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Detection of Electricity Theft in Metering Systems using Convolutional Neural Network

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ABSTRACT: Financial instability, revenue loss, and operational inefficiencies are some of the factors associated with electricity theft in Nigeria and worldwide. In consequence, the problem of electricity theft will continue to undermine the growth of the power utility sector if not adequately mitigated. Traditional electricity theft detection methods, such as manual inspections, rule-based models, and statistical analytics are increasingly ineffective against emerging and advanced tampering techniques. Hence, this paper presents an intelligent energy metering system based on deep Artificial Neural Network (ANN) for real-time anomaly detection of electricity consumption patterns. Historical energy consumption data of 2,400 metered customers for 24 months in Southwestern Nigeria were used in this study. The data was first pre-processed and then partitioned into 80% training dataset and 20% testing dataset. The training dataset was used to train a Convolutional Neural Network (CNN) model, a subset of ANN based on Deep Learning (DL). The developed CNN model was tested with the testing dataset, and the performance was evaluated using precision, recall, F1-score and accuracy. Simulation results showed that the CNN model demonstrates high classification performance with an accuracy of 96.87%, precision of 96.88%, recall of 97.83% and F1-score of 96.77%. In addition, the proposed CNN model outperformed some existing methods.

KEYWORDS: Advanced metering system, Artificial Neural Network, Convolutional Neural Network, Deep Learning, Electricity theft detection, Machine Learning, Utility sector.

I. INTRODUCTION

Electrical energy efficiency is key to the growth of the electricity industry as well as other sectors of an economy. However, energy theft is a major concern in the electricity industry as it leads to technical and non-technical losses, which undermine the achievement of the power sector in the country. Furthermore, energy theft has contributed globally to the financial instability of the power sector (Kumar & Singh, 2019). The reports according to the World Bank indicate that over $96 billion was lost annually to electricity theft worldwide (Appiah et al., 2023). Electricity theft refers to the illegal means of accessing electrical energy consumption (Raham et al., 2020). This can occur through various means, such as tampering with the incoming cable before it enters the meter; introducing resistors, diodes and capacitors; removing manufacturer components to reduce energy consumption, and meter tampering (Chandrasekhar et al., 2020). All these illicit acts pose a significant financial burden on utility companies thereby creating a void in operational costs, reducing revenue and increasing the price of electricity supply to consumers (Xie, 2023). This results in inefficiency in operational delivery to the consumers and poses a challenge to the financial stability of the electricity industry. In developing nations like Nigeria, energy theft can reach up to 50% of total generation (Quasim et al., 2023). This problem negatively affects the economic viability of power distribution companies (Gaur & Gupta, 2016).

The traditional ways of inspecting and monitoring meters for identifying energy defaulters have become obsolete and have proven increasingly inefficient in addressing modern sophisticated theft techniques (Saleem et al., 2019). In consequence, the introduction of Advanced Metering Systems (AMS) that utilize Artificial Intelligence (AI) would enhance energy theft detection with a degree of accuracy (Banerjee et al., 2025). The application of Artificial Neural Network (ANN), a branch of Machine Learning (ML), has the capability to detect various infractions (Saeed et al., 2021). These ANNs are capable of analysing complex vending patterns from large datasets of the utility companies thereby making it easy to detect and identify any irregularities in energy consumption that may indicate any defaulters (Goodfellow et al., 2016). This paper, therefore, presents a deep ANN technique namely Convolutional Neural Network (CNN) for electricity theft detection for integration into an intelligent energy metering system.

A. Structure of the Paper

This paper is structured as follows: Section I introduces the topic, its objectives and the importance. Section II provides brief overviews on electricity (or electrical energy) theft, metering system and artificial intelligence integration. Section III provides the review of related works. In Section IV, the methodology for the proposed electricity theft detection model is presented. The performance of the proposed model is evaluated in Section V. Finally, the conclusion and recommendations for further work is in Section VI.

B. Research Approach and Objectives

The research approach encompasses acquisition of energy consumption data, system development framework, data pre-processing, model development and the validation phases.

