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Machine Learning-Based Energy Consumption Monitoring And Forecasting System For Sustainable Environment

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Abstract
The proposed energy consumption monitoring and forecasting system aims to enhance energy monitoring by seamlessly integrating electricity meters with RS485 to Ethernet TCP/IP converters, enabling efficient real-time data collection and analysis. It entails generating graphical depictions of electricity meter use, drawing insightful conclusions from data analysis to offer useful information on energy usage trends and monitoring the state of meters to guarantee optimal performance. The endeavor to present gathered data, graphs, and insights for simple interpretation includes the creation of an intuitive dashboard. Various real-time power consumption parameters through building a robust connection infrastructure are gathered for monitoring and analysis. Upon data collection, it is processed and resampled to form machine learning models to predict time series. The primary aim is to accurately predict energy consumption by employing historic consumption patterns, which would make better decision-making possible and effective resource allocation. By enabling more precise forecasting and monitoring, the system promotes energy conservation and reduces unnecessary power usage, thereby contributing to lower greenhouse gas emissions. This research supports sustainable energy management practices that help mitigate environmental impact and foster a greener future.
Keywords: Sustainable Environment, LSTM, Neural Networks, Machine Learning, Appearance Power, and Convolutional Neural Networks

INTRODUCTION

The rise in energy demand, accompanied by the increased demand for sustainable and optimized energy use, has made it necessary for new, innovative methods of tracking and predicting energy consumption. Conventional techniques of managing energy tend to be lacking in precise prediction of consumption rates and maximizing usage, giving way to inefficiency and increased expenses. In this regard, applying sophisticated machine learning methods offers a viable solution to improve the precision and reliability of monitoring and forecasting of energy consumption. Energy consumption monitoring and forecasting systems with machine learning involve massive records of past data along with real-time data for predicting future energy usage, detecting trends, and optimizing energy management. These systems collect information from diverse sources, such as smart meters, IoT sensors, and environmental data providers, and combine it to form an inclusive and dynamic model of energy consumption. The core aim of this study is to create a robust machine learning platform that is able to accurately monitor and predict energy consumption. This entails several critical components: data collection, preprocessing, exploratory data analysis, and the deployment of advanced machine learning algorithms. Through successful utilization of these elements, the system proposed is expected to offer actionable information that can result in considerable energy saving and enhanced operation efficiency. We will proceed to discuss the minute methodology of designing this system, such as data collection and preprocessing techniques, the exploratory data analysis (EDA) process, and implementation of different machine learning models, in the subsequent sections. The objective is to illustrate how machine learning can be utilized to design a complex energy management system capable of not just predicting future use with high accuracy but also ensuring proactive and optimized energy use.

With the suggested system, individuals and organizations can now predict and understand domestic energy consumption. The suggested system learns usage patterns through analysis of data like voltage, current, and appliance usage. The system assists energy suppliers to provide customized plans, maximize distribution, and detect prospective infrastructure requirements; homeowners monitor usage, determine areas for saving, and create individual energy objectives; researchers have insights into larger consumption patterns and create innovative energy-saving technologies. All these services are rendered by the capability of the system to predict and provide insight. Overall, the system inspires stakeholders to make informed decisions and facilitates efficient energy utilization. To obtain multiple metrics associated with power consumption, the project involves integrating the converter with electricity meters. Following preprocessing of this data to receive the required data, machine learning algorithms for time series forecasting will be created and evaluated. Due to its intuitive interface, scalability, and real-time monitoring feature, the system will provide stakeholders with accurate information on energy consumption patterns for well-informed decision-making and efficient resource management.

LITERATURE SURVEY

The interplay between energy consumption forecasting and machine learning has attracted significant scientific and industrial attention over the last few years. There have been many studies, which have applied various methodologies and techniques to increase the accuracy and effectiveness of models for energy forecasting. This section discusses major advancements and contributions within the field by presenting important trends, methods, and results found in the existing literature.

One of the original studies in the field is from [1] that first developed the application of LSTM for predicting energy consumption. Their research opened the door to future work as it showed what was possible for LSTM models when it came to learning consumption habits. After this, the development of machine learning algorithms represented a big step in the domain, and artificial neural networks (ANNs) and support vector machines (SVMs) were identified as very efficient tools for complex and non-linear data modelling. Researchers in [2] compared the state-of-the-art machine learning models based on modelling approach, type of energy, type of prediction, and area of application. According to the study, ensemble and hybrid models show enhanced performance and accuracy. In addition, it suggests that applying advanced data preparation methods—such as dealing with missing values, for instance—can enhance input data and model quality.

