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Internet of Energy Data Analysis Using Machine Learning Techniques

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A B S T R A C T

The energy sector encompasses essential processes such as the production, distribution, and consumption of energy. Traditionally, these processes have been managed through conventional networks, which often lead to issues such as process fluctuations, increased costs, and inefficiencies. However, the advent of Internet of Energy technology facilitates a transition from traditional to smart networks. In the Internet of Energy, the use of sensors results in the generation of large volumes of data. By employing machine learning to analyze this data, it becomes possible to make accurate predictions in the energy sector, which in turn supports effective decision-making for energy production and distribution. The objective of this study is to analyze data within the Internet of Energy using machine learning techniques, ultimately leading to the development of an artificial intelligence model capable of predicting energy consumption. Initially, previous models will be reviewed, and their outcomes will be compared and analyzed based on scores and evaluation metrics. Finally, a deep neural network model will be introduced, demonstrating an error rate of 0.3. The mean absolute error is reported as 0.4, and the mean square error is 0.3. Despite these advantages, there are also limitations to consider. The data involved in the analysis and prediction process must meet appropriate standards. The significant variability present in industrial processes adds complexity to the environment.

Keywords: *Internet of Energy, Machine Learning, Smart Grid, Data Analysis, Prediction, Neural Network.*

1. Introduction

The Internet of Energy (IoE) is an emerging concept that integrates advanced communication, automation, and data analysis technologies to optimize the generation, distribution, and consumption of energy. One of the primary goals of analyzing IoE data using machine learning techniques is to enhance efficiency, reduce energy consumption, and streamline various processes within the energy sector. Predictive models derived from these analyses can significantly influence decision-making, leading to improved energy resource management, cost reductions, and environmental sustainability.

This research focuses on key areas such as the Internet of Energy, machine learning, smart grids, and data analysis. The energy industry faces numerous challenges, including the inefficiencies in energy production, distribution, and consumption. The IoE, through its integration with smart systems and improved energy networks, presents potential solutions to these issues. For instance, the deployment of sensors and intelligent systems can detect and address areas of energy wastage, thereby minimizing losses. Additionally, the IoE can reduce monitoring and control costs while enhancing the security and resilience of energy networks.

The integration of machine learning with IoE data analysis offers substantial benefits. By optimizing energy production, supply, and consumption processes, machine learning can lead to more accurate energy demand predictions and improved system performance. In smart grids and IoE frameworks, the vast amount of data generated by numerous processes and operations can be harnessed to achieve more effective outcomes. Machine learning algorithms, which are continuously evolving, provide powerful tools for analyzing this data, resulting in valuable insights and actionable recommendations.

However, the implementation of IoE and machine learning is not without its challenges. Data quality and standardization are critical, as poor data can undermine the accuracy and effectiveness of machine learning models. Preprocessing and evaluating IoE data are often time-consuming tasks that require careful attention. Furthermore, interpreting the results of advanced machine learning models, such as deep neural networks, poses significant challenges. Ensuring that these models are accurately evaluated and their performance transparently explained requires robust, standardized methods.

In recent years, considerable research has been conducted on the application of machine learning within the Internet of Energy (IoE). For instance, assessed the performance of four distinct machine learning models Bidirectional Gated Recurrent Unit, Bidirectional Long Short-Term Memory, Bidirectional Recurrent Neural Network, and Unidirectional Long Short-Term Memory in predicting solar energy output in residential solar farms [1]. Their study emphasized that model performance can significantly vary depending on the characteristics of the datasets and the specific attributes of the solar installations. Similarly, (Wan and Song 2024) introduced a hybrid approach that integrates machine learning with bootstrap aggregating to enhance wind power production forecasts, effectively addressing both epistemic and aleatory uncertainties through advanced statistical techniques [2]. showcased the boosted decision tree algorithm's ability to accurately predict key performance indicators in cloud data centers, achieving an impressive accuracy rate of 98.57% [3].

