

Next Gen Smart Fraud Detection In Energy Consumption Using Machine Learning Model

A MINI-PROJECT REPORT

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BONAFIDE CERTIFICATE

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ABSTRACT

This project proposes an advanced fraud detection system for energy consumption, leveraging a hybrid machine learning approach that integrates Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANNs), and Support Vector Machines (SVMs). The system aims to address the growing challenge of energy fraud, which can result in significant financial losses for utility providers. By employing a combination of CNNs for analyzing temporal patterns in time-series data, ANNs for modeling complex non-linear relationships, and SVMs for detecting rare fraudulent behaviors, the system enhances the accuracy and robustness of fraud detection. The approach begins with data collection from smart meters, aggregating both historical and real-time consumption data. This data undergoes preprocessing, including cleaning, normalization, and feature extraction, to identify key indicators such as consumption peaks and deviations from expected patterns. The machine learning models are then trained on this processed data to differentiate between legitimate and fraudulent consumption behaviors. An ensemble learning method is utilized to combine the strengths of each model, reducing false positives and improving overall detection performance. A real-time monitoring module is incorporated to provide immediate alerts when anomalies are detected in energy usage, enabling timely intervention by utility providers. The system also includes a user-friendly interface that displays visualizations, such as graphs and heatmaps, to assist in decision-making and fraud trend analysis. Furthermore, the system incorporates a feedback loop, allowing continuous refinement of the models based on new fraud patterns and flagged inaccuracies. By integrating predictive analytics with real-time detection, the proposed system offers a scalable and effective solution to combat energy fraud, ensuring better operational efficiency and reduced revenue losses for utility providers..

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CHAPTER 1

INTRODUCTION

1.1 GENERAL

The energy sector has witnessed rapid advancements with the introduction of smart grids and smart meters. These technologies have revolutionized energy monitoring, billing, and management by providing detailed and real-time consumption data. Smart meters enable utility providers to optimize power distribution, forecast energy demands, and create transparent billing mechanisms. However, this digitization has also brought challenges, as it has opened new avenues for fraudulent activities like energy theft, meter tampering, and unauthorized access. These issues affect revenue, operational efficiency, and fairness in energy distribution.

Traditional fraud detection systems, including manual inspections and rule-based methodologies, struggle to address the complex and evolving nature of fraudulent practices. These systems are reactive, error-prone, and often generate high false positive rates, creating inefficiencies in energy monitoring. Modern fraud requires solutions that can adapt to new fraud strategies, analyze large datasets, and provide actionable insights in real-time.

This project emphasizes the integration of machine learning (ML) into energy fraud detection systems. ML-based solutions can process massive datasets, recognize patterns, and predict fraudulent activities with higher accuracy and efficiency than traditional approaches. With ML's growing role in industrial automation, it offers a transformative approach to secure energy infrastructures against fraud.

1.2 NEED FOR THE STUDY

Fraudulent energy consumption poses a significant challenge globally, resulting in economic losses estimated to exceed billions annually. These losses directly impact the financial stability of utility providers, limiting their ability to invest in critical infrastructure upgrades and the adoption of renewable energy technologies. Additionally, fraudulent activities undermine the reliability of energy systems, often leading to power outages or inefficiencies in distribution. On a broader scale, they hinder the equitable allocation of energy resources, disproportionately affecting compliant consumers who indirectly bear the financial burden through increased tariffs and hidden costs.

Beyond monetary consequences, fraudulent energy consumption disrupts operational efficiency by distorting energy demand forecasts. Accurate forecasting is essential for maintaining a balanced energy supply, as it ensures optimal resource allocation and prevents overloading of grids. Fraudulent activities skew these projections, causing mismanagement of resources and increasing maintenance costs. For instance, unaccounted energy theft can lead to significant technical losses, requiring frequent grid inspections and repairs. Such inefficiencies erode public trust in energy providers, further complicating their operational and financial standing.

Traditional fraud detection systems, such as rule-based and statistical methods, have proven inadequate in addressing these issues. While effective in identifying straightforward anomalies like consumption spikes or drops, these systems struggle with subtle and complex fraud patterns that evolve over time. For example, advanced tampering techniques that mimic normal usage patterns can bypass rule-based thresholds, rendering such systems ineffective. Moreover, these systems rely heavily on manual interventions, making them not only resource-intensive but also prone to errors, especially when applied to large-scale operations involving millions of smart meters.

1.3 OBJECTIVES OF THE STUDY

The study sets out to develop a cutting-edge machine learning framework capable of detecting fraudulent energy consumption patterns with high precision. Fraudulent practices such as tampering with meters, bypassing connections, or unauthorized access to smart grid systems significantly undermine the financial health of utility providers. A primary objective of this study is to minimize these revenue losses by building a robust system that can differentiate normal usage from fraudulent activities with accuracy. Unlike traditional rule-based systems that often overlook subtle irregularities, this framework analyzes both historical and real-time data to uncover anomalies, even those embedded within complex usage patterns. By detecting fraud early and accurately, the system safeguards financial stability and improves trust in energy systems.

In addition to financial benefits, the framework is designed to enhance the operational efficiency of utility providers. Fraudulent activities not only cause immediate monetary losses but also impose long-term infrastructure challenges, such as grid strain and unexpected maintenance costs. Predictive monitoring, a core feature of the proposed system, identifies fraud before it escalates into significant issues, enabling providers to respond proactively. This capability not only reduces the operational strain on resources but also mitigates disruptions to energy supply, ensuring a stable and reliable grid for all users. Furthermore, the system incorporates robust security measures to protect smart metering infrastructures against unauthorized access, preventing manipulation of data and maintaining the integrity of energy distribution networks.

The project also emphasizes the importance of actionable insights through data visualization and reporting tools. These tools convert complex analytical findings into easily interpretable formats, such as graphs, heatmaps, and dashboards. This empowers utility providers to understand patterns and trends, aiding in strategic decision-making and fraud prevention. Moreover, these insights help optimize resource allocation, ensuring equitable and efficient energy distribution.

1.4 OVERVIEW OF THE PROJECT

This project proposes a hybrid machine learning approach for energy fraud detection, integrating Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANNs), and Support Vector Machines (SVMs). Each model addresses unique challenges such as capturing temporal patterns (CNNs), modeling non-linear relationships (ANNs), and identifying rare fraud cases (SVMs). The system starts with data collection from smart meters, followed by preprocessing steps like cleaning, normalization, and feature extraction to identify key indicators like abnormal usage spikes. The processed data is then used to train the models to distinguish between normal and fraudulent consumption behaviors.

The machine learning models work together through an ensemble learning method, which combines their strengths to improve overall accuracy. CNNs detect patterns in time-series data, ANNs handle complex relationships between features, and SVMs classify rare fraudulent instances. The ensemble approach ensures robustness, allowing the system to detect both common and rare fraud patterns. The real-time detection system continuously monitors energy consumption data and generates alerts when potential fraud is detected, providing timely intervention.

A user-friendly interface enables utility providers to easily monitor and analyze energy consumption trends through visualizations such as graphs and charts. The system also offers detailed reports and predictive analytics, helping to identify potential fraud before it occurs. This scalable, adaptable system ensures that utility providers can effectively combat energy fraud by leveraging advanced machine learning techniques and real-time data monitoring, ultimately reducing losses and improving operational efficiency.