The specific objectives of this study are:

1. To develop a Convolutional Neural Network (CNN) model for an electricity-theft detection system;
2. To simulate the developed CNN model.
3. To evaluate the performance of the CNN model and make comparison with some existing detection method using accuracy, recall, precision, and F1-score as the performance metrics.

II. OVERVIEW OF ELECTRICITY THEFT, METERING SYSTEM AND ARTIFICIAL INTELLIGENCE INTEGRATION

Owing to the critical need for a more accurate measurement and real-time monitoring of energy consumption, metering technology has evolved over the years from analogue to digital and smart meters. This section discusses some of the developments in electricity metering system.

A. Concept of Electricity Theft

Electricity theft encompasses unauthorised consumption and illegal manipulation of energy distribution systems (Smith & Nwachukwu, 2020). It is broadly categorised into technical and non-technical losses. Technical losses arise from inefficiencies in the distribution network whereas non-technical losses result from activities like meter tampering, bypassing, illegal connections and billing irregularities (Jokar et al., 2016). Non-technical losses have a substantial impact on the financial sustainability of utility companies and the stability of the energy grid (Raham et al., 2020).

In Nigeria, the prevalence of electricity theft is driven by a combination of socio-economic factors, such as high poverty levels, limited regulatory enforcement, and inadequate consumer education (Ogundijo et al., 2019). The non-technical losses in Nigeria account for between 25% and 40% of the total electricity generated (NERC, 2021). This poses significant challenges to achieving universal energy access, grid modernisation and economic growth.

B. Energy Metering Technologies

An electricity (or energy) meter, shown in Figure 1, is a device that measures the amount of electrical energy consumed by a customer. The evolution in metering technologies from analogue meters to digital and now smart meters was driven by the need for accurate measurement, real-time monitoring of energy consumption and theft detection capabilities to the benefit of the utility companies and their customers (Kumar & Hussain, 2021). This chapter provides a comprehensive review of the literature relevant to the development of an Artificial Neural Network (ANN)-based energy metering system that detects electricity theft.

Digital energy meters use sampled instantaneous voltage, $V[t]$, and current, $I[t]$, to compute power and energy. The electrical power at a discrete time instant, t, is given as:

$$P[t] = V[t] * I[t] \tag{1}$$

The total energy consumed, E, is computed as:

$$E = \sum_{t=1}^{T} P[t] \tag{2}$$

where $P[t]$ is the power measured in Watts (W), $V[t]$ is the voltage measured in Volts (V), $I[t]$ is the current measured in Ampere (A), T is the total sample time.

Figure 1: Three-phase electronic digital meter

In practice, the energy consumption, which is a function of the phase angle $\emptyset$, is given as:

$$E_{\emptyset} = \mathrm{V} \cdot \mathrm{I} \cdot \cos \emptyset \, t \tag{3}$$

C. Integration of Artificial Intelligence (AI) in Advanced Metering System (AMS)

Recent advances in metering technology focus on embedding AI into metering systems. Intelligent energy meters are powered by AI algorithms such as ML and ANN. Deep Learning (DL) or Deep Neural Network (DNN) models such as Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) are capable of analysing large-scale data for pattern recognition (Ajayi et al., 2021). Studies have shown that AI-integrated meters can detect theft patterns with up to 95% accuracy (Iftikhar et al., 2024).

***Artificial Neural Network (ANN)*:** Artificial Neural Networks (ANNs) are computational models inspired by the structure of biological neural networks. They consist of layers of interconnected neurons, each performing specific computations to process input data and generate output predictions (Haykin, 2021). These neural networks are mostly employed for forecasting, pattern recognition, anomaly detection and predictive analytics, making them an integral part of detecting intellectual theft and other advanced system applications (Wang et al., 2020). To enable computers to learn and make decisions like humans, ANNs attempt to replicate the network of neurons that constitutes the human brain (Aggarwal, 2018).