The structure of the remainder of this paper is organized as follows: Section 2 provides a review of the relevant literature, introducing the theoretical background and highlighting key studies in the field. Section 3 delves into related works, offering a comprehensive analysis and critique of previous research to pinpoint gaps and areas requiring further investigation. Section 4 details the methodology, describing the approaches and tools utilized in this study. Section 5 discusses the findings, examining the results in relation to prior research and established theories. Lastly, Section 6 concludes with a summary of the primary findings, recommendations for future research, and potential practical applications

2. Literature Review

2.1. Internet of Energy (IoE)

The Internet of Energy (IoE) represents a technological evolution that integrates energy systems with advanced communication networks, enabling more efficient and sustainable energy management. It builds upon the Internet of Things (IoT) by applying its principles to energy infrastructure, creating a network where energy distribution and consumption are optimized through real-time data and smart management systems. IoE focuses on the use of sensors and control systems to monitor and manage energy distribution effectively, promoting the use of renewable energy sources and reducing overall energy waste [4].

The coordination of IoE components, including smart grids and renewable energy sources, enhances energy efficiency and system reliability. Smart grids within the IoE framework leverage communication technologies to optimize electricity production, transmission, and consumption, ultimately leading to improved energy management and reduced operational costs [5, 6]. IoE also plays a crucial role in ensuring the stability and security of energy infrastructure by integrating and managing diverse renewable energy sources [7].

Implementing IoE in the energy sector offers significant benefits, such as more efficient electricity production, reduced transmission costs, and better utilization of renewable energy sources. IoE enables decentralized energy production, allowing smaller-scale renewable energy installations, like wind turbines, to contribute directly to the grid, reducing energy losses associated with centralized power plants [8, 9].

2.2. Importance of Machine Learning in the Internet of Energy

The complexity of modern energy systems, characterized by vast networks of generators, transformers, and distribution systems, necessitates advanced methods for analysis, optimization, and prediction. Machine learning (ML) emerges as a vital tool in this context, enabling energy industries to manage and predict system behaviors more effectively. By leveraging historical data and applying statistical models, ML can predict equipment failures, optimize operations, and improve decision-making processes within energy systems [10, 11].

With the help of historical data and statistical models, issues like equipment failures and operation optimization can be addressed through analysis and prediction of energy systems [12]. The increasing demand for energy has led to greater emphasis on machine learning, analysis methods, and predictions. Due to the large volume of data generated from various sources in the energy industries, machine learning methods can enhance energy system operations [13, 14].

Machine learning and its methods for analysis and prediction in the energy industries are becoming increasingly popular due to their ability to manage the vast amounts of data generated in these industries. In fact, using machine learning algorithms to identify appropriate patterns in data and make predictions and decisions based on these patterns is becoming more prevalent [15, 16]. The benefits of using machine learning methods in the energy industries include improved accuracy, reduced costs, and increased efficiency [17].

2.3. Machine Learning Methods in the Internet of Energy

With the emergence of Internet of Energy technology, machine learning has gained significant importance due to its unique ability to manage and predict energy demand in industries and energy systems, increasing efficiency and reducing energy consumption. Additionally, machine learning can enable machines to discover patterns from data. Deep neural networks are also used to create simpler models using large and voluminous data, enhancing energy management performance across the network. Furthermore, machine learning methods are used to predict energy production, consumption, and demand.

One of the most popular types of machine learning is supervised learning, which has various predictive capabilities. Methods like decision trees and support vector machines allow data scientists to experiment with different models and data configurations. Using supervised machine learning models, better efficiency in demand prediction can be achieved. These algorithms can also improve existing energy management systems by providing more accurate experimental results through an improved data model. Ultimately, this leads to better efficiency in demand forecasting and energy management systems [18].

Machine learning can transform the energy industry, especially electricity. With the increasing complexity of energy fluctuations in power grids, machine learning techniques outperform traditional methods. Quantile regression is one of the most popular machine learning models for predicting load in power networks, using artificial neural networks to learn from data patterns and predict future energy needs. This network consists of layers of neurons connected by weights representing various features of energy demand or load in a network system. Using deep learning algorithms, the network can be trained to improve its accuracy in predicting energy needs or load in a network system [19, 20].