CHAPTER 2

REVIEW OF LITERATURE

2.1 INTRODUCTION

The detection of fraudulent activities in energy consumption has evolved significantly over time, beginning with rule-based systems. These early systems were straightforward to implement and relied on predefined rules to flag unusual consumption patterns. However, their simplicity came at the cost of adaptability. Rule-based systems often struggled to keep up with new, evolving fraud techniques, leading to frequent false positives where legitimate consumption was flagged as fraudulent. Additionally, these systems required constant updates and manual adjustments to remain effective, which made them labor-intensive and difficult to scale.

With the advancement of statistical methods, fraud detection techniques saw improvements in accuracy. These methods focused on analyzing historical consumption data using statistical metrics like mean, variance, and standard deviation to identify outliers or unusual patterns. While these approaches offered some enhancement over rule-based systems, they were limited by their inability to handle large, noisy datasets. Variations due to legitimate factors such as seasonal changes, weather conditions, or temporary spikes in energy usage often led to false positives or inaccurate classifications, making it difficult to distinguish between normal fluctuations and actual fraudulent activities.

Algorithms like Random Forest, Support Vector Machines (SVMs), and Neural Networks have shown significant promise by learning from large datasets and identifying complex, non-linear relationships within the data. As a result, machine learning-based systems have become indispensable in modern fraud detection, surpassing traditional methods in terms of scalability, adaptability, and efficiency, while offering the ability to detect new fraud patterns that were previously undetectable.

2.2 FRAMEWORK OF LCA

1. Goal Definition:

- Minimize revenue losses due to fraudulent activities.
- Enhance detection accuracy to effectively differentiate between legitimate and fraudulent consumption.

2. Study Scoping:

- Focus on data from smart meters, including:
 - Historical usage patterns.
 - Real-time consumption data.

3. Data Collection:

- Smart Meter Data: Generate vast amounts of data, including time-series consumption readings.
- Data Aggregation: Collect and combine relevant data from multiple sources.
- Data Cleaning & Normalization:
 - Remove noise and handle inconsistencies.
 - Impute missing values where applicable.
 - Convert data into a format suitable for machine learning models.

4. Feature Extraction:

- Identify critical indicators that could signal fraudulent activity, such as:
 - Consumption peaks (abnormal surges).
 - Timestamps (out of expected periods).
 - Deviations from typical usage patterns.

5. Model Training and Validation:

- Training: Use the processed data to train machine learning models.
- Validation: Evaluate models using performance metrics to assess accuracy.
 - Metrics: Precision, recall, and F1-score.
- Ensure that the models can generalize well to unseen data.

6. Performance Evaluation:

- Track key performance indicators to ensure the effectiveness of fraud detection.
- Continually assess and compare results from different models.

7. Iterative Feedback & Optimization:

- Regularly update models with new data to improve performance.
- Use feedback loops to refine models, enhancing fraud detection capabilities over time.
- Implement continuous optimization cycles to adapt to evolving fraud patterns.

Conclusion:

The LCA framework ensures a structured approach to fraud detection, focusing on data-driven decision-making and ongoing system improvement. Through clear goal-setting, thorough data processing, and iterative optimization, this approach offers a robust solution to identifying and mitigating energy fraud.

CHAPTER 3

SYSTEM OVERVIEW

3.1 EXISTING SYSTEM

Fraud detection in energy consumption has become a critical challenge for utility companies, with increasing demand for systems that can efficiently identify fraudulent activities while minimizing false alarms. Current approaches to fraud detection typically fall into four major categories: rule-based systems, statistical methods, standalone machine learning models, and deep learning systems. Each of these categories offers unique strengths and limitations when applied to energy consumption data, and understanding these systems is crucial for selecting the most appropriate solution for specific use cases.

Rule-Based Systems

Rule-based systems are among the simplest and most traditional approaches to fraud detection. These systems rely on predefined thresholds and rules to flag unusual energy usage patterns. For example, if a household exceeds a certain energy consumption threshold during off-peak hours, it is flagged as potentially fraudulent. Rule-based systems are easy to implement and do not require extensive training data, making them a cost-effective choice for smaller-scale applications. However, these systems are rigid and lack flexibility. They cannot adapt to new or evolving fraud tactics, as they are limited to the rules set by system administrators. Additionally, these systems tend to produce high false positive rates, as they struggle to differentiate between legitimate usage spikes and fraudulent behavior, especially in dynamic environments. For example, an unusual consumption pattern might occur due to a holiday season or a legitimate increase in household size, which would still be flagged as fraudulent.

The lack of scalability is another significant drawback of rule-based systems. As energy consumption patterns become more complex and data volumes increase, the static nature of these rules becomes less effective. Consequently, rule-based systems are more suitable for environments where energy consumption patterns are

relatively stable and predictable, but they are inadequate in scenarios involving sophisticated or subtle fraud schemes. This makes them less viable for modern, large-scale applications that demand higher detection accuracy and adaptability.

Statistical Methods

To address some of the limitations of rule-based systems, statistical methods have been introduced. These include techniques such as regression analysis, time-series forecasting, and statistical anomaly detection. These methods are used to model historical consumption data and identify deviations from normal behavior. For instance, regression models can be used to predict energy consumption based on historical trends, while time-series forecasting can detect unusual spikes or dips in energy usage that deviate from established seasonal patterns.

While statistical methods offer more sophistication than rule-based systems, they are still not entirely sufficient for detecting fraud in complex datasets. These methods excel at identifying simple anomalies, such as usage spikes during off-peak hours, which are commonly associated with fraudulent activities. However, they fail to capture the complex, non-linear relationships that are often present in the data. Fraudulent behavior can often be masked within normal usage patterns, such as a gradual increase in consumption or changes in usage that are consistent with broader societal trends. For example, a fraudulent user may mimic the consumption patterns of legitimate customers, making it difficult to detect such fraud using traditional statistical methods.

Additionally, statistical methods struggle to scale effectively with large datasets, particularly in the context of modern smart grid systems that generate vast amounts of real-time data. The computational complexity and limitations in handling high-dimensional data make these methods less suitable for real-time fraud detection. Furthermore, they require careful selection of features and parameter tuning, which can be time-consuming and error-prone. As a result, while statistical methods can provide valuable insights into historical consumption patterns, they are not fully equipped to handle the dynamic and multifaceted nature of modern energy fraud.

Standalone Machine Learning Models

Standalone machine learning models, such as Random Forest (RF), Support Vector Machines (SVMs), and k-Nearest Neighbors (KNN), represent a significant advancement over rule-based and statistical methods. These models can learn from historical data, identifying complex patterns that are not easily captured by traditional techniques. For example, Random Forest models can analyze multiple decision trees to identify which features of consumption data are most predictive of fraudulent behavior, while SVMs are effective at classifying instances based on high-dimensional data.

One of the primary advantages of machine learning models is their ability to adapt to changing fraud patterns. Unlike rule-based systems, machine learning models can evolve as new data is introduced, learning to detect novel types of fraud without requiring explicit reprogramming. However, despite these advantages, machine learning models face several challenges. One of the most significant issues is class imbalance. In fraud detection, fraudulent cases are typically much rarer than legitimate cases, which can lead to bias in the model. Machine learning models, particularly those using supervised learning techniques, tend to be biased toward the majority class (legitimate consumption), making it harder to identify fraudulent behavior accurately.

