucial for accurately identifying and mitigating sophisticated fraudulent activities in the energy sector.
3.1	Prepare and present variety of documents such as project or laboratory reports according to computing standards and protocols	Our team diligently prepared and submitted comprehensive reports on the electricity fraud detection project, adhering to computing standards. The documents were meticulously crafted, ensuring accuracy, proper formatting, and adherence to technical protocols.
3.2	Able to communicate effectively with peers in well organized and logical manner using adequate technical knowledge to solve computational domain problems and issues.	The project team demonstrated effective communication and collaboration, utilizing technical expertise to address and resolve complex issues in the electricity fraud detection domain, leading to a cohesive and successful project outcome.
4.1	Aware of ethical and professional responsibilities while designing and implementing computing solutions and innovations.	In developing the electricity fraud detection system, we consulted with energy sector professionals to incorporate domain-specific knowledge and requirements, ensuring our approach was ethically sound and professionally responsible.

	Evaluate computational engineering solutions considering	
4.2	environmental, societal, and economic contexts.	While our electricity fraud detection system is technologically advanced, we acknowledged
		potential societal and economic challenges,
		environmental sustainability and ethical
		considerations in the energy sector.
	Participate in the development and selection of ideas to meet	
5.1	established objective and goals.	Our team actively engaged in brainstorming and
		refining ideas, leading to the selection of the
		most viable solution for electricity fraud
		detection that aligned with our established
		objectives and goals.
	Able to plan, share and execute task responsibilities to function	
5.2	effectively by creating collaborative and inclusive environment	Task responsibilities were equitably distributed
	in a team.	among the team members, fostering a
		collaborative environment that enhanced the
		effectiveness and coordination in developing
		the electricity fraud detection system.
	Alilia to mark and a superior at the superior and the superior at the	
6.1	Ability to perform experimentations and further analyze the	We conducted various tests on our electricity
	obtained results.	fraud detection system, analyzing the results to
		refine and improve the prototypes, culminating
		in the development of an effective final product.
6.2	Ability to analyze and interpret data, make necessary	I., 4114.: -: 4 C 1 1-44: : -4 :
6.2	judgement(s) and draw conclusion(s).	In the electricity fraud detection project, various
		machine learning models were rigorously tested
		with our dataset. After thorough analysis and
		interpretation, the model demonstrating the
		highest accuracy in detecting fraudulent
		activities was selected, ensuring the most
		effective and reliable fraud prediction.
	Able to explore and utilize resources to enhance self-learning.	
7.1		Throughout the development of the electricity
		fraud detection system, the team proactively
		engaged in self-learning by researching the
		latest technological advances and studying
		relevant research papers. This continuous
		learning approach was instrumental in

	incorporating cutting-edge methodologies into our system, enhancing its effectiveness and
Table 15: A-K Mapping	adaptability.

#### 7.7 Brief Analytical Assessment

## Q1. What sources of information did your team explore to arrive at the list of possible project problems?

**Ans:** For our electricity fraud detection project, we extensively researched online, reviewing various websites and academic research papers to understand the existing solutions and their limitations. We discovered that there was no available product in the market offering a more cost-effective or superior solution than ours. Additionally, we consulted with utility companies and energy sector professionals who expressed a strong interest in our project due to the lack of similar, effective solutions currently available.

### Q2. What analytical, computational and/or experimental methods did your project team use to obtain solutions to the problems in the project?

**Ans:** We implemented advanced analytics and machine learning models to process and analyse data from smart meters and IoT devices within the electricity distribution network. This approach allowed for real-time detection of fraudulent activities like meter tampering and unauthorized connections. Our system's ability to adapt to dynamic data sets and evolving fraud tactics was a critical aspect of our solution.

## Q3. Did the project demand demonstration of knowledge of fundamentals, scientific and/or engineering principles? If yes, how did you apply?

**Ans:** Absolutely, a strong foundation in engineering and scientific principles was essential for our project. We applied our knowledge from academic courses to design and prototype the system, integrating concepts from electrical engineering, data science, and computer engineering. Understanding the fundamentals of machine learning, data analysis, and IoT technology was crucial in developing an effective solution for electricity fraud detection.

#### Q4. What resources did you use to learn new material for the production of the project?

**Ans:** To augment our knowledge, we explored a variety of online resources, including academic journals, industry publications, and technical forums. We also delved into research papers that provided insights into the latest advancements in fraud detection technologies and machine learning applications in the energy sector. This research was pivotal in keeping our approach up-to-date and innovative.

# Q5. Does the project make you appreciate the need to solve problems in real life using engineering and could the project development make you proficient with software development tools and environments?

Ans: This project significantly heightened our appreciation for applying engineering solutions to real-world problems. It not only reinforced our interest in tackling complex challenges but also enhanced our proficiency with various software development tools and environments, particularly in machine learning and analytics. The hands-on experience with designing and implementing a sophisticated system for electricity fraud detection was invaluable for our professional growth.

### **APPENDIX A: REFERENCES**

- [1] Zidi, S., Mihoub, A., Qaisar, S.M., Krichen, M. and Al-Haija, Q.A., 2023. Theft detection dataset for benchmarking and machine learning based classification in a smart grid environment. Journal of King Saud University-Computer and Information Sciences, 35(1), pp.13-25.
- [2] Badr, M.M., Ibrahem, M.I., Kholidy, H.A., Fouda, M.M. and Ismail, M., 2023. Review of the Data-Driven Methods for Electricity Fraud Detection in Smart Metering Systems. Energies, 16(6), p.2852.
- [3] Calamaro, N., Beck, Y., Ben Melech, R. and Shmilovitz, D., 2021. An Energy-Fraud Detection-System Capable of Distinguishing Frauds from Other Energy Flow Anomalies in an Urban Environment. Sustainability, 13(19), p.10696.

### APPENDIX B: PLAGIARISM REPORT

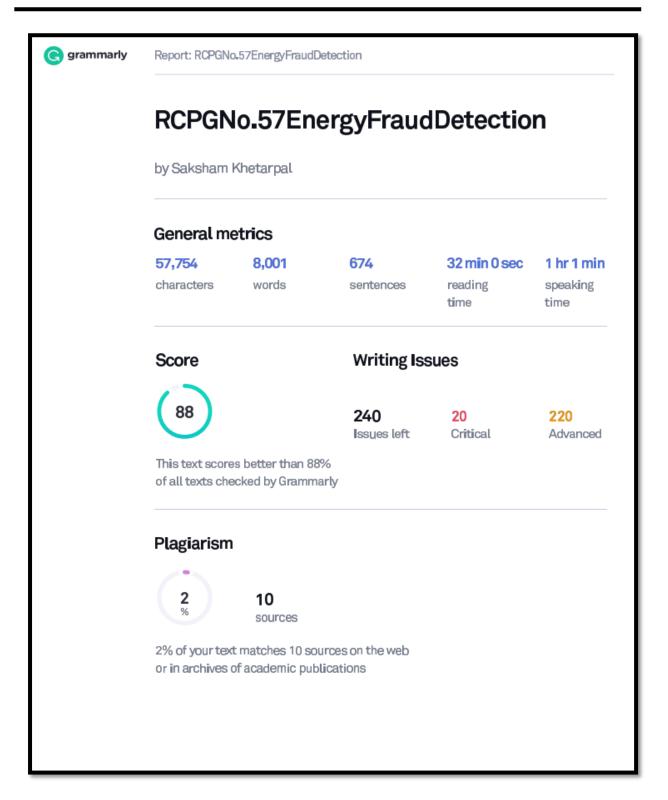


Fig 22: Plagiarism Report