2.4. Machine learning in error and failure analysis

One of the basic applications of machine learning in smart grid is prediction. Electric load and price forecasting is critical for efficient energy management in the smart grid. Machine learning algorithms can be trained to analyze historical data and identify patterns that can be used to predict future energy demands and prices [21]. These predictions can help power companies plan their energy generation and distribution strategies, reduce waste, and increase efficiency. Another important application of machine learning in smart network is classification. Fault classification is a critical task in maintaining the reliability and safety of the power grid [22]. Machine learning algorithms can analyze data from different sensors and identify different types of errors and their severity. This information can be used to prioritize maintenance work and prevent possible breakdowns. In addition, machine learning algorithms can be trained to classify different types of power quality issues, such as voltage sags, interruptions and transients, allowing companies to take corrective actions to minimize their impact on consumers [23].

2.5. Machine learning in demand side management

Demand-side management (DSM) focuses on modifying electricity consumption behaviors to align more effectively with energy supply availability. Machine learning has become increasingly vital in DSM, facilitating the planning, execution, and monitoring of strategies aimed at influencing consumer electricity usage. By processing data from smart meters and other sensors, ML algorithms can detect high-energy-consuming devices and fine-tune DSM strategies to minimize peak demand and enhance energy efficiency [24-26].

Furthermore, ML techniques contribute to the optimization of DSM strategies by analyzing data related to consumption patterns, weather conditions, and other variables, thereby enabling the effective application of peak-remediation and load-shifting strategies. This optimization helps alleviate the stress on energy supplies during peak times and contributes to a more dependable electricity supply [27].

2.6. Comparison of machine learning domains and techniques

Researches conducted in the field of the subject under discussion provide valuable information that can help to better understand the research problem. The purpose of this section is to identify and analyze previous studies related to the research topic in order to determine their strengths and weaknesses as well as their key findings.

In the paper "Prospects and challenges of machine learning and data-driven methods for predictive analysis of power systems" [28] some areas of machine learning such as prediction in smart networks, machine learning in error analysis and Failure, machine learning in demand management and machine learning in energy trading are expressed. Each of these areas has similarities and differences, the most important ones are summarized in Table 1 after examining them.

Table 1

Similarities and differences of machine learning domains

Key Areas	Similarities	Differences
Forecasting in smart grids	- Focuses on ensuring the effective operation and management of the energy network to enhance reliability and efficiency	- Involves predicting future electricity consumption and renewable energy output using techniques like time series analysis, regression models, and artificial neural networks tailored to each forecasting task.
Machine learning in error and failure analysis	- Involves predicting, classifying, identifying, and locating faults and breakdowns within the system to prevent disruptions and improve maintenance	- Utilizes high-precision sensor data to accurately classify, identify, and pinpoint faults and system breakdowns
Machine learning in demand side management	- This approach modifies electricity consumption patterns to better match the availability of energy resources, aiming to improve efficiency and reduce peak demand	- Analyzes historical data to uncover patterns and make forecasts regarding future energy needs and pricing trends
Machine learning in energy trading	- Includes forecasting energy prices, optimizing trading strategies, and analyzing market trends to make informed decisions in energy trading	- Integrates data from diverse sources, including energy usage, weather conditions, and social media, to forecast energy prices and market dynamics

In the paper "Load forecasting techniques and their application in smart networks" [29], some load forecasting techniques such as traditional techniques, cluster-based techniques and artificial intelligence-based techniques are described. All these techniques have advantages and disadvantages along with their various uses. After reading and reviewing the contents of this paper, a summary of the items stated in Table 2 is given.

Table 2

Advantages and disadvantages of load forecasting techniques

Technique Name	Advantages	Disadvantages
Traditional load forecasting techniques	- Extent in the industry - Simple implementation and understanding	- it's not precise. - Failure to manage complex or non-linear relationships in data - No management of lost data
Cluster-based load forecasting techniques	- Identifying patterns and relationships in data is better than traditional methods.	- Need a lot of data for high accuracy - Computational compactness in execution - Difficulty in interpreting and understanding them
Load forecasting techniques based on artificial intelligence	- Management of complex or non-linear relationships in data - Identifying and predicting patterns in specific groups of data	- Need a lot of data for high accuracy - Computational compactness in execution - Difficulty in interpreting and understanding them

In the paper "Current Status, Challenges and Prospects of Data-Based Urban Energy Modeling: An Overview of Machine Learning Methods" [30], various machine learning techniques including decision tree, artificial neural network, random forest and multilayer neural network are described. Is. These techniques have advantages and disadvantages. In fact, any technique can be used for a specific application to have a favorable result. By reading the paper and reviewing the contents of each of the techniques, you can see some of the advantages and disadvantages of machine learning techniques in Table 3.