Convolutional Neural Network (CNN): Convolutional Neural Network (CNN) is a class of DL that is capable of learning a compact and discriminative feature representation with large-scale data. Several works have shown that CNNs have achieved great successes in the machine vision community by significantly improving performance in classification problems. CNN can be used to unveil intricate patterns data. A CNN model encompasses multiple convolutional layers, each succeeded by max-pooling operations for feature down-sampling. It contains dropout mechanisms to mitigate overfitting (Sarker, 2022). A CNN architecture extracts spatial features from the input sequence and outputs a sequence of feature vectors (Patel & Bhattacharya, 2022).

III.RELATED WORK

A novel pattern-based Energy Theft Detection (ETD) technique in smart meters was presented by Jokar et al. (2015). Wang et al. (2020) provides a comprehensive review of smart metering analyses and ANN applications representing a paradigm shift in theft detection, encompassing both technological advancement and philosophical considerations of energy security.

An ANN-based strategy was employed by Gupta et al. (2022) in smart grids with the aim of enhancing theft detection accuracy. Their findings indicate the robustness of ANN in identifying anomalies and enhancing operational efficiency.

Otuoze et al. (2024) employed analytical and empirical methods to detect and confirm electricity theft in Advanced Metering Infrastructure (AMI). The strategy demonstrated a high accuracy rate that significantly improves upon traditional techniques. Iftikhar et al. (2024) employed a hybrid system that integrates different ML techniques for electricity theft detection, resulting in significant improvements in detection accuracy.

From the reviewed literature, to the best of our knowledge, no work as considered the use of a two-dimensional CNN technique on real-time energy consumption data; hence, this study.

IV. METHODOLOGY

A. Dataset Description and Pre-processing

This study employs electricity consumption dataset sourced from the utility company. The initial raw data contained 2000 records of metered electricity consumers, covering a period of 24 months. However, out of the total of 2000 consumers, only 800 were actually involved in energy theft while 1200 were not involved in energy theft. In order to avoid bias, data augmentation was done to balance the number of "With Energy Theft" and "Without Energy Theft" classes to make 1200 for each class. Aside from data augmentation, some other pre-processing tasks included data balancing, data labelling, handling of missing values, and data reshaping. The pre-processing steps are illustrated in Algorithm 1.

"With Theft" samples are denoted by 1 while "Without Theft" are denoted by 0. Simulations were done using MATLAB software package.

A sample of 1D energy record for 24 months (dimension 1x24) is given below:

[6.6000 5.2800 6.6000 7.9800 7.9800 16.0900 19.0900 15.0600 10.0000 7.9800 22.2000 66.6000 44.4000 44.4000 88.3600 22.2000 248.6600 260.8600 195.6500 195.6500 19.0100 13.3200 8.8800 66.6000]

The 2D version of an energy record (dimension 24x24) for CNN training is given below:

[6.6000 5.2800 6.6000 … 19.0100 13.3200 8.8800 66.6000
6.6000 5.2800 6.6000 … 19.0100 13.3200 8.8800 66.6000
.
.
.
6.6000 5.2800 6.6000 … 19.0100 13.3200 8.8800 66.6000]

Algorithm 1: Data Preprocessing

Input: Initial raw energy data (KWH) containing 800 records of With-Theft cases and
1200 records of Without-Theft cases
Output: E_{Final_data} (final processed energy data containing 2400 records)
C_{Labels} (class labels of all the records)
Begin
// Augmentation the With-Theft records
Rdata ←Load energy data of With-Theft of records, S/Ns 1 to 800
Index←Generate 400 random integers between 1 and 800
Adata ←Select records of S/Ns in the *Index* from *Rdata*.
$E_{With-Theft}$ ←*Rdata* merge to *Adata*

E_{All_data} ←$E_{With-Theft}$ merge to $E_{Without-Theft}$

// Fill missing data
// Replace non-numeric (NaN) energy values with numeric values for both cases
for each record **do**

for each month **do**
If non-numeric energy reading is found
Replace it with the previous month's reading
end for
end for
Perform cumulative sum of each record in E_{All_data} to improve discriminant.
$C_{Labels} \leftarrow$ Categorical label of each record as With-Theft (1) or Without-Theft (0)
// Reshape each record in E_{All_data} from 1D to 2D for CNN training
for each record in E_{All_data} **do**
Convert the one-dimensional record to two-dimensional record of size 24x24
$E_{Final\_data} \leftarrow 2D(E_{All\_data})$
end for
End