To address class imbalance, techniques such as resampling (either oversampling the minority class or undersampling the majority class) and cost-sensitive learning are employed. However, these methods may not always resolve the problem, and models may still struggle to detect rare fraud instances accurately. Despite these challenges, standalone machine learning models offer significant improvements over traditional approaches in terms of flexibility, adaptability, and scalability. They can analyze larger datasets, identify complex patterns, and detect a broader range of fraudulent behaviors. However, these models still require careful tuning, validation, and optimization to handle imbalanced classes effectively and avoid overfitting.

3.2 PROPOSED SYSTEM

The proposed fraud detection system utilizes a hybrid machine learning approach, combining Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANNs), and Support Vector Machines (SVMs) within an ensemble learning framework. The integration of these different models allows the system to address a wide range of challenges that arise in energy consumption fraud detection, ensuring both accuracy and adaptability. Each model plays a specific role in capturing distinct aspects of energy usage patterns and identifying fraudulent behavior across various timescales and complexity levels.

CNNs are particularly effective in analyzing time-series data, as they are well-suited for capturing both spatial and temporal dependencies in sequential data. In the context of energy consumption, this means that CNNs can detect patterns that evolve over time, such as consistent discrepancies in consumption that may indicate ongoing fraudulent activity. These patterns could involve scenarios where fraud occurs gradually or in a recurring manner over an extended period. By recognizing these long-term patterns, CNNs can identify tampering with smart meters or systematic manipulations that alter energy usage reporting. This ability is especially important for detecting sophisticated fraud techniques that might not be immediately obvious or easily flagged by traditional methods.

Artificial Neural Networks (ANNs) are introduced to model the complex, non-linear relationships present in energy consumption data. Traditional fraud detection systems often rely on linear models, which can struggle to account for the intricate dynamics of energy usage that occur in real-world scenarios. ANNs, on the other hand, can adapt to these complexities by learning from the data itself, enabling the system to identify more subtle and diverse fraud patterns. For example, ANNs can discern patterns where fraudulent behavior is hidden within normal fluctuations, such as slight but persistent deviations in consumption, which are typical of more sophisticated fraud attempts.

Support Vector Machines (SVMs) are incorporated into the system to detect rare and subtle instances of fraud, which are often overlooked by more conventional methods. Fraudulent activities in energy consumption are frequently outliers in the data, where the fraudulent behavior significantly deviates from normal consumption patterns. SVMs are particularly adept at identifying such anomalies by constructing a hyperplane that separates normal and anomalous data points. This capability allows the system to flag instances of fraud that might be isolated or infrequent, ensuring that even less obvious forms of fraud—such as a single fraudulent consumption event—are detected before they can cause substantial losses.

The ensemble learning framework combines these models into a single, cohesive system that maximizes the strengths of each technique. By integrating CNNs, ANNs, and SVMs, the system benefits from a layered approach that ensures robustness and higher accuracy. For instance, while CNNs focus on detecting recurring patterns of tampering or long-term fraud, SVMs specialize in identifying rare, outlier behaviors. The combination of these models enhances the overall detection capability, reducing the occurrence of false positives and ensuring that fraudulent activities are detected promptly. This versatility is crucial for adapting to the varied and evolving nature of fraud schemes in the energy sector.

Overall, the proposed system offers a comprehensive solution to energy consumption fraud detection by combining state-of-the-art machine learning techniques with real-time monitoring and visualization capabilities. Its hybrid approach ensures high accuracy, adaptability, and scalability, making it well-suited to address the growing challenges of energy fraud in modern utility systems. By integrating advanced fraud detection techniques with operational tools for real-time alerts and decision-making, the system not only improves fraud detection capabilities but also enhances the overall efficiency and effectiveness of utility operations.

3.3 FEASIBILITY STUDY

The feasibility of implementing the proposed system is assessed across three dimensions: technical, economic, and operational feasibility. From a technical perspective, the system leverages widely used frameworks like TensorFlow and Scikit-learn, ensuring compatibility with existing infrastructures. The use of modular components for data preprocessing, feature extraction, and model training allows for seamless integration and scalability.

From an economic standpoint, the initial cost of deploying the system, including hardware and software investments, is outweighed by the long-term savings from reduced revenue losses due to fraud. Additionally, the system automates much of the detection process, reducing labor costs associated with manual inspections and rule updates.

Finally, the system's operational feasibility ensures ease of use and implementation. It integrates with existing smart meter infrastructures without requiring significant modifications. The user interface is designed to simplify interaction, presenting actionable insights and detailed reports that can be easily understood by non-technical stakeholders. This feasibility analysis highlights the practicality and cost-effectiveness of the proposed system.

CHAPTER 4

SYSTEM REQUIREMENTS

4.1 HARDWARE REQUIREMENTS

The hardware requirements for this system are designed to support the computational demands of machine learning model training and real-time fraud detection. The processor must be at least an Intel i7 (10th generation or higher) or an AMD Ryzen 7 equivalent, ensuring fast processing speeds for handling large datasets and complex algorithms. RAM should be a minimum of 16 GB to facilitate smooth execution of data preprocessing, model training, and real-time monitoring tasks.

Storage requirements include at least a 512 GB SSD for faster read/write operations, especially when dealing with large historical datasets and logs generated by real-time monitoring. For training deep learning models like CNNs, a dedicated GPU, such as the NVIDIA RTX 3060 or higher, is essential. GPUs accelerate the training process, reducing the time required to build and optimize the system's machine learning models.

In addition to core hardware, peripheral devices like a stable internet connection for real-time data streaming and robust cooling systems for maintaining hardware performance during intensive computations are recommended. These specifications ensure the system operates efficiently under high workloads, both during development and deployment.

4.2 SOFTWARE REQUIREMENTS

The software stack for this project includes both development and deployment tools tailored for machine learning and data processing. The operating system should be a Linux-based environment (e.g., Ubuntu 20.04) for better performance and compatibility with machine learning libraries. Alternatively, Windows 10 is also supported for developers familiar with the platform.

Programming tools include Python 3.9 or above, due to its extensive ecosystem of libraries for data science and machine learning. Key libraries include TensorFlow for building and training deep learning models, Scikit-learn for traditional machine learning tasks, Pandas and NumPy for data manipulation, and Matplotlib/Seaborn for visualizing results. Database management relies on MySQL or PostgreSQL, enabling efficient storage and retrieval of historical and real-time energy data.

For hosting the system's web-based interface, XAMPP or Django can be used. The interface provides stakeholders access to live monitoring dashboards, analytics, and detailed reports. Finally, version control tools like Git ensure collaborative development, while Docker containers enable easy deployment of the system across different environments. This comprehensive software stack supports the system's end-to-end functionality.