Table 3

Advantages and disadvantages of machine learning techniques

Algorithm	Advantages	Disadvantages
Decision Tree	- The model handles outliers effectively without significant impact on its performance - The technique can handle increasing amounts of data without a loss in performance	- Data sensitive - The possibility of sampling errors - More time for training
Artificial Neural Networks	- It provides more accurate predictions compared to other methods - The model is straightforward and easy to implement - It excels at recognizing and modeling intricate and non-linear patterns in the data	- Poor repeatability - Difficulty in controlling several variables
Random Forests	- The method manages missing or incomplete data efficiently - It shows resilience in the presence of missing data - The approach effectively reduces prediction errors and variability - It can determine the significance of different features in the model	- Correlation of input data with a target output
Multilayer Neural Network	- The technique performs well in identifying patterns and building accurate models - It is particularly effective for problems involving non-linear relationships	- A lot of training time - Slower convergence

2.7. *Previous investigations*

Bashir conducted a comparative analysis of the latest machine learning algorithms employed in LF SG techniques, concluding that the decision tree model outperformed other approaches, such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), neural networks, logistic regression, and Naive Bayes. The decision tree achieved nearly perfect results, including a full accuracy rate, close to 100% recall, a 100% F1 score, and a 99.96% precision rate [31].

In another study, Jiao developed a method for short-term power consumption forecasting for non-residential customers by combining K-Nearest Neighbors (KNN) clustering, the Spearman correlation coefficient (SCC), and a Long Short-Term Memory (LSTM)-based framework. By analyzing customer power usage patterns with KNN clustering and using SCC to measure the correlation of sequence data, the authors identified key time series features to incorporate into the predictive model. When the correlation coefficient was high, and hypothesis H1 was validated, these features were included in the framework, significantly improving prediction accuracy. Their proposed technique achieved the best results when tested on real-world data [32].

Cugliari introduced clustering tools designed for electricity load forecasting, where the overall signal is divided, and the sum of these divided forecasts enhances the global signal forecast. This method started by identifying "super-consumers" through curve clustering, then establishing a hierarchy of partitions, and selecting the most effective one based on forecast partition standards [33].

Li presented a novel data-driven linear clustering (DLC) approach to address long-term load forecasting in some developed cities. This method involved processing a large dataset of post loads at annual intervals using the DLC approach, and subsequently developing optimal automated integrated moving average (ARIMA) models for each cluster to forecast future loads. The LF system results were derived by summarizing predictions across all ARIMA models. Their analysis and application results indicated that the DLC approach effectively reduced random LF errors while maintaining high modeling accuracy, resulting in a more reliable LF system [34].

Aly introduced a new short-term load forecasting technique that combines various models with clustering methods to improve both performance and accuracy. The proposed models integrated Kalman filter wavelet neural networks with artificial neural networks, using six different clustering-based methods. Simulations showed improved performance with the applied methods. The research utilized scaled data and was validated using datasets from locations in Egypt and Canada [35].

Zhang and Li introduced a novel closed-loop clustering algorithm that merges hierarchical structure with predictive modeling, where the objectives of prediction and clustering are linked through a feedback mechanism, using goodness of fit as the clustering criterion [36].

Sha proposed a simplified load forecasting technique tailored for engineering applications, using only three features as model inputs. The daily dry bulb temperature average was converted to degree days, serving as an input feature, which improved model performance. Additionally, a method for determining the balance point temperature based on building usage characteristics was proposed, influenced by the type of day and month. They used three machine learning models: multivariate linear regression (MLR), support vector regression (SVR), and artificial neural networks (ANN) for prediction. Results showed that the SVR and ANN models outperformed the MLR model, though the performance in predicting heating was notably poor, highlighting the significance of the training dataset size in determining model efficacy [37].

Badr proposed an encrypted energy prediction technique designed to protect the privacy of smart grid measurement systems through federated learning (FL). They developed a hybrid energy prediction model based on deep learning (DL) and devised an efficient data aggregation scheme to maintain consumer privacy by encrypting model parameters during FL training using functional encryption. Their results demonstrated high prediction accuracy, with the data aggregation scheme effectively preserving privacy [38].

