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Electricity Theft-Detection in Smart Grids Based on Deep Learning

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Abstract: *Utility companies are quite concerned about electricity theft. Individual user power usage is one of the vast amounts of data that the smart grid (SG) system generates. Machine learning and deep learning methods can precisely identify electricity theft customers using this data. We develop a convolutional neural network (CNN) model for automatically detecting electricity theft. This study takes into account experimentation to determine the sequential model's (SM) ideal configuration for categorizing and identifying electricity theft. The precision was up to 0.92. This makes it possible to create high-performance electricity signal classifiers for a variety of applications. Using an SM to extract the data from the electricity consumption dataset and a CNN to design electricity signal classifier models..*

Keywords*:* Deep Learning

I. INTRODUCTION

The term "smart grid" (SG) refers to the ever-expanding distribution of renewable and distributed energy sources with the goals of achieving flexibility, self-healing, effectiveness, and sustainability. The concept of SG is recognized over the use of makeshift infrastructure enclosing the legacy electrical grid. The cyberinfrastructure enables the collection and analysis of data from numerous distributed endpoints, such as smart meters, circuit breakers, and phasor determination units.These networks typically include some upgrades that will increase the dependability, efficiency, and delivery of continuous energy sources to homes and businesses. Additionally, SG includes several renewable energy sources, including distributed generation (DG), distributed storage (DS), and power from the sun, wind, and other sources.Smart meters, controllers, phasor measurement units, collector nodes, flexible AC transmission systems, advanced conductor devices, electric power generators, electric power substations, transmission and distribution lines, controllers, and distribution and transmission control centers are the components of the smart grid. These grids typically include some upgrades that will advance the Because of this, smart sensor grids for smart meters enable businesses to manage and control the SG when equipped with the necessary communication and information technology. Electrical energy has become crucial to human existence. During the generation, distribution, and transition of electrical energy, there are frequently losses of electrical energy. Non-technical losses (NTLs) and technical losses (TLs) are two categories into which electrical energy losses can be broadly divided. Theft of power is one of the major non-technical losses. There are numerous investigations being conducted to find electricitytheft.

II. LITERATURE REVIEW

Jokar, N. Arianpoo, V.C.M. Leung,[1] "Electricity theft detection in AMI using customers‟ As one of the major factors of the nontechnical losses (NTLs) in distribution networks, the electricity theft causes significant harm to power grids, which influences power supply quality and reduces operating profits. In order to help utility companies solve the problems of inefficient electricity inspection and irregular power consumption, a novel hybrid convolutional neural network-random forest (CNN-RF) model for automatic electricity theft detection is presented in this paper.

Patrick Glauner et al. “Large-scale detection of non-technical losses in imbalanced data sets” significant impact on the economy, as they can account for up to 40 percent of total losses in some countries. All available electricity. Costly on-site inspections are required to detect NTL. Therefore, it is important to accurately estimate customers' NTLs using machine learning. The fact that regular and irregular customer classes are very unbalanced, NTL shares can change, and related

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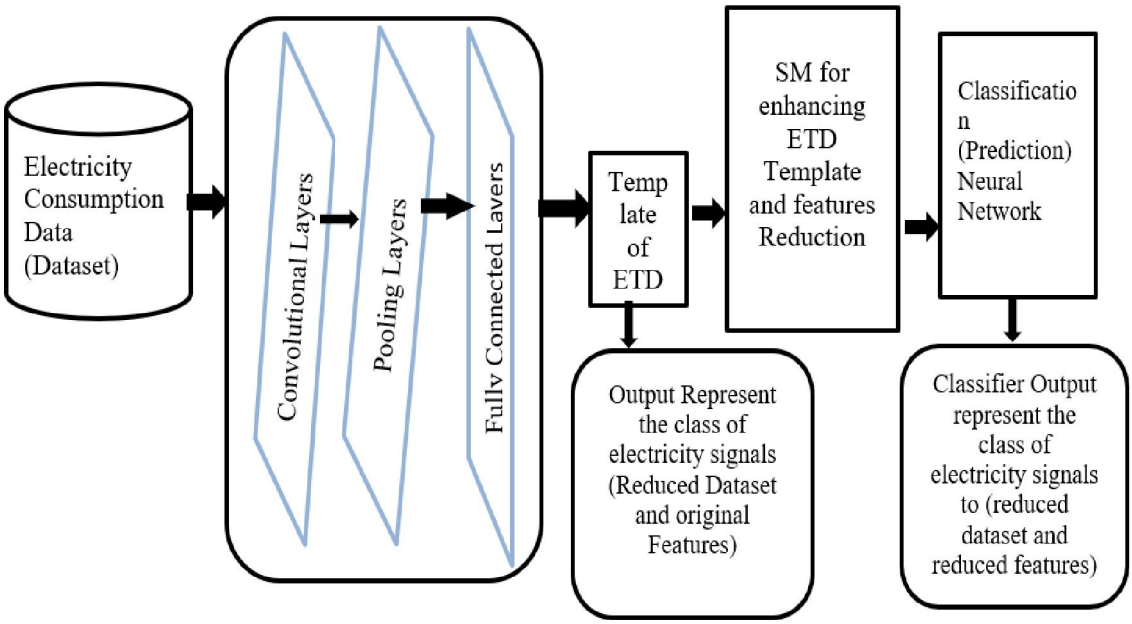
studies have so far largely ignored these factors make it difficult, if not impossible, to put the results into practice. In this paper, we propose a comprehensive method to evaluate Boolean rules, fuzzy logic and support vector machine for three NTL detection models for various NTL relationships on a huge realNon-technical losses (NTL), such as electricity theft, have a -world dataset of 100,000 consumers.