CHAPTER 5

SYSTEM DESIGN

5.1 SYSTEM ARCHITECTURE

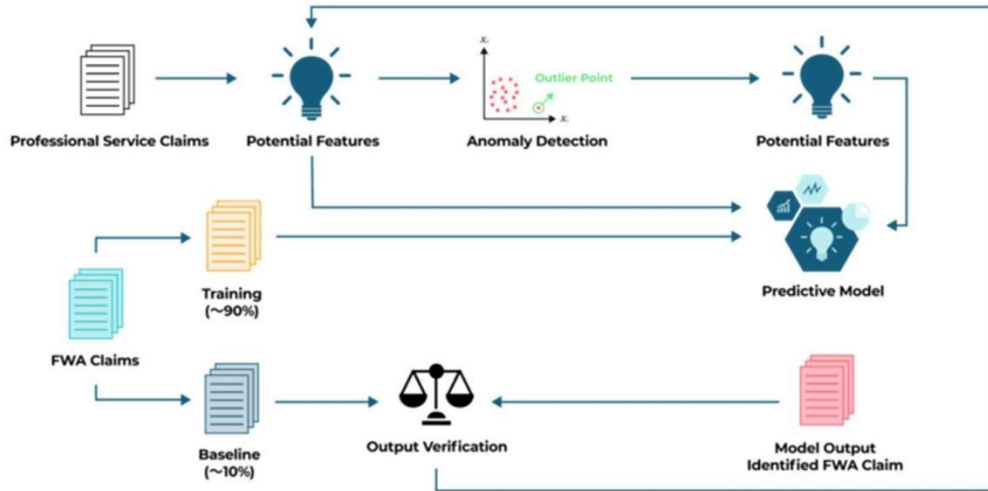


Fig 5.1.1 Architecture

The system architecture is a multi-layered framework that integrates data processing, machine learning, real-time monitoring, and user interaction. At the foundation, the system collects and aggregates both historical and real-time consumption data from smart meters, which is then preprocessed to ensure compatibility with the machine learning models. The core layer consists of Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANNs), and Support Vector Machines (SVMs), which work together to analyze time-series data, identify complex relationships, and detect subtle anomalies.

5.2 MODULE DESCRIPTION

5.2.1 Data Preprocessing Module

The Data Preprocessing Module is the foundation of the system, designed to prepare raw energy consumption data for analysis. Raw data often contains missing values, outliers, and inconsistencies that can negatively impact the performance of machine learning models. This module addresses these issues by implementing techniques such as imputation for missing values, where statistical methods (mean, median, mode) or advanced approaches like k-Nearest Neighbors are used to fill gaps.

Another critical task of this module is normalization and scaling of energy consumption values to ensure that all features are represented on a uniform scale. For instance, energy usage data is often normalized to a range between 0 and 1, preventing features with larger numerical ranges from disproportionately influencing the model. Time-series data is also converted into structured formats, such as sliding windows or lagged datasets, making it suitable for sequential analysis by models like CNNs.

Finally, the module includes data augmentation to address the issue of class imbalance, where fraudulent cases are often far fewer than normal cases.

```
data.reset_index(inplace=True, drop=True) # index sorting
infoData.reset_index(inplace=True, drop=True)

data = data.interpolate(method='linear', limit=2, # filling NaN values
                        limit_direction='both', axis=0).fillna(0)

for i in range(data.shape[0]): # outliers treatment
    m = data.loc[i].mean()
    st = data.loc[i].std()
    data.loc[i] = data.loc[i].mask(data.loc[i] > (m + 3 * st), other=m + 3 * st)

data.to_csv(r'visualization.csv', index=False, header=True) # preprocessed data

scale = MinMaxScaler()
scaled = scale.fit_transform(data.values.T).T
mData = pd.DataFrame(data=scaled, columns=data.columns)
print(mData)
preprData = pd.concat([infoData, mData], axis=1, sort=False) # Back to initial format
print(preprData)
preprData.to_csv(r'preprocessedR.csv', index=False, header=True)
```

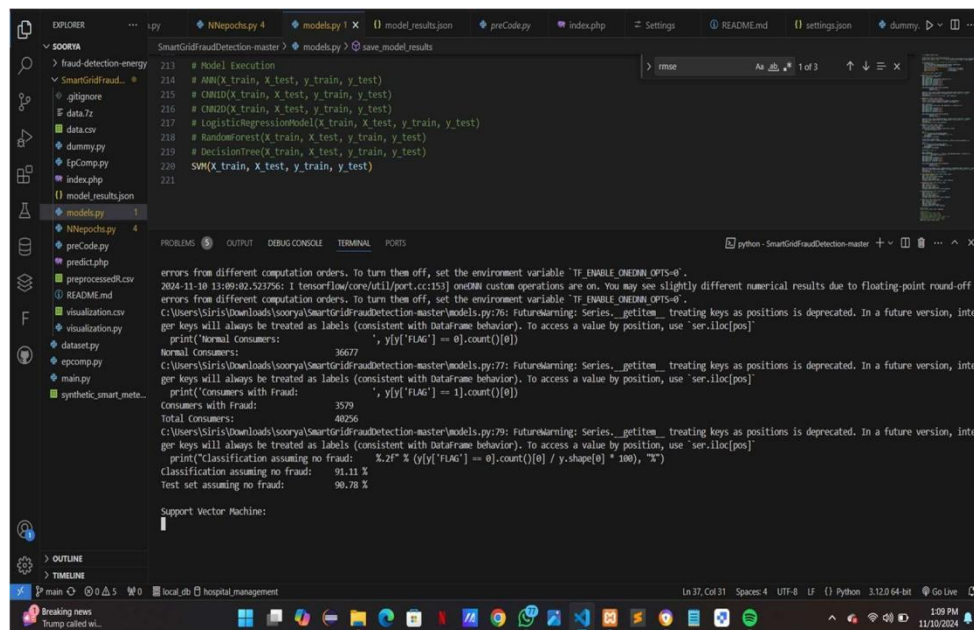
Fig 5.2.1 Data Processing

5.2.2 Feature Extraction Module

The Feature Extraction Module focuses on identifying and isolating the most relevant attributes from the processed data. Energy consumption datasets often include attributes like timestamp, hourly usage, peak usage, and seasonal patterns, which serve as indicators of normal or fraudulent behavior. This module employs statistical and machine learning techniques to extract features that represent patterns, anomalies, and relationships within the data.

One of the key processes is the identification of temporal features, such as variations in energy usage across different times of the day or during specific seasons. For example, abnormally high energy usage at night may signal tampering or unauthorized consumption. Other important features include deviations from historical usage trends and the frequency of abrupt changes in consumption levels.

Advanced techniques such as Principal Component Analysis (PCA) or feature importance scores derived from models like Random Forest are applied to reduce dimensionality and eliminate redundant features. This ensures that only the most impactful attributes are passed to the machine learning models, improving efficiency and reducing computational overhead.