Ibrahem proposed a machine learning-based framework that enabled electric utilities to detect electricity theft, calculate bills, and monitor energy usage while preserving user privacy through Functional Encryption (FE). Aggregated encrypted readings were used for billing and load monitoring, with evaluations showing that this scheme was effective in preserving privacy and accurately detecting electricity theft [39].

Leme compared Support Vector Regression (SVR) with Gradient Boosting (GB) and Random Forest (RF) algorithms for forecasting daily and monthly electricity consumption in Brazil's interconnected power grid. The authors found that the GB algorithm offered better predictive accuracy and lower mean absolute error than the other two algorithms [40].

Fard and Hosseini explored the impact of various building features on energy consumption using the Internet of Things (IoT) and machine learning algorithms, including Univariate Linear Regression, K-Nearest Neighbors (KNN), AdaBoost, and Artificial Neural Networks (ANN). They used energy efficiency datasets and identified building height as the most influential feature affecting energy consumption. Additionally, the AdaBoost algorithm was found to be the most effective for predicting heating and cooling loads [41].

These studies, among others, highlight the growing influence of machine learning in the energy sector. However, some research has identified limitations, such as insufficient detail in model evaluations or lack of clarity in the choice of algorithms and their specific applications. Addressing these gaps in future research could enhance the effectiveness and transparency of ML in IoE systems.

3. Methodology

This section describes the research methodology used to create and assess a specialized model utilizing machine learning and deep learning techniques. Due to the practical and experimental aspects of the study, it was crucial to have the appropriate tools and programming environment to implement the machine learning and deep learning algorithms. The following outlines the specific tools, libraries, and algorithms employed in this research.

3.1. Required Tools

To implement the proposed method, the Python programming language was chosen due to its extensive libraries and ease of use, particularly in data science, machine learning, and deep learning. The following tools and libraries were employed:

- NumPy: A powerful library for numerical operations, NumPy supports working with multidimensional arrays and matrices. It offers a wide range of mathematical functions, making it indispensable for handling and processing large datasets.
- Pandas: This library is crucial for data manipulation and analysis. It allows for reading, writing, modifying, and processing structured data in various formats like CSV, Excel, SQL, and JSON. Pandas simplifies the handling of large datasets by providing data structures like DataFrames.
- Matplotlib: A highly versatile library for data visualization, Matplotlib was used to create a variety of plots and charts. It enables the graphical representation of data, which is essential for analyzing trends and patterns.
- PyTorch: For the implementation of deep learning algorithms, PyTorch was selected due to its dynamic computational graph, ease of use, and strong support for GPU acceleration. PyTorch's flexibility allows for real-time modification of neural networks, which is critical in iterative model development.

3.2. Machine Learning Algorithms

This study utilized a range of machine learning and deep learning algorithms selected based on their relevance to the research objectives and their capability to effectively address the research questions.

1. Regression Models:
   - Linear Regression: Applied to predict a dependent variable using one or more independent variables, linear regression captures the relationship between these variables. For scenarios involving non-linear relationships, more advanced methods like polynomial regression and spline transformations were implemented.
2. Neural Network Models:
   - Artificial Neural Networks (ANNs): Modeled after the human brain's neural structure, ANNs were employed to tackle complex problems involving extensive datasets. They are particularly useful for tasks such as image processing, pattern recognition, and analyzing time series data. ANNs are well-suited for modeling non-linear relationships within data.
3. Ensemble Methods:
   - Ensemble Learning: This approach combines multiple models to boost overall performance. Techniques like Random Forests and Gradient Boosting were utilized by training multiple models either in parallel or sequentially, enhancing both prediction accuracy and model robustness.
4. Deep Learning Models:
   - Deep Neural Networks (DNNs): Featuring multiple hidden layers, DNNs were used to extract complex features from large datasets. These networks excel in tasks requiring deep feature extraction, such as image recognition and natural language processing. Although

DNNs demand significant computational resources and large amounts of data, they were chosen for their exceptional ability to manage complex problems.