Authors in [3] reported accurate prediction techniques are crucial for optimizing the use of renewable energy. The review examined model analysis, with particular attention on parameter selection, data pretreatment, and performance assessment. To improve real-time data collecting for more accurate renewable energy projections, it also recommended merging ML models with sensor networks and Internet of Things devices. For accurate predictions of building energy use, authors in [4] compared machine learning algorithms. Authors in [4] considered variables related to input/output, building kinds, and historical data. Because energy consumption data is temporally oriented, it is also recommended using specialized time series forecasting methods like LSTM and ARIMA to get better forecasts. Smart grids are created when IoT is integrated with the electrical grid, increasing sustainability and efficiency. Two-way communication is made possible by smart meters, which also provide comprehensive use data but cause privacy issues. Building energy management systems use automation and Internet of Things sensors to optimize use. IoT facilitates the integration of distributed solar and storage, lowering dependency on the main grid. For an energy system to be robust, cybersecurity and analytics development must continue to get priority [5]. Conventional electrical metering systems are labor-intensive, error-prone, and hampered by manual procedures. To address these issues, the suggested Smart Energy Meter makes use of Internet of Things technologies to offer real-time monitoring, remote control, and automated payment via mobile devices. Smart meters through the Internet of Things have benefits such as reduced labor expense and improved quality of services. But due to the history of meter tampering, the implementation of such systems in India is challenging. Nonetheless, IoT-based smart meters are still a viable choice for automated billing and monitoring of energy through their projected benefits such as improved efficiency and reduced pilferage [6]. Power systems get smarter by incorporating advanced metering infrastructure (AMI) and smart meters, enhancing reliability and efficiency. Two-way communication enables customers and utilities to track detailed energy usage, and this enhances billing accuracy and reduces costs. Advanced consumption details assist consumers in making informed decisions, and integrated control simplifies management of dispersed generating assets. Strong security measures are required to ensure privacy, and communications infrastructure is needed to connect smart devices [7]. Advanced metering infrastructure (AMI), which converts traditional meters into "smart meters" to monitor energy in real time, is facilitated through the integration of

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smart devices. Remote reading automates costs and enhances billing accuracy, and advanced consumption statistics stimulate energy conservation on the customers' side. But aggressive governmental responses are needed to address privacy and security issues. For electrical grids to become more sustainable and efficient, smart meter infrastructure is essential, which means that cybersecurity and communication systems innovation must continue [8]. Conservation initiatives are hampered by legacy metering, which depends on manual procedures. Smart grids allow for the transfer of consumption data in real time while modernizing infrastructure. Making the switch to advanced metering infrastructure (AMI) lowers expenses and increases billing precision. Customers can see use trends more clearly, which helps with conservation efforts. To ensure sustainable power infrastructure and realize the full potential of AMI, ongoing innovation is essential [9]. The growing demand for energy in homes is being addressed by smart metering technology, which makes efficient distribution possible and gives users the ability to monitor use. To better understand customer behavior and how it relates to power rates, this study examines data from smart meters. Efficient techniques for real-time consumption analysis are demonstrated via case studies and ARIMA modelling. Subsequent investigations may examine sophisticated modelling methodologies to augment prediction precision and encourage energy preservation [10].
Predicting energy consumption is a critical component of effective energy management in buildings, which is essential for sustainability. This study investigates the support vector machine, artificial neural network, and k-neighbor techniques using cloud-based machine learning on Microsoft Azure to generate predictive models. Applications in Malaysian commercial buildings demonstrate how successful Support Vector Machines are in making precise predictions in real-world scenarios. The paper outlines the benefits of cloud-based predictive modelling and makes recommendations for future lines of inquiry to raise prediction accuracy even more [11]. Forecasting energy use accurately is essential for all industries as it affects everyday living, business, and competition at home. Three time series models are examined in this paper, which focuses on the importance of demand forecasting: CNN, LSTM neural network, and ensemble (Facebook Prophet and XGBoost). An analysis of historical data from 2020 and 2014–2019 reveals the difficulties brought on by the COVID-19 epidemic. Even though the models' RMSE is larger, their MAPE indicates that they are performing rather well, and adding more features like temperature and COVID-19 variables should help. The study highlights the necessity of improving forecasting techniques to achieve greater accuracy in changing socioeconomic contexts [12]. To facilitate effective energy monitoring and management, the study suggests a state-of-the-art Commercial Building Energy Management System (CBEMS) that utilizes Internet of Things-based Smart Compact Energy Meters (SCEMs). The system maximizes energy efficiency and enables Demand Side Management (DSM) techniques by utilizing cutting-edge hardware and real-time operating systems. Considerable decrease in peak demand and energy utilization are shown in a real-world deployment. The ability of IoT-based SCEMs to identify power quality faults with high accuracy highlights their disruptive potential to improve operational efficiency in commercial buildings [13]. Authors in [14] investigated machine learning techniques such random forest, KNN, XGBOOST, linear regression, and ANN to predict the power use with accuracy is essential for sustainability, cost-cutting, and energy management electricity use. Following a comprehensive analysis, KNN emerges as the most accurate agricultural production forecaster, with a 90.92% accuracy rate. For accurate predictions, choosing the right characteristics and models is essential. This highlights the necessity of ongoing observation and model update to accommodate shifting circumstances.
From the study of various literatures of the domain it appears that the area of unmet research need is in the combination and refinement of machine learning methods especially designed for renewable energy forecasts in various building contexts. The convergence of machine learning, renewable energy, and building environments is not well-focused upon, even though several studies touch on energy consumption prediction and building energy management. Particularly, research is required on the following subjects: modifying machine learning models to account for various building settings, including types of buildings, localities, and energy sources, to anticipate energy in the short-, medium-, and long-term. Using cutting-edge machine learning architectures, such LSTM, to capture intricate reexamining how sensor networks and Internet of Things devices might be integrated into buildings to improve data collecting and produce more precise and timely projections of renewable energy. Relationships between building environment data and energy use.