B. Model Design and Training

The framework for the proposed CNN model is shown in Figure 2. The CNN was created as a directed acyclic graph network. The processed data representing monthly kilowatts hour (kWh) readings was used to train the CNN model. The feature extraction by the CNN is expressed as:

$$F = \sigma\,(W * E_{Final\_data} + b) \qquad (4)$$

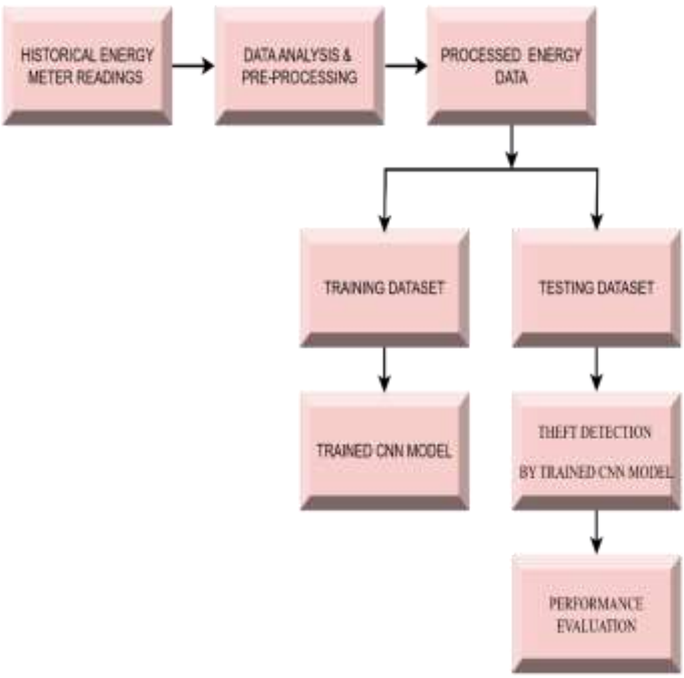


Figure 2: Framework for the developed CNN model for electricity theft detection

where F is the feature map, σ is activation function i.e. Rectified Linear Unit (ReLU), W is convolutional filter weights, E_{Final_data} is input data, and b is the bias term.
The trained CNN model is given as:

$$O = \sigma\,(W * F + b) \qquad (5)$$

where O is the output feature map. The CNN model's training Loss Function, L, for the Energy Theft Detection (ETD) is given as:

$$L = \sum(y\_true - y\_pred)^2 \qquad (6)$$

where L is the loss via the Mean Squared Error (MSE), y_true is the actual energy consumption, and y_pred is the predicted energy consumption.

C. Evaluation Metrics

Standard classification metrics namely Accuracy, Precision, Recall, and F1-score were employed to evaluate the effectiveness of the proposed CNN model for ETD. These metrics offer valuable insights into the model's predictive accuracy and reliability in distinguishing legitimate from fraudulent energy consumption patterns. The model are briefly described as follows:

Accuracy: This is the proportion of correct predictions out of total predictions.

$$Accuracy = \frac{(TP+TN)}{TP+TN+FN+FP} \qquad (7)$$

where TP, TN, FP and FN denote True Positives, True Negatives, False Positives and False Negatives, respectively.
Precision: This is the proportion of true positive predictions among all positive predictions.

$$\text{Precision} = \frac{TP}{TP+FP} \qquad (8)$$

Recall: This is the ability to correctly identify all actual theft cases.

$$Recall = \frac{TP}{TP+FN} \qquad (9)$$

F1-score: This is the harmonic mean of precision and recall, balancing false positives and false negatives.

$$\text{F1}-\text{score} = 2\left(\frac{\text{Precision}*\text{Recall}}{\text{Precision}+\text{Recall}}\right) \qquad (10)$$

The system simulation parameters are presented in Table I.

