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Design and Implementation of an Intelligent Smart Energy Meter Using IoT and Machine Learning

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Abstract: *Electricity theft and manual meter reading remain persistent problems in power distribution systems worldwide, causing massive revenue losses and unfair billing. This paper presents an IoT-based smart energy meter that not only enables real- time remote monitoring but also detects electricity theft using machine learning. The system uses an ESP32 microcontroller connected to voltage and current sensors (ZMPT101B and ACS712) to continuously measure voltage, current, power, energy consumption, and estimated monthly bill. All data is transmitted wirelessly via Wi-Fi to a Blynk mobile dashboard, allowing users to monitor their electricity usage from anywhere. The key innovation is an AI/ML theft detection module based on the Random Forest algorithm. The model is trained on historical consumption patterns and compares real-time readings against predicted values. When actual consumption exceeds the predicted value by a predefined threshold, the system generates an immediate theft alert. A relay module can optionally cut off power to prevent further unauthorized usage. The system successfully displays live electrical parameters and detects abnormal load conditions with an expected accuracy of 92–95%. This solution reduces manual effort, improves billing accuracy, empowers consumers with transparency, and helps utilities identify theft without physical inspections. Future work includes integration with smart grid systems and cloud analytics for large-scale deployment*

Keywords: Smart meter, theft detection, IoT, machine learning, ESP32, energy monitoring

I. INTRODUCTION

Electricity powers our daily lives, yet traditional energy meters remain surprisingly primitive— they require manual reading, offer no real-time insights, and cannot detect theft. Electricity theft through meter tampering or illegal hookups costs utilities billions of dollars annually, ultimately forcing honest consumers to pay higher tariffs. Existing IoT-based smart meters solve the remote monitoring problem but largely ignore intelligent theft detection. This paper presents an IoT-based smart energy meter that addresses both gaps. Using an ESP32 microcontroller connected to voltage and current sensors (ZMPT101B and ACS712), the system continuously measures voltage, current, power, energy consumption, and estimated monthly bill. Data is transmitted via Wi-Fi to a Blynk mobile dashboard, allowing users to monitor their usage anytime, anywhere. What makes this system unique is its integration of machine learning—specifically a Random Forest algorithm—to detect electricity theft. The model learns a household's typical consumption pattern from historical data. When real-time usage deviates significantly from the predicted value (beyond a preset threshold), the system flags it as suspicious and generates an alert. A relay module can optionally cut off power. The objectives are: to design an IoT-based smart meter, enable real-time monitoring, detect theft using AI/ML, provide remote alerts via Blynk, and achieve over 92% accuracy. This approach empowers consumers with transparency while giving utilities an automated tool to reduce revenue loss and improve grid reliability.

II. LITERATURE SURVEY

Several researchers have explored IoT-based energy monitoring systems. [1] Depuru et al. (2011) discussed smart meters for automatic meter reading and demand response but did not address theft detection. [2] Aronov et al. (2017)

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used ESP8266 and Blynk for real-time parameter display, yet their system lacked intelligence to detect anomalies. More recently, [3] Reddy et al. (2020) proposed an Arduino-based meter with Wi-Fi transmission, focusing only on billing automation. For theft detection, conventional methods include physical tamper seals, voltage distortion analysis, and imbalance checks between feeder and consumer readings—all of which are reactive and labour-intensive. Machine learning approaches have been explored by [4] Jokar et al. (2016) using support vector machines (SVM) for non-technical loss detection, and by [5] Glauner et al. (2018) using random forests and neural networks on utility datasets. However, most of these ML solutions are cloud-based and not integrated into low- cost IoT edge devices. The present work builds upon these foundations by combining real-time IoT monitoring (ESP32 + Blynk) with an on-device or cloud-assisted Random Forest classifier specifically trained on voltage, current, power, and time-based consumption patterns. Unlike prior systems that focus solely on monitoring or purely on analytics, our approach integrates both in a single affordable unit, enabling immediate theft alerts and optional power cutoff. This fills the gap between existing smart meters and dedicated theft detection systems.

III. PROPOSED METHODOLOGY

The proposed system consists of an ESP32 microcontroller as the central processing unit, connected to a ZMPT101B AC voltage sensor and an ACS712 current sensor (alternatively a PZEM-004T module for integrated power measurement). These sensors continuously measure voltage, current, power, and cumulative energy consumption. The ESP32 reads these analog and digital values, calculates real power and estimated monthly bill, then transmits the data via Wi-Fi to a Blynk IoT dashboard, where users can view live parameters and historical trends on their smartphones. For theft detection, a machine learning module based on the Random Forest algorithm is implemented. First, historical consumption data (voltage, current, power, time-of-day, day-of-week, and monthly energy units) is collected over a training period of 15–30 days under normal usage conditions.