RESEARCH DATA

This study uses an eight-factor dataset of energy consumption, which is the average of readings from three electric meters during a one-minute period for different energy characteristics. The energy in watt-hour spent by each meter is indicated by the following: global voltage (in volts), global intensity (current intensity in ampere), global active power (in kilowatts), global reactive power (in kilowatts), and sub_metering_1, sub_metering_2, and sub_metering_3.

DATA SOURCE

The Kaggle repository hosted the dataset utilized in the study, which was supplied by the UC Irvine Machine Learning Repository. The dataset is made up of 2075259 measurements that were taken during a 47-month period, from December 2006 to November 2010.

Algorithms:

This study employs five machine learning approaches to forecast energy usage. Since we have a minute-average dataset, four of the five strategies are time series prediction algorithms. The methods employed are:

a. Long Short-Term Memory (LSTM)
b. Long Short-Term Memory (LSTM) with K-Fold Cross Validation
c. Convolutional Neural Network (CNN) with K-Fold Cross Validation
d. K-Fold Cross Validation combined with Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM)
e. Lasso Regression

Time-Series Techniques

Since time-series data are capable of recording complex patterns and temporal relations apparent in sequential data, machine learning algorithms such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) often utilize them [15]. LSTMs excel at modeling long-term relationships for applications such as forecasting and anomaly detection, while CNNs are more suited to extracting spatial-temporal features from time-series data. The model can execute better in activity recognition and time-series forecasting by combining the advantages of CNNs and LSTMs, allowing it to recognize both local and long-distance patterns. Moreover, the use of methods such as K-Fold Cross Validation strengthens the model's testing and makes it robust against various segments of time series data, leading to more precise predictions and conclusions.

METHODOLOGY

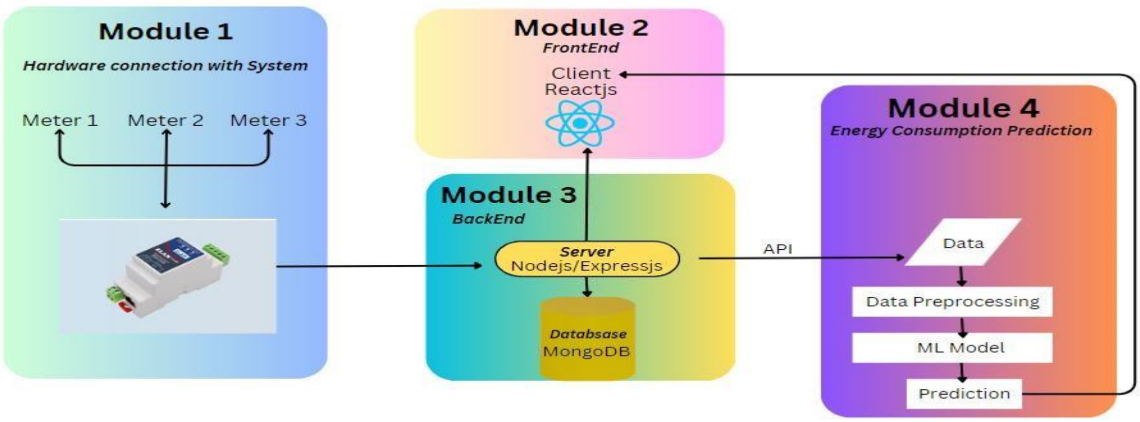

Figure 1. System Architecture

Figure 1 depicts the entire system architecture, and the detailed description of the architecture is given below

Backend:

The processing and storing of the information gathered from the energy meters falls under the purview of this module. It is composed of the following sub-modules and is constructed with Node.js and Express.js: API An interface for the Frontend module to access and work with the data is provided by this sub-module. Database: This sub-module houses the gathered information.