TABLE I: SYSTEM SIMULATION PARAMETERS

Parameter	Specification
Input data sample to CNN model	24x24 dimension
Number of convolutional Layer	3
CNN output layer transfer function	softmax

Minimum batch size	5
Maximum epoch	20
Initial learning rate	0.0001
Optimizer	sgdm

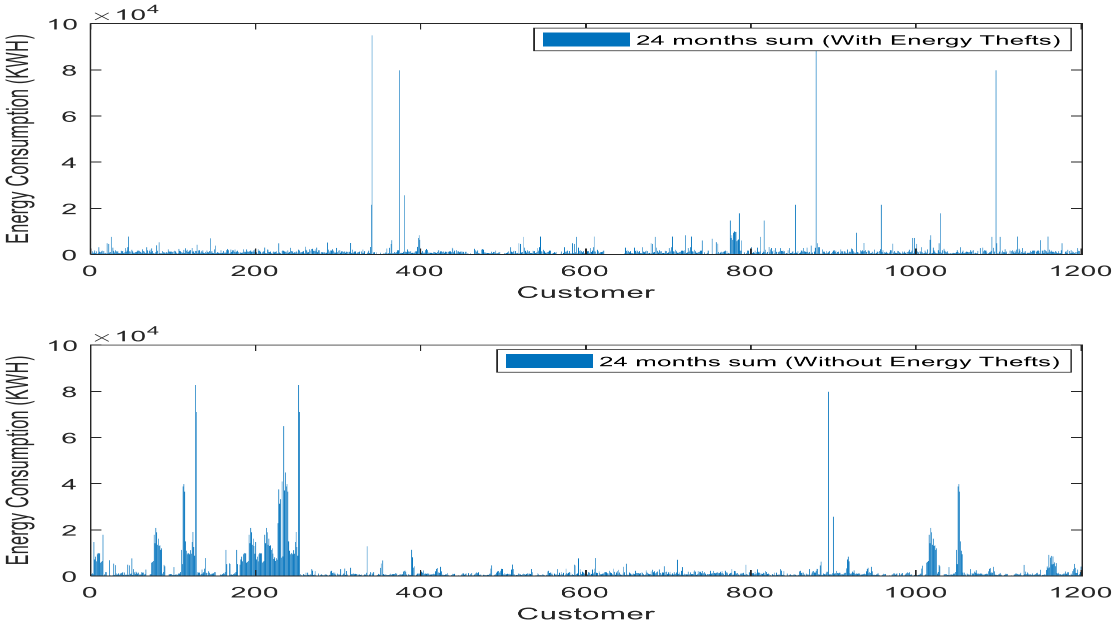
V. RESULTS AND DISCUSSION

The results of the performance of the proposed CNN model for ETD system are presented in this Section. Visual tools such as confusion matrix and performance plots are presented for interpretation of the results. The CNN model was trained to classify customers' energy consumption patterns as either "Without Energy Theft" or "With Energy Theft". Figure 3 shows the electricity consumption patterns for 1200 customers for each of the two classes: "Without Energy Theft" or "With Energy Theft". The pattern shows consumption variability in which the "Without Energy Theft" customers consumed more energy than the "With Energy Theft" customers. However, the plot cannot reveal the true classes of the energy consumptions; thus, the need for a more robust method which our proposed CNN model aims to achieve.

A. *Performance of the Proposed CNN Model*

The training process of the CNN model is shown in Figure 4. The figure reveals the gradual increase in accuracy and corresponding decrease in the loss function curves during the training until the maximum epoch was reached. Figure 5 presents results of the CNN model's classification of meter readings of customers in the testing dataset. The model correctly classified 465 meters out of a total of 480. The confusion matrix of the detection results shown in Figure 6 clearly illustrates that the model accurately classified 240 without-theft meters and 225 with-theft meters. In other words, TP was 225 (with-theft classified as with-theft), TN was 240 (without-theft classified as without-theft),