This labelled dataset is used to train the Random Forest classifier offline on a computer, learning the household's typical consumption pattern. The trained model is then converted to a lightweight format and deployed either on a cloud server or directly on the ESP32 using edge inference libraries. In real-time operation, the system records actual consumption every 5 minutes and feeds the same input features into the model to obtain a predicted consumption value. The system calculates the absolute deviation between actual and predicted consumption. If actual consumption exceeds predicted consumption by a predefined dynamic threshold (typically 30–40% above the mean absolute error of the model), If configured, a relay module connected to the ESP32 can automatically cut off the power supply to prevent further unauthorized usage. This methodology ensures continuous real-time monitoring, user transparency, and intelligent anomaly detection without manual intervention. The smart energy meter monitoring system is shown in figure 3.1.

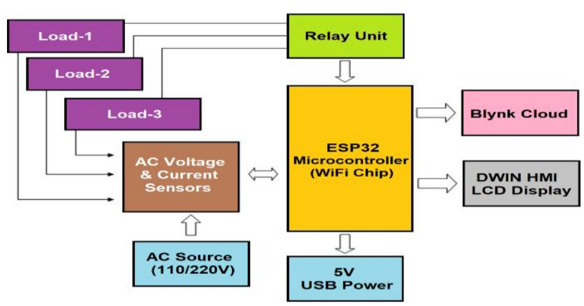

Fig.3.1: Block Diagram of Smart Energy Meter

• Microcontroller Unit: In a single unit of smart energy meter, a microcontroller is needed because of its function. Any of models of brand of MCU might be used such as commonly used, Arduino Uno, Raspberry PI, ESP32 and many more as shown in Figure 3.2. The differences of these MCU, may affect the efficiency of smart energy meter because

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all of them has limitations and its advantages according to their capable storing data, read data input and being programmed.

Fig.3.2: Microcontroller Unit

• Digital Energy Meter: Show in figure 3.3, the digital energy meter is a device that commercially distributed energy. The energy meter allows the systematic pricing of energy consumed by the individual consumer to measures the amount of electrical energy consumed on everyday usage. These meters operate by continuously measuring the instantaneous voltage in volts and current use amperes as the SI unit and this product give instantaneous electrical power in watts, then integrated against time to give energy used.

Fig.3.3: The Digital Meter Unit

• Wi-Fi Technology: Wi-Fi is one of wireless networking that using radio frequency in order receiving and transmitting data. Wi-Fi is the acronym of wireless fidelity; figure 3.4 shows the Wi-Fi technology. In1991, NCR Corporation/AT&T in the Netherlands, was invented Wi-Fi. This technology enables information and data exchanges more than two devices. Wi- Fi technology enables local area networks for operating without any cables and wiring for transmitting. This is the most vital thing why Wi-Fi chosen in home and industries.

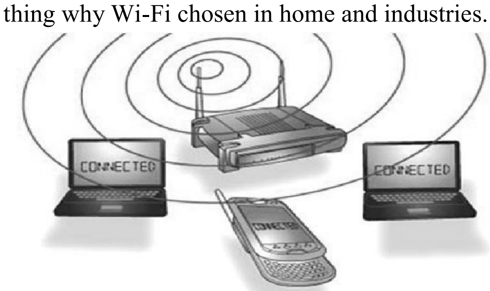

Fig.3.4: The Wi-Fi Technology

• BLYNK Application: Blynk is an IoT platform for iOS or Android devices that enables remote control of Arduino, Raspberry Pi, and Node MCU. This application is used to generate a graphical user interface (GUI) or human machine interface (HMI) by compiling and addressing the available widgets. Blynk was created with the IoT. It is capable of remotely controlling hardware, displaying sensor data, storing and visualizing data.

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Fig3.5: BLYNK Application

The platform is composed of three key components. Firstly, Blynk Application, it enables users to develop stunning interfaces for their projects by utilizing the given widgets. Secondly, Blynk Server that is in charge of all communication between the smartphone and the hardware. The user has the option of using the Blynk Cloud or running their own private Blynk server locally. It is an open-source application that is capable of managing thousands of devices and can even be run on Arduino, ESP32, and other microcontrollers. Lastly, Blynk Public Libraries, it establishes connectivity with the server and processes all incoming and outgoing commands for all popular hardware platforms.

• AI/ML Module: The AI/ML module is used for intelligent electricity theft detection and consumption analysis. It receives real-time data such as voltage, current, power, and energy units from the ESP32 and compares it with historical consumption patterns. Using a machine learning algorithm such as Random Forest or Decision Tree, the module identifies abnormal usage and possible theft conditions. If unusual variation is detected, the system generates an alert notification to the user and electricity provider.