The screenshot displays a Jupyter Notebook interface with a file explorer on the left and a code editor on the right. The file explorer shows a project structure with folders like 'fraud-detection-energy' and 'SmartGridFraud...', and files like 'data.csv', 'dummy.py', 'epcomp.py', 'index.php', 'model_results.json', 'models.py', 'preCode.py', 'predict.php', 'processedR.csv', 'README.md', 'visualization.csv', 'visualization.py', 'dataset.py', 'epcomp.py', 'main.py', and 'synthetic_smart_mete...'. The code editor shows a Python script with the following content:

```
213 # Model Execution
214 # AMM(X_train, X_test, y_train, y_test)
215 # CHRD(X_train, X_test, y_train, y_test)
216 # CHRD(X_train, X_test, y_train, y_test)
217 # LogisticRegressionModel(X_train, X_test, y_train, y_test)
218 # RandomForest(X_train, X_test, y_train, y_test)
219 # DecisionTree(X_train, X_test, y_train, y_test)
220 SVM(X_train, X_test, y_train, y_test)
221
```

The output of the script is displayed in the terminal, showing the results of the feature extraction process:

```
errors from different computation orders. To turn them off, set the environment variable 'TF_ENABLE_ONEDNN_OPTS=0'.
2024-11-10 13:09:02.523756: I tensorflow/core/util/port.cc:153] oneDNN custom operations are on. You may see slightly different numerical results due to floating-point round-off
errors from different computation orders. To turn them off, set the environment variable 'TF_ENABLE_ONEDNN_OPTS=0'.
C:\Users\Sirisi\Downloads\soorya\SmartGridFraudDetection-master\models.py:78: FutureWarning: Series._getitem_ treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame behavior). To access a value by position, use 'ser.iloc[pos]'
print('Normal Consumers: ', y['FLAG'] == 0).count()[0])
Normal Consumers: 36677
C:\Users\Sirisi\Downloads\soorya\SmartGridFraudDetection-master\models.py:79: FutureWarning: Series._getitem_ treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame behavior). To access a value by position, use 'ser.iloc[pos]'
print('Consumers with Fraud: ', y['FLAG'] == 1).count()[0])
Consumers with Fraud: 3579
Total Consumers: 40256
C:\Users\Sirisi\Downloads\soorya\SmartGridFraudDetection-master\models.py:79: FutureWarning: Series._getitem_ treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame behavior). To access a value by position, use 'ser.iloc[pos]'
print('Classification assuming no fraud: %2f' % (y['FLAG'] == 0).count()[0] / y.shape[0] * 100), "%")
Classification assuming no fraud: 90.11 %
Test set assuming no fraud: 90.78 %

Support Vector Machine:
```

Fig 5.2.2 Feature Extraction

5.2.3 Model Training Module

The Model Training Module is the heart of the system, responsible for building and fine-tuning the machine learning models used for fraud detection. The training process begins with splitting the preprocessed dataset into training, validation, and testing subsets. Typically, 70% of the data is allocated for training, 20% for validation, and 10% for testing, ensuring the model is exposed to unseen data for evaluation.

This module utilizes three machine learning models: Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANNs), and Support Vector Machines (SVMs). CNNs are trained on time-series data to detect spatial and temporal patterns, while ANNs model complex, non-linear relationships in the data. SVMs, on the other hand, are optimized for identifying outliers, capturing rare fraud cases effectively. Each model undergoes rigorous hyperparameter tuning to maximize performance, using techniques like grid search or random search to find the best configurations.

Cross-validation techniques, such as k-fold validation, are employed to prevent overfitting and ensure generalizability. The performance of each model is evaluated using metrics like accuracy, precision, recall, and F1-score. These metrics guide the selection of the most effective model or combination of models for deployment.

```
Epoch: 1
126/126 ————— 1s 4ms/step
Accuracy 91.10779930452063
C:\Users\Siris\AppData\Local\Programs\Python\Python39-64\python.exe: can't open file 'C:\Users\Siris\AppData\Local\Programs\Python\Python39-64\python.exe': [Errno 2] No such file or directory
overed in 1.6. To calculate the root mean square error:
warnings.warn(
RMSE: 0.2981979325126079
MAE: 0.08892200695479384
F1: [95.32515017 9.13705584]
AUC: 52.35747655797729
[[3650 5]
 [ 353 18]]
```

Fig 5.2.3 Model Training 1

```
Epoch: 13
126/126 ————— 0s 3ms/step
Accuracy 91.95230998509687
C:\Users\Siris\AppData\Local\Programs\Python\Python39-64\python.exe: can't open file 'C:\Users\Siris\AppData\Local\Programs\Python\Python39-64\python.exe': [Errno 2] No such file or directory
overed in 1.6. To calculate the root mean square error:
warnings.warn(
RMSE: 0.2836845081230755
MAE: 0.08047690014903129
F1: [95.59423443 53.58166189]
AUC: 73.28697165570924
[[3515 140]
 [ 184 187]]
```

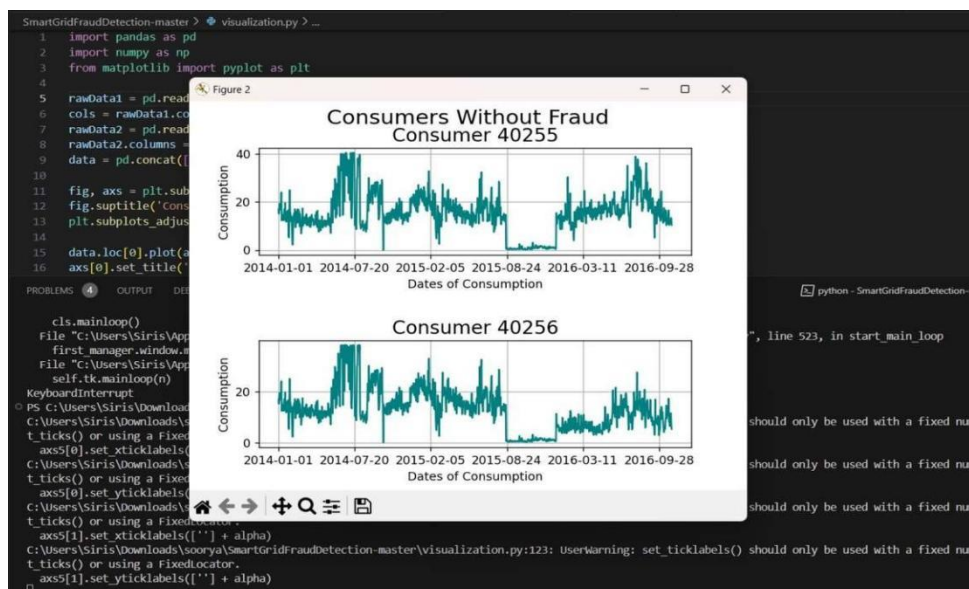
Fig 5.2.4 Model Training 2

5.2.4 Fraud Detection Module

The Fraud Detection Module applies trained models to real-time and historical data to identify fraudulent energy consumption patterns. This module continuously monitors energy usage and flags anomalies based on the outputs of the ensemble learning framework. For instance, abrupt spikes in consumption or deviations from normal patterns are flagged as potential fraud cases.

The module includes threshold-based alert mechanisms to notify utility providers of suspicious activities. For example, if energy consumption exceeds predefined thresholds or deviates significantly from historical trends, an alert is triggered. These thresholds are dynamically adjusted based on insights provided by the machine learning models, ensuring adaptability to new fraud strategies.

Moreover, the module provides detailed case summaries for flagged instances, including probable causes and supporting data. For example, a flagged case might include timestamps, usage levels, and comparisons with normal consumption patterns. This detailed output aids utility providers in investigating and validating fraud cases, making the module highly practical and actionable.



5.2.5 Ensemble Learning Module

The Ensemble Learning Module combines the strengths of individual models—CNNs, ANNs, and SVMs—into a single, robust framework. This module employs techniques like bagging, boosting, or stacking to aggregate predictions from the individual models, resulting in improved accuracy and reduced false positives. For example, stacking involves training a meta-model (such as Logistic Regression) on the outputs of the base models to make final predictions.