Figure 3: Electrical energy consumption of the customers



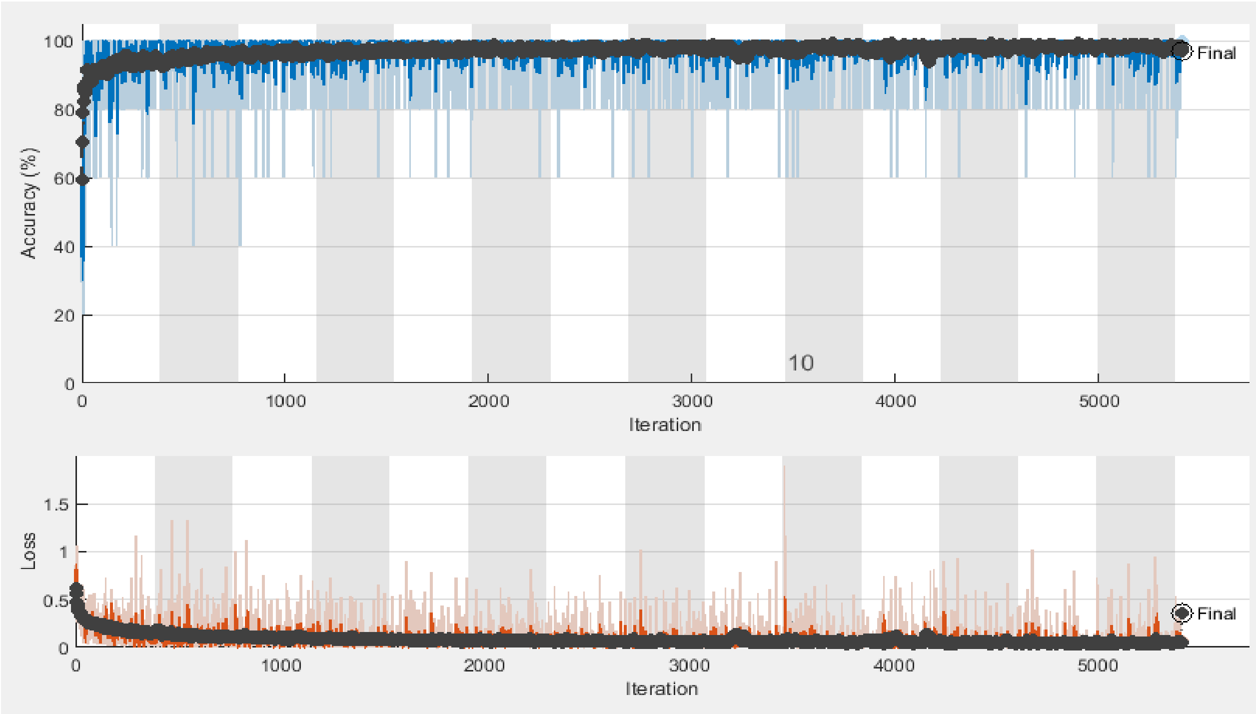


Figure 4: The proposed CNN model's training process

FP was 10 (with-theft classified as without-theft) and FN was (without-theft classified as with-theft). Only fifteen misclassifications, which is about 3% of the total tested sampled, were obtained. This demonstrates the reliability of the developed CNN model as it achieved an excellent detection (or classification) rate of 97%.

B. ***Comparison of the Proposed CNN Model with Selected Existing Methods***

Figure 7 shows the performance of the proposed CNN model versus the Support Vector Machine (SVM) model (Jindal et al., 2020) and the Anomaly Detection Formula (ADF) method (Jokar et al., 2016; Park & Kim, 2020) for electricity theft detection. The proposed CNN model achieved Accuracy,