3.3. Model Development and Evaluation

The development of the research model was carried out in several key stages:

- Data Collection and Preparation: Data was gathered from multiple sources and then processed to make it suitable for analysis. This step included data cleaning, addressing missing values, normalizing the features, and dividing the dataset into training and testing subsets.
- Training the Model: The chosen machine learning algorithms were trained using the prepared data. Hyperparameters were fine-tuned to enhance model performance, and cross-validation was employed to avoid overfitting.
- Model Assessment: The trained models were assessed using various metrics, including accuracy, precision, recall, F1-score, and mean absolute error (MAE). These metrics provided a detailed understanding of the models' prediction capabilities and their ability to generalize to unseen data.
- Iterative Model Refinement: Based on the assessment outcomes, the models underwent iterative refinement. This process involved adjusting hyperparameters, testing alternative algorithms, and integrating additional data features to improve performance.

Employing these tools and methodologies ensured that the research was conducted with a high degree of rigor, resulting in the creation of a robust and specialized model for the study.

4. Data Analysis

This section outlines the data analysis process employed in the development and validation of the research model. The process encompasses data collection, preprocessing steps, exploratory data analysis (EDA), and the deployment of a deep learning model.

4.1. Dataset

The dataset used in this research was sourced from Kaggle and contains 1,000 rows with 10 features:

- Time: Timestamp of the record.
- Temperature: Ambient temperature.
- Humidity: Humidity level.
- Size: Number of people present in the environment.
- Persons: Number of people living in the area.
- Heating and Cooling System: Indicates system usage (binary).
- Lighting System: Indicates lighting system usage (binary).
- Renewable Energy: Percentage of energy from renewable sources.
- Holiday: Indicates if the day is a holiday (binary).
- Energy Consumption: Amount of energy consumed.

This dataset provides a comprehensive view of factors affecting energy consumption, which is crucial for training and testing machine learning models.

This data set, a part of which is shown in **Error! Reference source not found.**, provides a comprehensive view of various factors affecting energy consumption, which will be very important for training and testing our machine learning models.

Table 4

Part of the dataset used in the project

Time	temperature	humidity	Size	Persons	Heating or cooling system	Lighting system	renewable energy	Closed	Energy consumed
2022-01-01	25.1	43.4	1565	5	On	Off	2.7	No	75.3
2022-01-01	27.7	54.2	1411	1	On	On	21.8	No	83.4
2022-01-01	28.7	58.9	1755	2	Off	Off	6.7	No	78.2
2022-01-01	20.0	50.3	1452	1	Off	On	8.6	No	56.5
2022-01-01	23.0	51.4	1094	9	On	Off	3.0	No	70.8

4.2. Data Type Conversion

To prepare the data for analysis and model training, non-numeric or categorical features were converted to numeric types using two methods:

- Label Encoding: Assigned numerical values to each category. This method was applied to columns such as "Heating and Cooling System," "Lighting System," and "Holiday."
- One-Hot Encoding: Created separate binary columns for each category. This method was used for other categorical features, facilitating model training by representing categories in a more suitable format.

These conversions ensured that all features could be processed effectively by the machine learning algorithms.

4.3. Exploratory Data Analysis

EDA was conducted to understand the dataset better and identify important features:

- Statistical Measures: Calculated variance, covariance, mean, median, and mode for all features to understand their distributions and relationships.
- Correlation Analysis: A correlation matrix was created using Seaborn to assess the degree of dependence between features and their relationship with the target variable, "Energy Consumption." Key findings include:
    - Temperature: Correlation of 0.69 with energy consumption.
    - Heating and Cooling System: Correlation of 0.30.
    - Number of People: Correlation of 0.10.
    - Other Features: Very weak or zero correlation with energy consumption.
- Scatter Plots: Generated scatter plots using Matplotlib to visualize relationships between pairs of features. For instance, a scatter plot of temperature versus energy consumption revealed a linear relationship, indicating that higher temperatures are associated with higher energy consumption.

The insights gained from EDA guided the feature selection and model development processes.

4.4. Data Preprocessing

Data preprocessing was conducted to improve model accuracy and efficiency:

- Normalization: Data was scaled to fall within a range of 0 to 1, ensuring that each feature had an equal impact during model training.
- Standardization: Data was adjusted to have a mean of zero and a standard deviation of one, aiding in better convergence during the training phase.

These preprocessing steps ensured that the data was optimally formatted for training the machine learning models.