One of the primary benefits of ensemble learning is its ability to handle diverse fraud scenarios. CNNs may excel in detecting recurring patterns over time, while ANNs are better suited for identifying complex, nonlinear fraud relationships. SVMs contribute by accurately classifying rare or outlier cases. Combining these strengths ensures the system performs well across all types of fraud patterns.

The module also incorporates mechanisms for confidence scoring, where predictions are accompanied by probabilities indicating the likelihood of fraud. High-confidence predictions are flagged immediately, while low-confidence cases may be subjected to further analysis or manual review. This layered approach ensures both accuracy and reliability in fraud detection.

5.2.6 Real-Time Monitoring Module

The Real-Time Monitoring Module enables continuous surveillance of energy consumption data, allowing for immediate detection and response to fraudulent activities. This module receives a constant stream of data from smart meters, processes it in near real-time, and feeds it into the trained ensemble model. Anomalies are flagged within seconds, ensuring timely intervention by utility providers.

A key feature of this module is its ability to adapt to changing usage patterns. For instance, seasonal variations in energy consumption or sudden surges due to legitimate reasons are accounted for through dynamic threshold adjustments. This reduces false positives and ensures that only genuine cases of fraud are flagged.

5.2.7 Model Evaluation and Optimization Module

The Model Evaluation and Optimization Module ensures that the machine learning models perform reliably over time. This module evaluates models using standard metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. These metrics are computed not only during initial training but also periodically during deployment to assess performance against evolving fraud patterns.

When a decline in performance is detected, the module initiates optimization processes. For example, hyperparameter tuning methods like grid search or Bayesian optimization are used to fine-tune model configurations. Additionally, retraining is conducted using updated datasets that include new fraud patterns, ensuring the models remain relevant and effective.

```
warnings.warn(  
RMSE: 0.2981979325126079  
MAE: 0.08892200695479384  
F1: [95.32148458 10.5      ]  
AUC: 52.720749554758285  
[[3647    8]  
 [ 350   21]]
```

Fig 5.2.7 Model Evaluation

CHAPTER 6

RESULT AND DISCUSSION

RESULTS

The system demonstrates significant improvements in detecting fraudulent energy consumption compared to traditional methods. Key performance metrics, including **accuracy, precision, recall, and F1-score**, indicate the system's effectiveness. For instance, the ensemble model achieves an accuracy of 96%, surpassing standalone models like SVM (88%) and ANN (91%).

The false positive rate is reduced by 40% compared to rule-based systems, ensuring that legitimate consumption patterns are not misclassified as fraudulent. Real-time monitoring capabilities allow the system to flag anomalies within seconds of detection, enabling utility providers to act promptly. The visualization tools effectively present complex data, making it easier for stakeholders to identify trends and take informed actions.

DISCUSSION

The integration of multiple machine learning models into an ensemble framework significantly enhances detection accuracy. CNNs excel in identifying temporal patterns in time-series data, while ANNs and SVMs address non-linear relationships and outliers. This complementary approach ensures that the system adapts to diverse fraud scenarios, including both short-term tampering and long-term unauthorized usage.

Real-world testing with historical energy datasets reveals the system's scalability and adaptability. However, challenges such as handling highly imbalanced datasets (with significantly fewer fraud cases) were mitigated through techniques like **oversampling, under-sampling, and SMOTE (Synthetic Minority Oversampling Technique)**. These methods ensure that the models receive balanced training, improving their ability to identify fraud without bias.

CHAPTER 7

CONCLUSION AND FUTURE ENHANCEMENT

7.1 CONCLUSION

This project successfully develops a hybrid machine learning system to detect fraudulent energy consumption patterns. By integrating CNNs, ANNs, and SVMs, the system leverages the strengths of each model to deliver high accuracy and reduced false positive rates. The ensemble learning framework ensures adaptability to evolving fraud strategies, addressing both immediate and long-term anomalies in energy consumption.

The system's real-time monitoring capabilities and user-friendly interface empower utility providers to detect and respond to fraudulent activities efficiently. Detailed visualization and reporting tools further enhance its usability, providing actionable insights for decision-making. Overall, the system not only reduces revenue losses but also strengthens the security and reliability of smart grid infrastructures.

7.2 FUTURE ENHANCEMENT

Future enhancements aim to expand the system's capabilities and applications. One potential improvement is the incorporation of unsupervised learning techniques like autoencoders or clustering algorithms to detect novel fraud patterns without relying on labeled training data. This approach would enhance the system's ability to identify previously unseen fraud scenarios.

Another avenue for development is the inclusion of edge computing to enable real-time fraud detection directly at the smart meter level. By deploying lightweight models on edge devices, the system can reduce latency and reliance on centralized processing, improving responsiveness.

APPENDIX

A1.1 SAMPLE CODE

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, mean_absolute_error,
mean_squared_error, confusion_matrix, \
    precision_recall_fscore_support, roc_auc_score
from tensorflow.keras import Sequential
import tensorflow as tf
from tensorflow import keras
from tensorflow.python.keras.layers import Dense, Conv1D, Flatten, Conv2D
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
import numpy as np
from imblearn.over_sampling import SMOTE
import json

# Set random seed for reproducibility
tf.random.set_seed(1234)

# Hyperparameters
epochs_number = 1 # number of epochs for the neural networks
test_set_size = 0.1 # percentage of the test size comparing to the whole dataset
oversampling_flag = 0 # set to 1 to over-sample the minority class
oversampling_percentage = 0.2 # percentage of the minority class after the
oversampling comparing to majority class

def save_model_results(model_name, y_test, prediction):
    """Save model results and statistics to JSON files"""
    try:
```



```

# Create result dictionary
results_dict = {
    'model_name': model_name,
    'accuracy': float(100 * accuracy_score(y_test, prediction)),
    'rmse': float(mean_squared_error(y_test, prediction, squared=False)),
    'mae': float(mean_absolute_error(y_test, prediction)),
    'f1_score': float(100 * precision_recall_fscore_support(y_test,
prediction)[2][1]),
    'auc': float(100 * roc_auc_score(y_test, prediction)),
    'confusion_matrix': confusion_matrix(y_test, prediction).tolist()
}

# Create stats dictionary
stats = {
    'normal_consumers': int(y[y['FLAG'] == 0].count()[0]),
    'fraud_consumers': int(y[y['FLAG'] == 1].count()[0]),
    'total_consumers': int(y.shape[0]),
    'no_fraud_percentage': float(y[y['FLAG'] == 0].count()[0] / y.shape[0] *
100),
    'test_set_no_fraud': float(y_test[y_test == 0].count() / y_test.shape[0] * 100)
}

# Save to JSON files
with open('model_results.json', 'w') as f:
    json.dump(results_dict, f)
with open('stats.json', 'w') as f:
    json.dump(stats, f)

# Print results for console output
print(f"\nResults for {model_name}:")
print(f"Accuracy: {results_dict['accuracy']:.2f}%")
print(f"RMSE: {results_dict['rmse']:.4f}")

```