Frontend:
This module oversees giving the system an interface. It is constructed with React.js and shows information in the form of a graph, including real-time energy consumption predictions and a comparison of actual and expected energy use.
Hardware connection with system:
The task of gathering information from the energy meters falls to this module. It communicates with the meters and gathers data on several parameters, such power and current, using a Modbus RTU TCP Gateway. The Backend module receives the data after that for processing and storing.

Energy Consumption Prediction:
The data is cleaned and ready for use by the ML model in this sub-module. This module oversees applying machine learning to forecast energy usage. Utilizing preprocessed data that will be trained using a variety of machine learning models, it is constructed in Python. Next, future time periods' energy use is predicted using the learned model.

Machine Learning Techniques for Prediction
Preprocessing for time-series techniques:
2 million rows of minute-by-minute electricity meter values are examined in this extensive undertaking. The data is then pre-processed for machine learning models so that they may be used to extract insightful information and forecast future usage. The data is further refined by condensing minute-level measurements into hourly snapshots. Sub-metering information is then aggregated into a single "meter value" characteristic to comprehend overall energy consumption. Reactive power has no direct effect on consumption; thus, we purposefully eliminate these columns to make the study easier and more targeted. The data is then divided into two sets (76% for training and 24% for assessing the model's predictive power usage forecasting capability) to train the model.

Long short-term memory (lstm):
A sequential model, which is a linear stack of layers, is the first model in architecture. The model is extended with two LSTM layers: a 300-unit layer and a 200-unit layer. Return_sequences=True indicates that the first LSTM layer sends the output for every input time step. Following each LSTM layer are dropout layers with a 0.2 dropout rate. There are then two Dense (completely linked) layers with one and one hundred neurons, respectively. The ReLU activation function is utilized in the initial Dense layer, while the second Dense layer adopts a default linear activation if no specific function is specified. LSTM layers capture sequential dependencies within the data, while dropout layers mitigate overfitting by randomly eliminating connections during training. Predictions are then generated from the learned features by the dense layers [16-17].

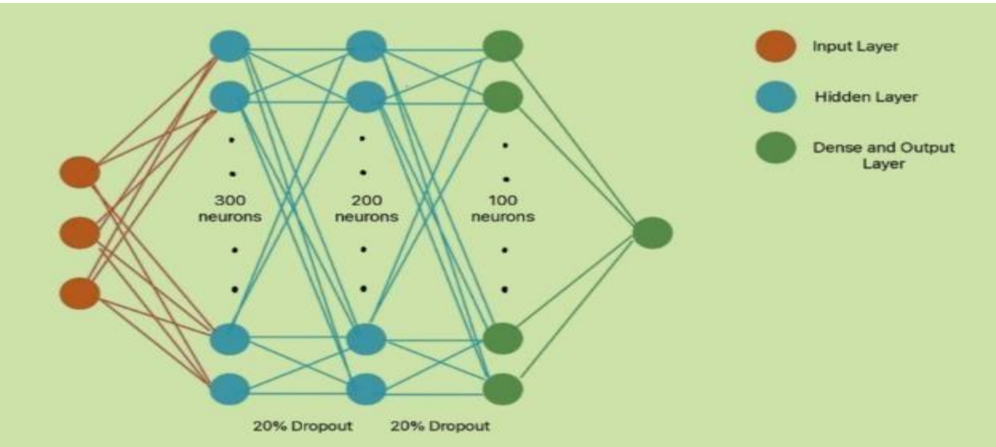

Figure 2 LSTM Architecture

As shown in figure 2 the LSTM cell is a crucial element in the LSTM architecture, serving as a specialized form of recurrent neural network (RNN) unit. Its goal is to solve the problem of vanishing gradients and efficiently capture long-term dependencies in data. Here's the mathematical representation of the LSTM cell:

$i_t = \sigma(w_i[h_{t-1}, x_t] + b_i)$
$f_t = \sigma(w_f[h_{t-1}, x_t] + b_f)$
$o_t = \sigma(w_o[h_{t-1}, x_t] + b_o)$

Where,

- i_t: input gate output
- f_t: forget gate output.
- o_t: output gate output
- σ: sigmoid function
- w_x: weight matrix for corresponding gate(x)
- h_{t-1}: previous LSTM block output at t-1
- x_t: current input
- b_x: biases for the corresponding gate(x)

