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Statical Framework for Detection of Electricity Theft Using Smart Grid

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ABSTRACT: Electricity theft is one of the major problems of electric utilities. Such electricity theft produces financial loss to the utility companies. It is not possible to inspect manually such theft in large amount of data. For detecting such electricity theft introduces a gradient boosting theft detector (GBTD) based on the three latest gradient boosting classifiers (GBCs): extreme gradient boosting (XGBoost), categorical boosting (Cat Boost), and light gradient boosting method (LightGBM). XGBoost is one machine learning algorithm which gives high accuracy in less time. In this we apply preprocessing on smart meter data then do feature selection. Practical application of the proposed GBTD for theft detection by minimizing FPR and reducing data storage space and improving time-complexity of the GBTD classifiers which detect non-technical loss (NTL) detection. It detects theft using anomaly behavior of user. Electricity Data of different user and society is given to find the thefts in which society are available.

I. INTRODUCTION

India loses more money to theft than any other country in the world. The state of Maharashtra which includes Mumbai—alone loses \$2.8 billion per year, more than all but eight countries in the world. In this proposed system we use dataset having electricity usage of a smart grid (SG) meter (or simply smart meter). Using this dataset we do feature selection and preprocessing on dataset. When we have large number of features in dataset then feature selection is very important part in our Machine Learning. As we use feature selection it gives us most important feature and this feature selection gives us more accuracy. Then we perform the preprocessing on that data. After that we use the superiority of XGBoost, a gradient boosting classifier (GBC), over other ML algorithms for nontechnical loss (NTL) detection. Gradient boosting is called gradient boosting because it uses a gradient descent algorithm to minimize loss when adding new trees. This approach supports both regression and classification predictive.

II. METHODOLOGY

Many electric utilities have financial loss due to electricity theft. They try to catch theft and use different techniques but for all things they required the human efforts. Although after using human power also they didn't get the thefts. In such situation electricity utilities have to bear loss. This proposed system helps to electricity utilities to detect electricity theft and they will not have to bear loss. Power theft is one of the most prevalent issues which not only cause economic losses but also irregular supply of electricity. It hampers functioning of industries and factories due to shortage of power supplied to them.

III. SOFTWARE REQUIREMENT SPECIFICATION

1) Hardware Interface: The application is intended to be a stand-alone, single-user system. The application will run on a Laptop. No further hardware devices or interfaces will be required.

2) Software Interface:

Inputs: The software will receive input from one source. First, the user interface. The user interface will supply the text and the analysis session.



Outputs: The output will be In audio format and text format.

Operating System: The software will run on the Laptop which will 8GB.

3) User Interfaces: The interface will meet the following requirements to conform to the users' needs. It will be simple

and easy to understand. Controls which allow the user to interact with the application will be clear and imply their functionality within the application. The interface will include user inputs as well as two graphics, outlined below.

The graphics displayed to the user will provide a visual representation of the output produced.

4) User Inputs (Mandatory): The user will be able to control the sentiment analysis of topics in two ways: First, by adding, editing, or removing keywords for each topic, and second by specifying the duration of each analysis session.

5) Graphic 1 Topic Mood Gauge: This graphic will consist of a simple gauge which shows the current mood of the Twitter community on a given topic. This will be done by displaying the percentage of the Twitter users who are for currently for or against the topic being analyzed. It will also display the total number of Tweets which have been processed in order to calculate this output.

6) Graphic 2 Topic Mood Time-Lapse: This graphic display an overview of the results of each past analysis session in the form of a graph. This graph should be displayed in a clear and meaningful manner that allows the user to easily interpret the trend of the sentiment toward the topic over all analysis sessions.

7) Error Notifications : Error notifications will be required within the application, presenting the user with appropriate messages which describe the error that has taken place. If applicable, error messages should suggest solutions to the problem

8) Communication Interface : Describe requirements associated with any communications functions required by this product, including e-mail, web browser, network server communications protocols, electronic forms, and so on. Define any pertinent message formatting. Identify any communication standards that will be used, such as FTP or HTTP. Specify any communication security or encryption issues, data transfer rates, and synchronization mechanism.