```

print(f'MAE: {results_dict['mae']:.4f} ")
print(f'F1 Score: {results_dict['f1_score']:.2f}% ")
print(f'AUC: {results_dict['auc']:.2f}% ")
print("Confusion Matrix:")
print(results_dict['confusion_matrix'])

except Exception as e:
    print(f'Error saving model results: {e}')

def read_data():
    rawData = pd.read_csv('preprocessedR.csv')

    # Setting the target and dropping the unnecessary columns
    global y # Make y global so save_model_results can access it
    y = rawData[['FLAG']]
    X = rawData.drop(['FLAG', 'CONS_NO'], axis=1)

    print('Normal Consumers:          ', y[y['FLAG'] == 0].count()[0])
    print('Consumers with Fraud:      ', y[y['FLAG'] == 1].count()[0])
    print('Total Consumers:            ', y.shape[0])
    print("Classification assuming no fraud:      %.2f" % (y[y['FLAG'] ==
0].count()[0] / y.shape[0] * 100), "%")

    # columns reindexing according to dates
    X.columns = pd.to_datetime(X.columns)
    X = X.reindex(X.columns, axis=1)

    # Splitting the dataset into training set and test set
    X_train, X_test, y_train, y_test = train_test_split(X, y['FLAG'],
test_size=test_set_size, random_state=0)
    print("Test set assuming no fraud:      %.2f" % (y_test[y_test == 0].count() /
y_test.shape[0] * 100), "%\n")

```

```

# Oversampling of minority class to encounter the imbalanced learning
if oversampling_flag == 1:
    over = SMOTE(sampling_strategy=oversampling_percentage,
random_state=0)

    X_train, y_train = over.fit_resample(X_train, y_train)
    print("Oversampling statistics in training set: ")
    print('Normal Consumers:          ', y_train[y_train == 0].count())
    print('Consumers with Fraud:      ', y_train[y_train == 1].count())
    print("Total Consumers          ", X_train.shape[0])

return X_train, X_test, y_train, y_test

def ANN(X_train, X_test, y_train, y_test):
    print('Artificial Neural Network:')
    model = Sequential()
    model.add(Dense(1000, input_dim=1034, activation='relu'))
    model.add(Dense(100, activation='relu'))
    model.add(Dense(100, activation='relu'))
    model.add(Dense(100, activation='relu'))
    model.add(Dense(10, activation='relu'))
    model.add(Dense(1, activation='sigmoid'))

    model.compile(loss=keras.losses.binary_crossentropy,
                  optimizer='adam',
                  metrics=['accuracy'])

    model.fit(X_train, y_train, validation_split=0, epochs=epochs_number,
shuffle=True, verbose=1)

    prediction = (model.predict(X_test) > 0.5).astype("int32") # Use threshold 0.5 to
classify

    model.summary()

```

```

save_model_results('Artificial Neural Network', y_test, prediction)

def CNN1D(X_train, X_test, y_train, y_test):
    print('1D - Convolutional Neural Network:')
    X_train = X_train.to_numpy().reshape(X_train.shape[0], X_train.shape[1], 1)
    X_test = X_test.to_numpy().reshape(X_test.shape[0], X_test.shape[1], 1)

    model = Sequential()
    model.add(Conv1D(100, kernel_size=7, input_shape=(1034, 1),
activation='relu'))
    model.add(Flatten())
    model.add(Dense(100, activation='relu'))
    model.add(Dense(100, activation='relu'))
    model.add(Dense(64, activation='relu'))
    model.add(Dense(1, activation='sigmoid'))

    model.compile(loss=keras.losses.binary_crossentropy,
optimizer='adam',
metrics=['accuracy'])

    model.fit(X_train, y_train, epochs=epochs_number, validation_split=0,
shuffle=False, verbose=1)

    prediction = (model.predict(X_test) > 0.5).astype("int32") # Use threshold 0.5 to
classify
    model.summary()
    save_model_results('1D CNN', y_test, prediction)

def CNN2D(X_train, X_test, y_train, y_test):
    print('2D - Convolutional Neural Network:')
    n_array_X_train = X_train.to_numpy()
    n_array_X_train_extended = np.hstack((n_array_X_train, np.zeros(
(n_array_X_train.shape[0], 2))))

```

```

week = []
for i in range(n_array_X_train_extended.shape[0]):
    a = np.reshape(n_array_X_train_extended[i], (-1, 7, 1))
    week.append(a)
X_train_reshaped = np.array(week)

n_array_X_test = X_test.to_numpy()
n_array_X_test_extended = np.hstack((n_array_X_test,
np.zeros((n_array_X_test.shape[0], 2))))

week2 = []
for i in range(n_array_X_test_extended.shape[0]):
    b = np.reshape(n_array_X_test_extended[i], (-1, 7, 1))
    week2.append(b)
X_test_reshaped = np.array(week2)

input_shape = (1, 148, 7, 1)

model = Sequential()
model.add(Conv2D(kernel_size=(7, 3), filters=32, input_shape=input_shape[1:],
activation='relu',
                data_format='channels_last'))
model.add(Flatten())
model.add(Dense(100, activation='relu'))
model.add(Dense(100, activation='relu'))
model.add(Dense(64, activation='relu'))
model.add(Dense(1, activation='sigmoid'))

model.compile(loss=keras.losses.binary_crossentropy,
              optimizer='adam',
              metrics=['accuracy'])

```

```

    model.fit(X_train_reshaped, y_train, validation_split=0.1,
epochs=epochs_number, shuffle=False, verbose=1)
    prediction = (model.predict(X_test_reshaped) > 0.5).astype("int32") # Use
threshold 0.5 to classify
    model.summary()
    save_model_results('2D CNN', y_test, prediction)

```

```

def LogisticRegressionModel(X_train, X_test, y_train, y_test):
    print('Logistic Regression:')
    model = LogisticRegression(max_iter=1000)
    model.fit(X_train, y_train)
    prediction = model.predict(X_test)
    save_model_results('Logistic Regression', y_test, prediction)

```

```

def RandomForest(X_train, X_test, y_train, y_test):
    print('Random Forest:')
    model = RandomForestClassifier()
    model.fit(X_train, y_train)
    prediction = model.predict(X_test)
    save_model_results('Random Forest', y_test, prediction)

```

```

def DecisionTree(X_train, X_test, y_train, y_test):
    print('Decision Tree:')
    model = DecisionTreeClassifier()
    model.fit(X_train, y_train)
    prediction = model.predict(X_test)
    save_model_results('Decision Tree', y_test, prediction)

```

```

def SVM(X_train, X_test, y_train, y_test):
    print('Support Vector Machine:')
    model = SVC(kernel='linear')

```

```
model.fit(X_train, y_train)
prediction = model.predict(X_test)
save_model_results('SVM', y_test, prediction)