The following are the equations for the cell state, candidate cell state, and final output:

$\bar{c_t} = \tanh(w_c[h_{t-1}, x_t] + b_c)$
$ct = ft * ct{-}1 + it * \bar{ct}$
$h_t = o_t * \tanh\,(c^t)$

Where,

- c_t: cell state at time t
- $\bar{c_t}$: candidate for cell state at time t

The Adam optimizer and mean squared error as the loss function are used to construct the model. With a batch size of 64, it is trained for 50 epochs and assessed using RMSE and R^2 Score.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Where,

- n: number of samples
- y_i: actual value
- $\hat{y_i}$: predicted value

$$R^2 = \frac{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\frac{1}{n}\sum_{i=1}^{n}(y_i-\bar{y}_i)^2}$$

Where,

- $\bar{y_i}$: mean of actual values.

K-Fold Cross Validation for Long Short-Term Memory (LSTM) Application:

The model architecture remains consistent with the prior method; it consists of an LSTM layer, dropout regularization is applied to prevent overfitting, an additional LSTM layer is incorporated, and entirely connected dense layers employ the ReLU activation function. Adam optimizer is utilized for optimization, while the mean squared error loss function is employed for training [18]. By using k-fold cross-validation with five splits, robust evaluation is guaranteed. As shown in figure 3, for each fold, the data is divided into training and testing sets. The model's performance is evaluated using the R^2 Score (Coefficient of Determination) and RMSE (Root Mean Squared Error). The model's overall efficacy is determined by averaging the RMSE and R^2 Score values over all folds.

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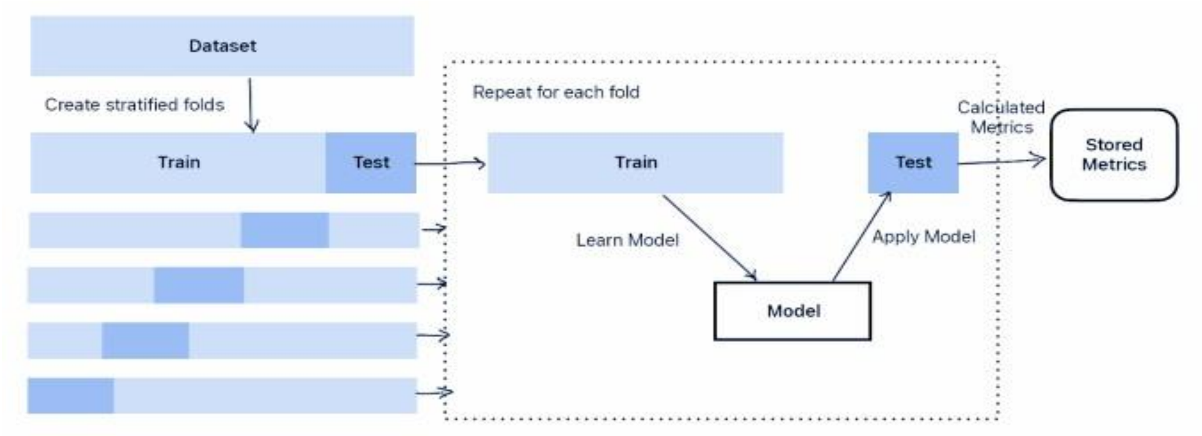

Figure 3 K-Fold demonstration

Convolutional Neural Network (CNN) with K-Fold Cross Validation:

Time series forecasting is done using a Convolutional Neural Network (CNN) model, and k-fold cross-validation is used to make sure the model is thoroughly evaluated as depicted in figure 3. Convolutional layers are used to extract features, max-pooling layers are used to reduce dimensionality, and dense layers are used to make predictions in CNN architecture [19]. The detailed architecture of CNN is shown in figure 4. Convolutional layers use filters to find patterns input data that are spatial. To preserve important information, the feature maps are down-sampled using max-pooling layers. The extracted features are converted into predictions using dense layers.