S.S.S.R. Depuru, L. Wang, and V. Devabhaktuni,[2] "Electricity theft: overview,issues, prevention and a smart meter based approach to control theft" A major problem in developing countries is non-technical loss (NTL) in electricity transmission. In many countries, it has been very difficult for service providers to identify and combat thieves. The majority of NTL consists of electricity theft. These losses affect the quality of supplies, increase the stress on the production company and change the rate for loyal consumers. This essay discusses the reasons that make consumers steal power. In light of these negative effects, several theft detection and evaluation techniques are discussed.

III. ARCHITECTURE

The architecture of the system is comparable to the plan of the object. It provides a theoretical framework for the systematic integration of mechanical systems with business logic. It provides examples of system structure, perspective, behaviour, characteristics, and capabilities. It is a way of visualizing the desired system so that people can easily understand it. The basic design of a system, or system architecture, consists of all its parts, their relationships, and the science that created them. This section describes the steps of the proposed model and the techniques used. Using CNN-based deep learning, this work aims to detect electricity theft from user energy consumption patterns. This classification model was instructed and trained using daily energy usage data from legitimate and fraudulent customers. The data processing algorithm first prepares the data so that it can be used to train the model. For better performance, the preparation phase also includes the generation of synthetic data. The proposed model is then hyper-tuned in the next step.



IV. ALGORITHM

4.1 Convolutional Neural Network

The core of deep learning algorithms is a neural network, a machine learning technique. Many machine learning algorithms use these algorithms. They seem to perform better than other methods in image classification in all parameters. They are quite easy to train. The built-in feature library allows you to design neural networks with a minimal amount of code. Node layers, convolutional layers, aggregation layers, hidden layers and output layers make up convolutional neural networks. All these layers are used in our image and each of them has a specific purpose. All image extraction occurs at

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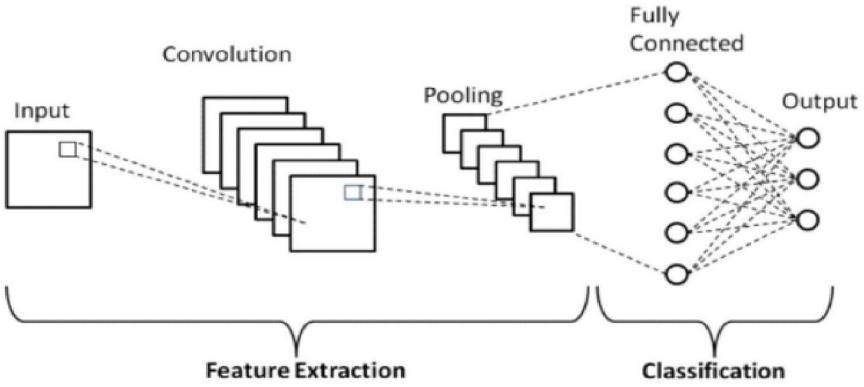
these levels. Weights are contained in the nodes of each layer. Each reverse calculation updates these weights. The CNN architecture consists of two main components.

- A convolutional feature extraction tool that extracts and identifies different features for investigation. A feature extraction network has many pairs of convolutional or convergence layers.
- A fully connected layer that uses the output of the convolution process and predicts the class using previously extracted features.

The goal of the CNN feature extraction model is to minimize the number of features in the dataset. It creates new functions that combine the existing functions of the original function into a single new function. The architecture diagram shows the many layers of a CNN.



- Convolutional Layer: This layer serves as CNN's foundation. The majority of computations take place at this stratum. Three inputs make up this layer. Data input is first. A filter is the second, and a feature map is the third.
- Pooling Layer: Using this layer, we can downscale the number of parameters in our input image. It functions similarly to how the convolution layer does. The sole distinction is that the pooling layer either takes the maximum value in the area of the input matrix or the average value in the area of the matrix, whereas the filters in convolution layers carry certain weights on which computation is conducted by activation function.
- Fully Connected Layer: The fully connected (FC) layer, which connects the neurons between two layers, is made up of the weights and biases as well as the neurons. These layers make up the final few years of a CNN Architecture and are often positioned prior to the output layer.

4.2 Sequential Model

A simple stack of layers with precisely one input tensor and one output tensor for each layer is suitable for SM. The dataset is the input for this SM algorithm, and the reduced dataset is the result. This algorithm's first step is to define the input shape so that it is compatible with the SM. After there are two situations in which to employ SM: The first scenario involves using the original completely connected layers of the SM to forecast electrical signals. You can accomplish this by sending the electrical signals to the SM, which will then return the electrical signals' class. The second example will build and train a given dataset using an array.

V. CONCLUSION AND FUTURE SCOPE

The most significant findings of this study are that supervised learning techniques outperform other techniques since they can train models with good performance using labelled data. Additionally, because pre-trained models are created using large datasets and sophisticated computers, they have a high power to address data on electricity consumption. When extracting data from a dataset using a standard CNN, accuracy may be lower than when utilising an SM to address data on electricity consumption. To improve the effectiveness of creating models and identifying fresh electricity signals, the dataset in this study was shrunk before the models were built.

The test results demonstrate that the suggested method outperforms alternative approaches. The findings demonstrate the accuracy and low false-positive rate of the proposed model for ETD. In the future, we will look at odd consumer

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behaviour based on their short-term usage to find power theft. We aim to develop a model that can recognise insider system attacks because this issue hasn't been properly addressed.

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