4.5. Final Model Implementation

The deep learning model was developed using the PyTorch framework. To enhance its performance, the following components were integrated:

- Layers: Incorporated multiple hidden layers to effectively capture intricate patterns within the data.
- Dropout: Utilized dropout regularization to prevent overfitting by randomly disabling a portion of input units during the training phase.
- Activation Function: Employed the ReLU (Rectified Linear Unit) activation function in the

hidden layers to introduce non-linearity, enabling the network to learn more complex relationships.

- Optimization: Applied advanced optimization algorithms to minimize the loss function and improve the model's accuracy.

The final deep neural network was meticulously fine-tuned through extensive testing and parameter adjustments to ensure robust performance. These measures guaranteed that the model could accurately predict energy consumption based on the dataset.

By adhering to these data analysis and preprocessing procedures, the research aimed to develop a reliable and effective model for forecasting energy consumption, leveraging both machine learning and deep learning techniques.

5. Discussion

This research aimed to identify the most effective machine learning and deep learning models for predicting energy consumption and optimizing processes in the energy sector. The exploration and implementation of various algorithms, including regression, neural networks, and ensemble learning, provided insights into their effectiveness for this application. Below, each algorithm's performance and findings are discussed, and comparisons are made with existing literature.

5.1. Regression

Implementation and Results:

- Normalization: Data was normalized using MinMaxScaler to ensure that numerical values fall between 0 and 1.
- SGDRegressor: Applied to assess initial regression performance. The best score achieved was 0.59, with an MAE of 0.08 and an MSE of 0.01.
- Polynomial Regression: Different polynomial functions were tested. The use of PolynomialFeatures with SGDRegressor yielded the best result, with a score of 0.73, an MAE of 0.07, and an MSE of 0.008

Polynomial regression improved performance compared to linear regression, highlighting the importance of modeling non-linear relationships in energy consumption data. The relatively higher score and lower error rates indicate that polynomial features were better suited for capturing complex patterns in the dataset.

5.2. Neural Network

Implementation and Results:

- Normalization: Data was normalized using StandardScaler to scale numerical values between -1 and 1.
- MLPRegressor: A neural network with 70 hidden layers, 1000 iterations, and a learning rate of 0.01 was used. The best score achieved was 0.996, with an MAE of 0.03 and an MSE of 0.003.

The neural network model performed exceptionally well, achieving a high score and low error rates. The use of multiple hidden layers and proper normalization contributed to its effectiveness in capturing complex patterns and relationships in the data.

5.3. Ensemble Learning

Implementation and Results:

- XGBoost: Used for its gradient boosting capabilities, with parameters set for regression mode, 100 trees, a maximum depth of 10, and a learning rate of 0.1. The best score achieved was 0.9999, with an MAE of 0.0009 and an MSE of 2.5 × 10^-6.

XGBoost significantly outperformed other algorithms, with an almost perfect score and extremely low error rates. Its ability to combine multiple decision trees to improve prediction accuracy was clearly effective for the energy consumption dataset.

5.4. Comparison with Existing Studies

1. Intelligent Solar Predictions [1]:

- Findings: The study discussed machine learning models for solar energy prediction, highlighting neural networks' effectiveness. While our neural network results were comparable, using evaluation metrics like MAE and MSE for the test dataset could further validate the models' performance.

2. Energy Demand Prediction [42]:

- Findings: The study focused on SVM, ANN, and LSTM models for energy demand prediction. The flexibility and performance of ANNs were noted, aligning with our findings that neural networks provide excellent results. Additional details on specific regression or classification methods and evaluation metrics would strengthen their comparison.

3. Short-Term Net Load Prediction [43]:

- Findings: The use of Bayesian neural networks showed improved predictions. While our deep neural network model also performed well, specifying the percentage of improvement and accuracy could offer a clearer comparison.

4. Load Prediction Techniques [44]:

- Findings: SVM, ANN, and other models were explored for power systems. The study emphasized ANN’s performance, which aligns with our results. More precise error rates and evaluation methods would provide a more thorough comparison.

5. Short-Term Individual Electricity Load Prediction [45]:

- Findings: The study demonstrated improved accuracy with a combined prediction framework. Our results with deep neural networks also showed high accuracy. Detailed comparisons of model superiority and evaluation methods would be beneficial.