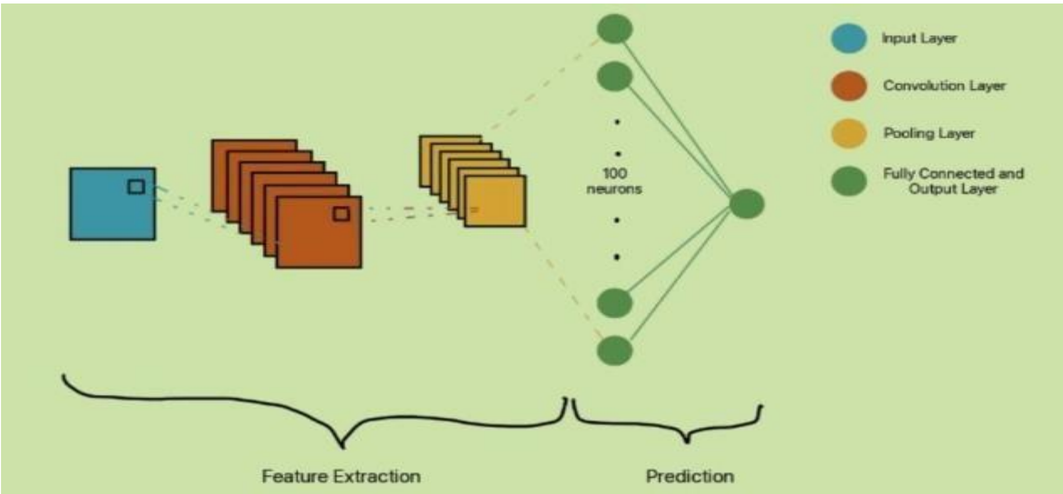

Figure 4 CNN architecture

The model is constructed by using the Adam optimizer for compilation and the mean squared error loss function. Using k-fold cross-validation with 5 splits, we make sure that the model's performance is thoroughly evaluated. For every fold, the dataset is split into training and testing sets [19-20].

Convolutional Neural Network (CNN) integrated with Long Short-Term Memory (LSTM) with K-Fold Cross Validation:

To make the output size compatible with later layers, the model starts with a ZeroPadding1D layer. For feature extraction, convolutional layers (Conv1D) with ReLU activation are included. The inclusion of a MaxPooling1D layer reduces the dimensionality of the feature maps. The output of the CNN layers is then flattened and reshaped to fit the LSTM layer's input shape after that. Using ReLU activation, an LSTM layer is added to capture temporal dependencies.

Finally, a Dense layer for regression is appended with linear activation. This entire processing pipeline is depicted in figure 5.

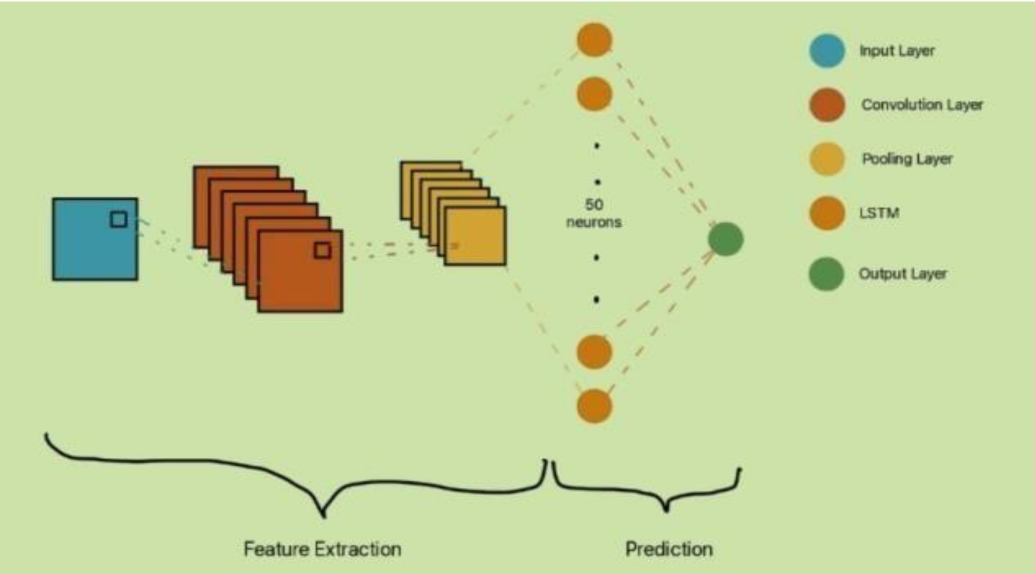

Figure 5 Hybrid of CNN and LSTM architecture

The model employs k-fold cross-validation for training. The data is divided into training and testing sets for each fold. Min-Max scaling is used to scale the training set of data. The hybrid model is trained with the Adam optimizer with mean squared error (MSE) loss on the scaled training data.

Preprocessing for Lasso Regression involves converting the 'Date' and 'Time' columns to string type. Any missing values marked as '?', 'nan', or numpy.nan are replaced with -1 across all columns using the 'replace' method. Subsequently, a SimpleImputer object is instantiated to replace -1 values (representing missing values) with the mean of every column, especially those that are listed in num_vars. The 'power_consumption' variable, which appears to be an estimate taken from the difference between 'Global_active_power' normalized to kW and the sum of sub-metering readings, is calculated using equations 1 and 2.