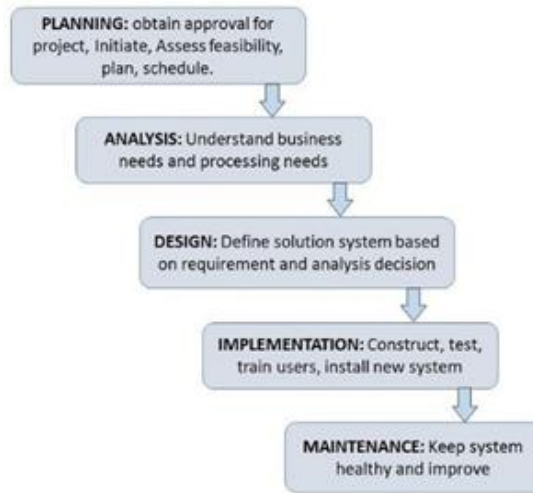
IV. ANALYSIS MODEL :SDLC MODEL TO BE APPLIED

Analysis model : SDLC model to be applied An effective System Development Life Cycle (SDLC) should result in a high quality system that meets customer expectations, reaches completion within time and cost evaluations, and works effectively and efficiently in the current and planned Information Technology infrastructure. System Development Life Cycle called (SDLC) is a conceptual model which includes policies and procedures for developing or altering systems throughout altering systems throughout their life cycles. SDLC is used by analysts to develop an information system.

SDLC includes the following activities:

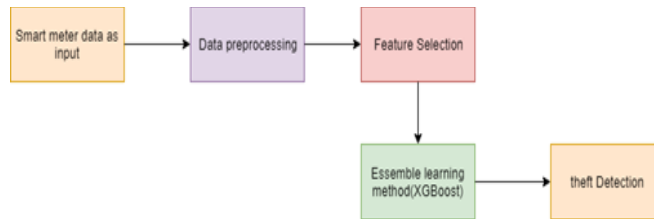
- Requirements
- Design
- Implementation
- Testing
- Deployment
- Operations
- Maintenance

Phases of SDLC: Systems Development Life Cycle is a systematic approach which explicitly breaks down the work into phases that are required to implement either new or modified Information System.