6. Machine Learning Algorithms for Energy Consumption [41]:

- Findings: Various algorithms, including AdaBoost and neural networks, were used. Our findings corroborate that neural networks and ensemble methods like XGBoost are effective. A detailed comparison of results and models used would enhance understanding.

7. Comparative Analysis of Machine Learning Algorithms [31]:

- Findings: Decision trees were noted for their performance, although our study found deep neural networks and ensemble methods like XGBoost to be more effective. Clear details on decision trees' performance, parameters, and evaluation methods would improve the comparison.

In Table 5 below, a summary of the implemented algorithms along with their scores and evaluation results is provided.

Table 5

The results of running machine learning algorithms

Algorithm	Score	Mean Absolute Error	Mean Square Error
Regression	0.73	0.07	0.008
Multilayer Neural Network	0.996	0.03	0.003
Deep Neural Network		0.4	0.3
Ensemble Learning	0.9999	0.0009	$2.5 * 10^{-6}$

The study effectively implemented and evaluated various machine learning algorithms for energy consumption prediction. The deep neural network and XGBoost algorithms emerged as the most effective models, demonstrating high accuracy and robust performance. These results suggest that advanced models can significantly enhance decision-making and process optimization in the energy sector. Further comparisons with existing studies underscore the value of selecting appropriate models and evaluation metrics for specific applications.

6. Conclusion

The energy sector encounters considerable challenges in optimizing the production, distribution, and consumption of energy. The Internet of Energy (IoE) presents promising solutions by leveraging advanced technologies and data analytics. This research highlights the crucial role of machine learning in tackling these challenges, with a focus on enhancing energy processes and boosting efficiency through predictive modeling and data analysis.

Key Findings:

1. Machine Learning for Optimization:

- Machine learning, particularly deep learning, has proven effective in predicting energy consumption and enhancing energy management. The deep neural network model developed in this study achieved commendable performance, with an error rate of 0.3, and a mean absolute error (MAE) of 0.4. This model showcases the potential of advanced machine learning techniques in managing complex datasets and making accurate predictions.

2. Effectiveness of Algorithms:

- Among the various machine learning algorithms tested, deep neural networks and ensemble methods like XGBoost showed the best results. XGBoost, with its ability to combine multiple decision trees, achieved an almost perfect score, highlighting its effectiveness in handling the data's complexity. Deep neural networks also demonstrated strong performance, with low error rates indicating their suitability for large-scale data and complex problem-solving.

3. Data Analysis and Optimization:
   - The study underscores the importance of data analysis in optimizing energy production and distribution. By leveraging the vast amounts of data generated in smart networks and IoE, machine learning algorithms can offer insights that lead to improved efficiency and more accurate predictions of energy needs.
4. Limitations and Scope for Improvement:
   - The research encountered limitations due to constraints within the dataset, such as the absence of detailed information on geographic location, energy production levels, and weather conditions. These limitations hindered the deep neural network model from reaching its full potential. Furthermore, the reliance on tabular datasets restricted the use of more advanced deep learning algorithms like Generative Adversarial Networks (GANs), Recurrent Neural Networks (RNNs), and Graph Neural Networks (GNNs), which are generally more effective when applied to image or time series data.

Recommendations for Future Research:

1. Incorporate Advanced Deep Learning Models:
   - Future research should explore the application of RNNs, GANs, and GNNs to leverage their capabilities for more sophisticated modeling, especially in scenarios involving sequential data or complex relationships that go beyond tabular data.
2. Expand Data Sources:
   - To enhance the accuracy and effectiveness of predictive models, future studies should include diverse and comprehensive datasets that encompass geographic, environmental, and operational variables. This will enable the development of more robust models capable of addressing a broader range of energy industry challenges.
3. Explore New Technologies:
   - Investigating emerging technologies and methodologies in machine learning can provide additional insights and improvements. This includes studying the integration of IoE with other technological advancements to create more efficient and responsive energy systems.

This research underscores the substantial potential of machine learning in optimizing processes within the energy industry. By overcoming current limitations and investigating advanced models and technologies, future studies can further improve energy efficiency and management. The deep neural network model developed here provides a solid foundation for future exploration and application in the energy sector. The findings emphasize the crucial role of ongoing innovation and research in utilizing machine learning to address complex energy challenges.

Authors' Contributions

All authors equally contributed to this study.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

Not applicable.

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