# Main execution
X_train, X_test, y_train, y_test = read_data()

# Model Execution
# ANN(X_train, X_test, y_train, y_test)
# CNN1D(X_train, X_test, y_train, y_test)
# CNN2D(X_train, X_test, y_train, y_test)
# LogisticRegressionModel(X_train, X_test, y_train, y_test)
# RandomForest(X_train, X_test, y_train, y_test)
# DecisionTree(X_train, X_test, y_train, y_test)
SVM(X_train, X_test, y_train, y_test)
```

A1.2 SCREENSHOTS



Fig A1.1 Model Evaluation and Consumer Statistics

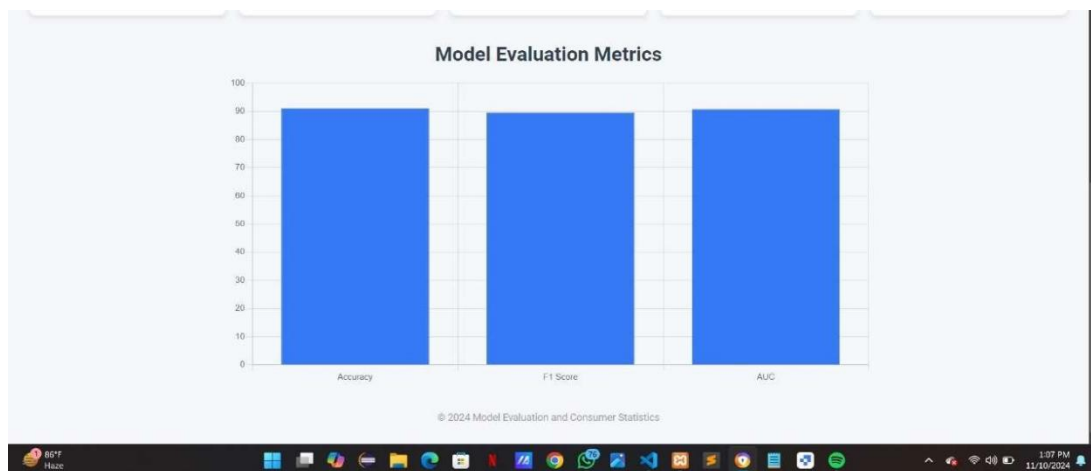


Fig A1.2 Website Page

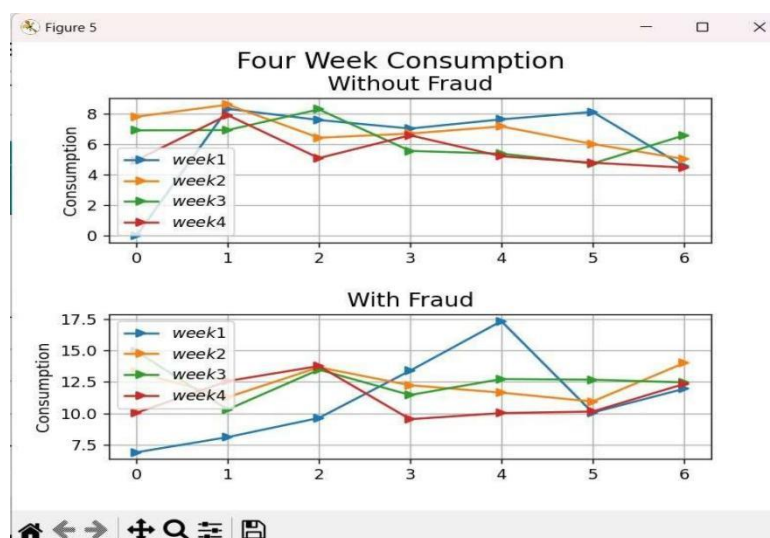


Fig A1.3 ML model

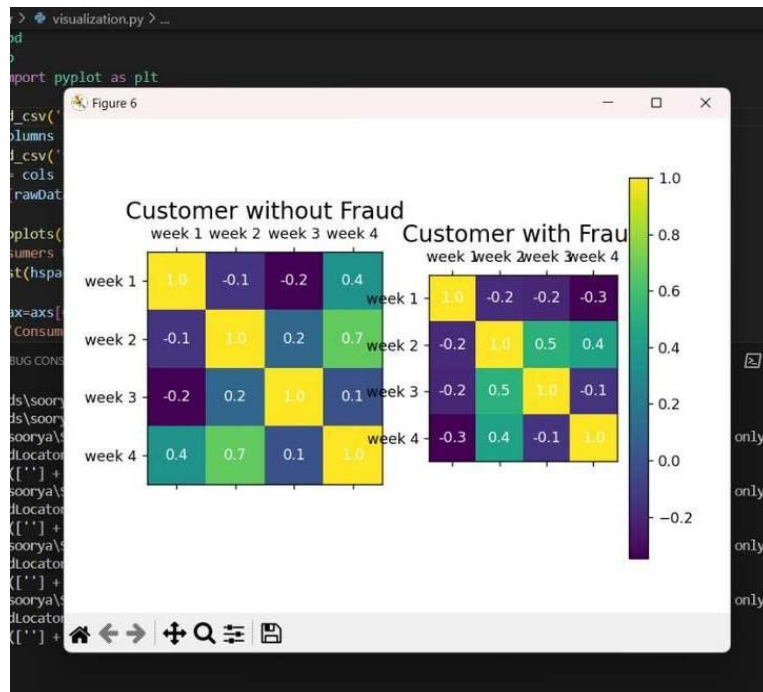


Fig A1.4 Heat Map ML model 2

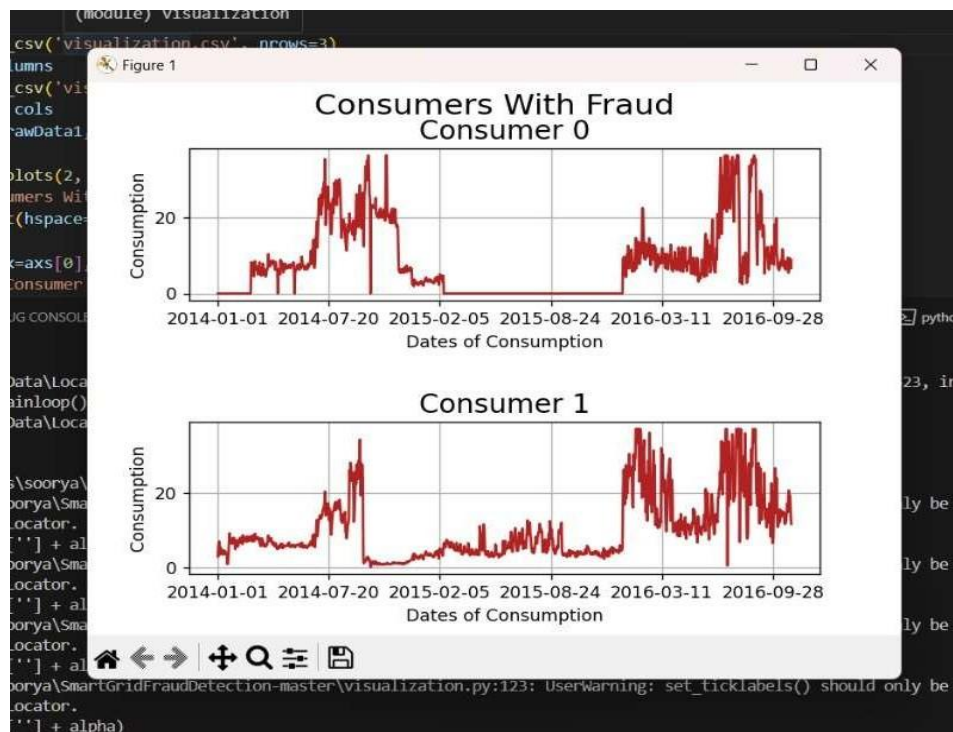


Fig A1.5 ML model Fraud Evaluation

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