Phases of SDLC

V. SYSTEM DESIGN



- i. System Architecture
- ii. Data Flow Diagrams / UML Diagrams

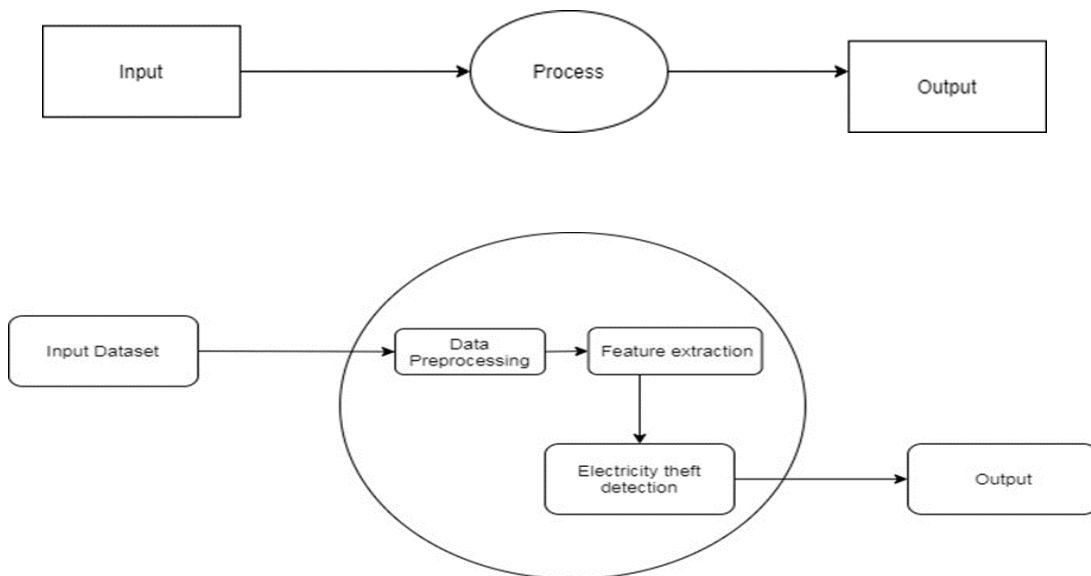


Fig: DFD Level 1

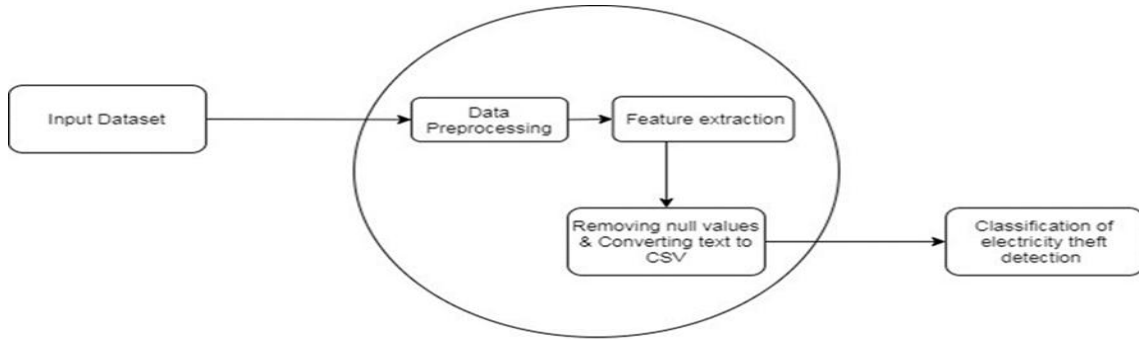


Fig: DFD Level 2

iii. Use-case Diagram

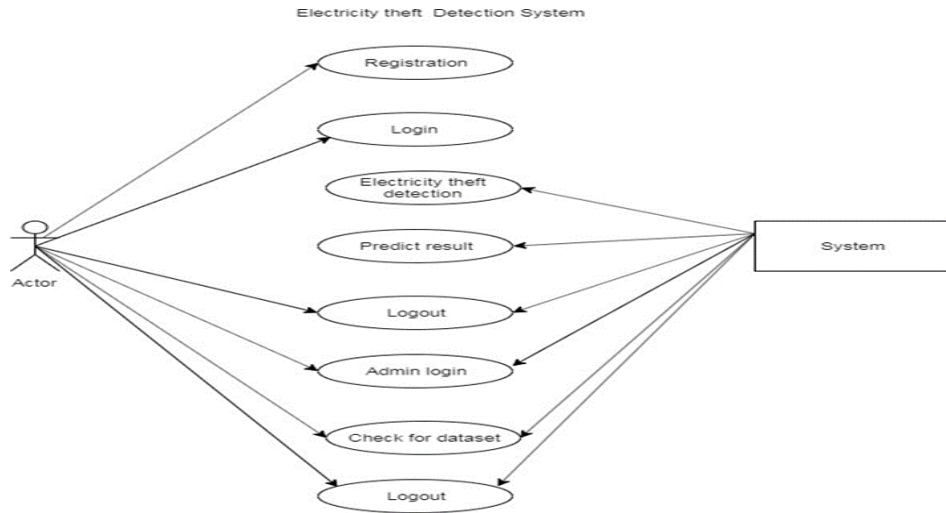


Fig: Use case diagram

iv. Sequence Diagram

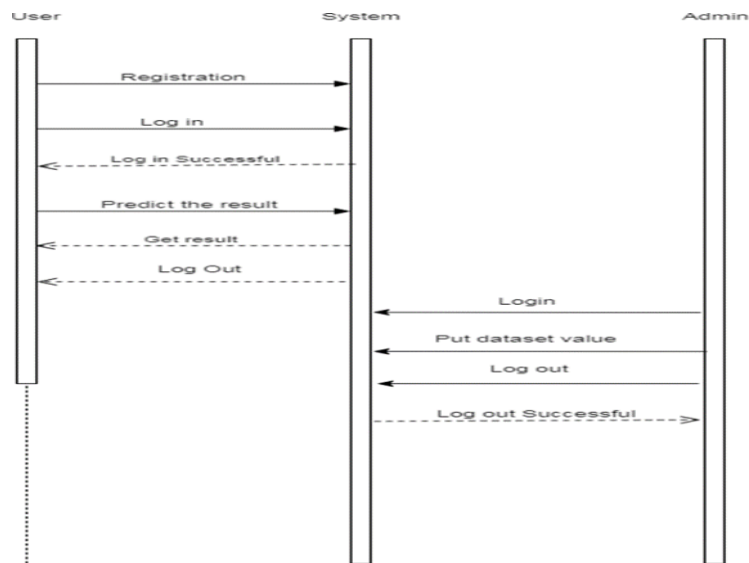


Fig: Sequence Diagram



VI. ADVANTAGES

- We perform a detailed security analysis and performance evaluation of the proposed data.
- Required less time
- Increase Efficiency
- improve the accuracy

VII. APPLICATIONS

- It is use to utilization of electricity.
- Power theft is one of the most prevalent issues which not only cause economic losses but also irregular supply of electricity.
- It hampers functioning of industries and factories , due to shortage of power supplied to them.

VIII. CONCLUSION

This proposed system detects the electricity theft using xgboost machine learning method .However Light GBM appeared to be the fastest classifier.This proposed system helps to electricity utilities to detect electricity theft and they will not have to bare loss. This is most important application of this project.

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