In Lasso Regression, the model is trained on the training dataset using the preprocessed data, and then predictions are made on the test dataset. When the Lasso Regression model is first initialized, no hyperparameters are specified. The target variable ('Global_active_power') for the test dataset is then predicted using the predict method after the model has been fitted to the training data (X_train and Y_train) using the fit technique. A regularization term that penalizes the absolute size of coefficients is incorporated into Lasso Regression. The Lasso Regression goal function integrates the L1 regularization term with the mean squared error (MSE).

$$Objective\ Function = MSE + \lambda \sum_{j=1}^{p} |\beta_j|$$

- MSE: measures the average squared difference between the actual and predicted values.
- β_j: coefficient of j^{th} feature
- λ: regularization parameter that controls the strength of the regularization. Higher values of result in more regularization, leading to sparser coefficient estimates.
- p: number of features

By changing the feature weights or coefficients to reduce prediction error and punishing large coefficient values to discourage overfitting and promote feature selection, the aim is to minimize this objective function.

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RESULT AND DISCUSSION

LSTM Model

Single LSTM model has an RMSE of 0.561 and R^2 Score of 0.501. LSTM with k-fold cross-validation (k=5) has slightly worse performance with RMSE of 0.615 and R^2 Score of 0.530. This indicates some overfitting or instability in the model's performance across different data splits.

Cnn Model

CNN with k-fold cross-validation (k=5) performs significantly better than both single LSTM and LSTM with k-fold in terms of RMSE, with an RMSE of 0.095, and similar R2 score to LSTM with k-fold, indicating a better generalization capability.

Hybrid LSTM and CNN Model

The fusion of CNN and LSTM with k-fold cross-validation (k=5): Demonstrates comparable performance to the CNN model regarding RMSE (0.094) and R2 score (0.534). This indicates that integrating CNN and LSTM does not yield notable enhancement over employing CNN alone under these circumstances.

Lasso Regression

Performs competitively with the neural network models in terms of RMSE (0.230) and significantly better in terms of R2 score (0.95). Lasso Regression's high R2 score suggests that it captures most of the variance in the data, possibly indicating a good fit to the underlying patterns.

Table 1 and figure 6 represent the detailed comparative analysis of the performances of algorithms, namely- LSTM, LSTM with K-fold 5, CNN with K-Fold 5, CNN+LSTM with K-fold 5.

Table 1: Comparison of algorithms

Algorithm	Parameters			
	Epochs	Batch Size	RMSE	R^2 Score
LSTM	50	64	0.561	0.501
LSTM with K-Fold (k = 5)	50	64	0.615	0.530
CNN with K-Fold (k = 5)	50	64	0.095	0.534
CNN + LSTM with K-Fold (k=5) (k = 5)	50	64	0.094	0.534
Lasso Regression	-	-	0.230	0.950