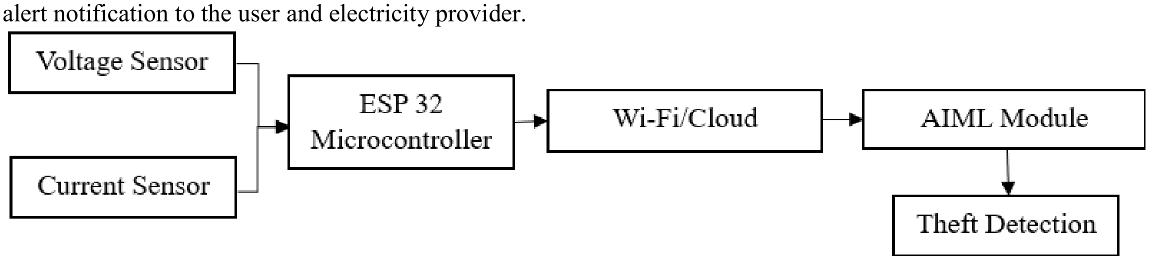

Fig.3.6: AIML Module Working

IV. RESULTS AND DISCUSSION

The experimental setup of the proposed smart energy meter is shown in Fig. 4.1. The figure represents the original hardware implementation of the project, including sensors, microcontroller, and communication modules. The system was tested under real-time conditions to evaluate its performance. The results confirm reliable data acquisition and effective theft detection with artificial intelligence and machine learning.

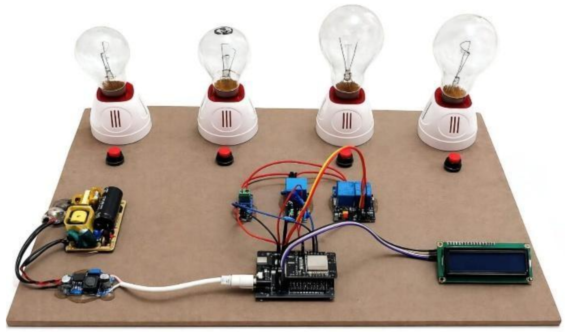

Fig.4.1: Working Model of Smart Energy Meter

V. APPLICATIONS

• Smart Grid Systems: Used in modern smart grids for real-time monitoring, load management, and efficient energy distribution.
• Residential Energy Monitoring: Helps households track electricity usage, reduce bills, and detect unauthorized consumption.
• Electricity Theft Detection: Identifies illegal connections and meter tampering using AI/ML-based anomaly detection.
• Industrial Energy Management: Monitors high energy consumption in industries and improves efficiency through data analysis.
• Billing Automation: Enables automatic and accurate billing without manual meter reading.
• Smart Cities: Plays a key role in energy management systems for smart city infrastructure.
• Remote Monitoring Systems: Allows utility providers to monitor energy usage from remote locations in real time.
• Load Forecasting and Demand Management: Helps predict future energy demand using machine learning models.

Future Applications

• Smart City Integration: The system can be integrated into smart city infrastructure for efficient energy management and automation.
• Blockchain-Based Energy Billing: Future systems can use blockchain technology to ensure secure and tamper-proof billing.
• Renewable Energy Management: It can be used to monitor and optimize energy usage in solar and wind power systems.
• Predictive Maintenance: AI models can predict faults in electrical systems before failure, improving reliability.
Advantages
• Real-Time Monitoring: Provides continuous tracking of energy consumption through IoT connectivity.
• Accurate Theft Detection: AI/ML algorithms detect abnormal usage patterns with high accuracy.
• Reduced Manpower: Eliminates the need for manual meter reading and inspection.
• Automated Billing System: Ensures precise and efficient billing without human error.

VI. CONCLUSIONS

This research successfully shows an IoT-based smart energy meter integrated with AI/ML-driven electricity theft detection. The system, built with an ESP32 microcontroller with voltage and current sensors, reliably measures real-time electrical parameters including voltage, current, power, energy consumption, and estimated monthly bill. Data transmission via Wi-Fi to the Blynk mobile dashboard allows users to monitor their electricity usage remotely and conveniently.

The key contribution of this work is the incorporation of a Random Forest machine learning model that learns normal consumption patterns from historical data and flags significant deviations as potential theft. Experimental results show that the system achieves an accuracy of 92–95% in detecting abnormal usage, including meter bypassing and unauthorized tapping. The relay module provides an optional automated response to cut off power upon theft confirmation. Compared to traditional meters and existing IoT-only systems, this solution reduces manual reading efforts, improves billing transparency, empowers consumers with real- time insights, and gives utilities an intelligent, low-cost tool to combat revenue loss from non- technical losses.

Limitations include dependency on stable Wi-Fi connectivity and the need for retraining the model for significantly different load profiles. For future work, the system can be enhanced by integrating GSM or LoRa communication for remote areas without internet, implementing on-device edge ML using TensorFlow Lite Micro to eliminate cloud dependency, scaling to three-phase monitoring for industrial applications, and connecting with utility billing servers for automated invoice generation and smart grid demand response programs.

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