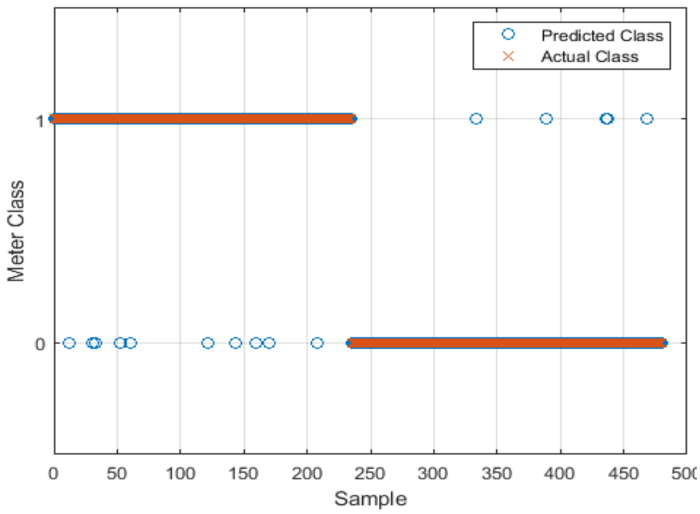


Figure 5: Classification of customers energy meter (0 denotes “With Energy Theft” and 1 denotes “Without Energy Theft”).

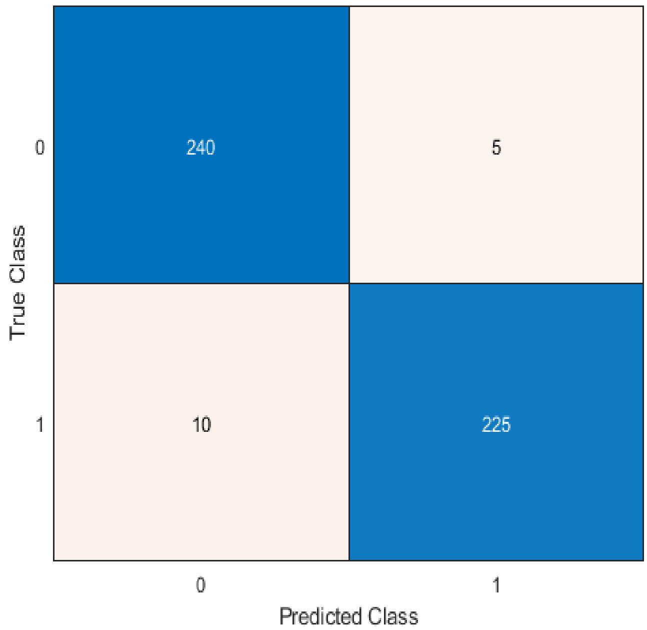


Figure 6: Confusion matrix of the classification results of the proposed CNN model.

Precision, Recall and F1-score values of about 96.88%, 96.88%, 97.83% and 96.77%, respectively. The SVM model gave about 89.78%, 88.58%, 87.83% and 86.87% in Accuracy, Precision, Recall, and F1-Score, respectively. Furthermore, the ADF method gave 55.21%, 35.42%, 53.73%, and 42.69% in Accuracy, Precision, Recall, and F1-Score, respectively. These results reveal that the proposed CNN model outperforms both the SVM and ADF methods. The high classification accuracy and low error rates of the proposed CNN model demonstrate its capability in detecting electricity theft in real-time data. The deep learning consumption patterns. architecture of the CNN model allowed it to adapt to subtle consumption patterns.

Generally, the proposed CNN model demonstrates an intelligent real-time application potential in Advanced Metering System (AMS). The proposed CNN model's high recall rate indicates strong detection sensitivity thereby minimizing the number of undetected defaulting customers. Its low false positive rate suggests that the model hardly classifies normal customers as defaulters thereby reducing the risk of unjust penalties. In addition, its high F1-score performance confirms the model's reliability.

CONCLUSIONS

In this paper, the application of a CNN model for detecting electricity theft in customers' energy consumption data in Nigeria's electricity distribution system was investigated. The proposed CNN model demonstrates superior performance compared to the SVM model and the traditional anomaly detection formula method. The proposed CNN model is capable of addressing the urgent need for advanced, real-time electricity-theft detection method to mitigate revenue losses and enhance operational efficiency of the electricity distribution networks. This AI-based approach offers a promising solution for modern power distribution networks. It would enhance the system to flag meters with inconsistent readings over several months. Future work should look in the direction of hybridizing different AI techniques as well as the addition of cryptography for security.

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