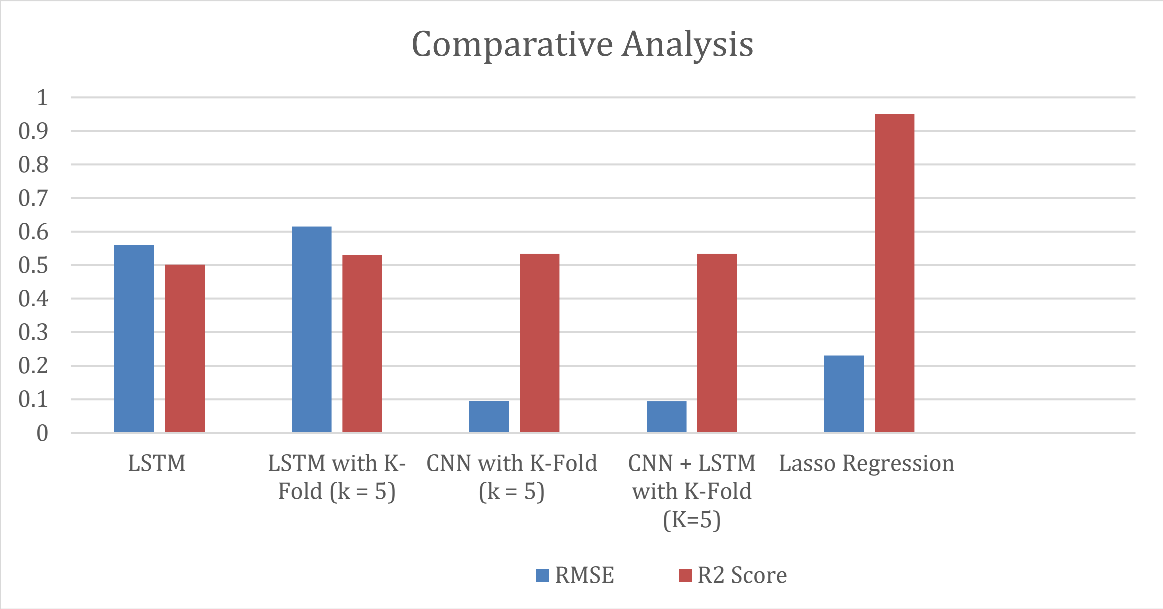

Figure 6 Comparative Analysis of Algorithms

Figure 7 illustrates the prediction results of the LSTM model compared to actual data. The graph shows how closely the model's output follows true values over time, indicating its effectiveness in capturing temporal patterns and trends in the dataset.

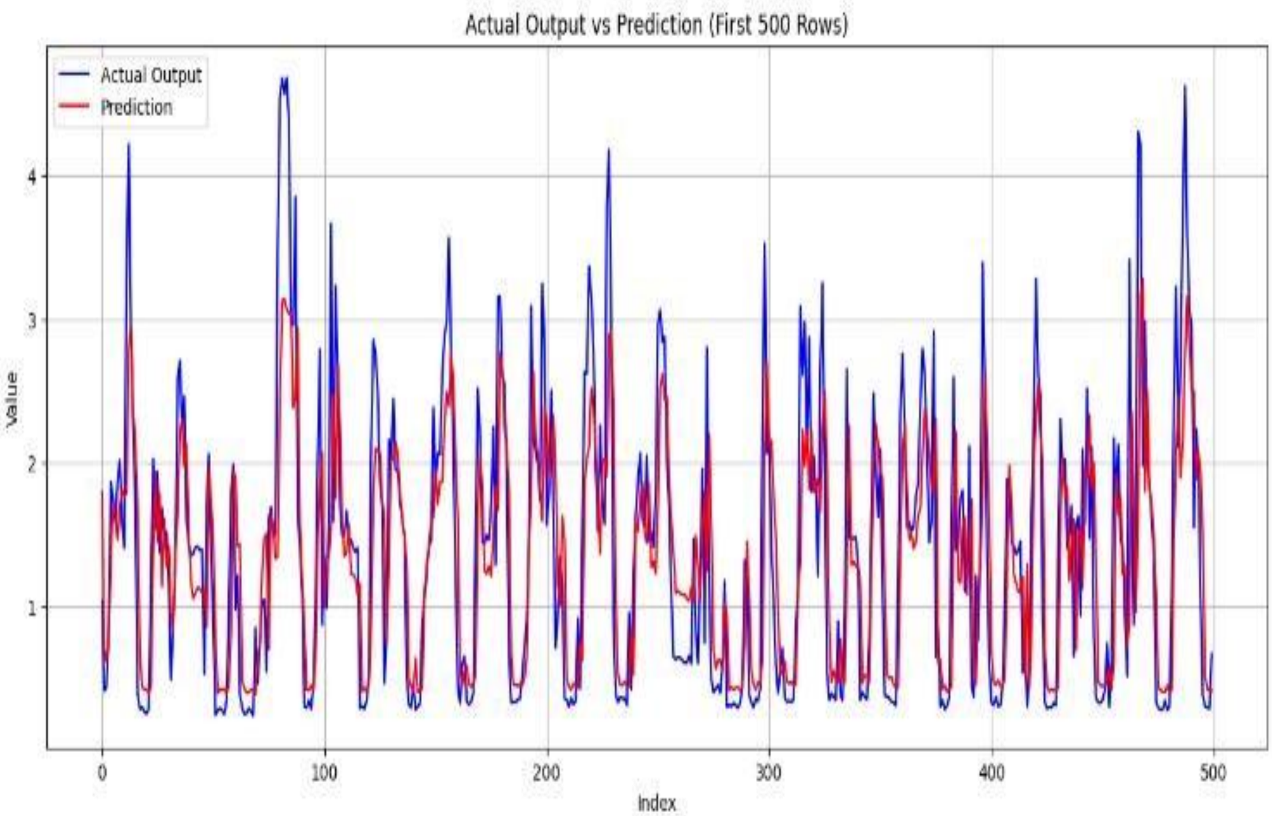

Figure 7. LSTM Model Prediction

Figure 8 illustrates the prediction results of the LSTM model using K-fold cross-validation. The plot demonstrates how the model generalizes across different data splits, with predicted values closely aligning with actual observations, highlighting its robustness and consistency.

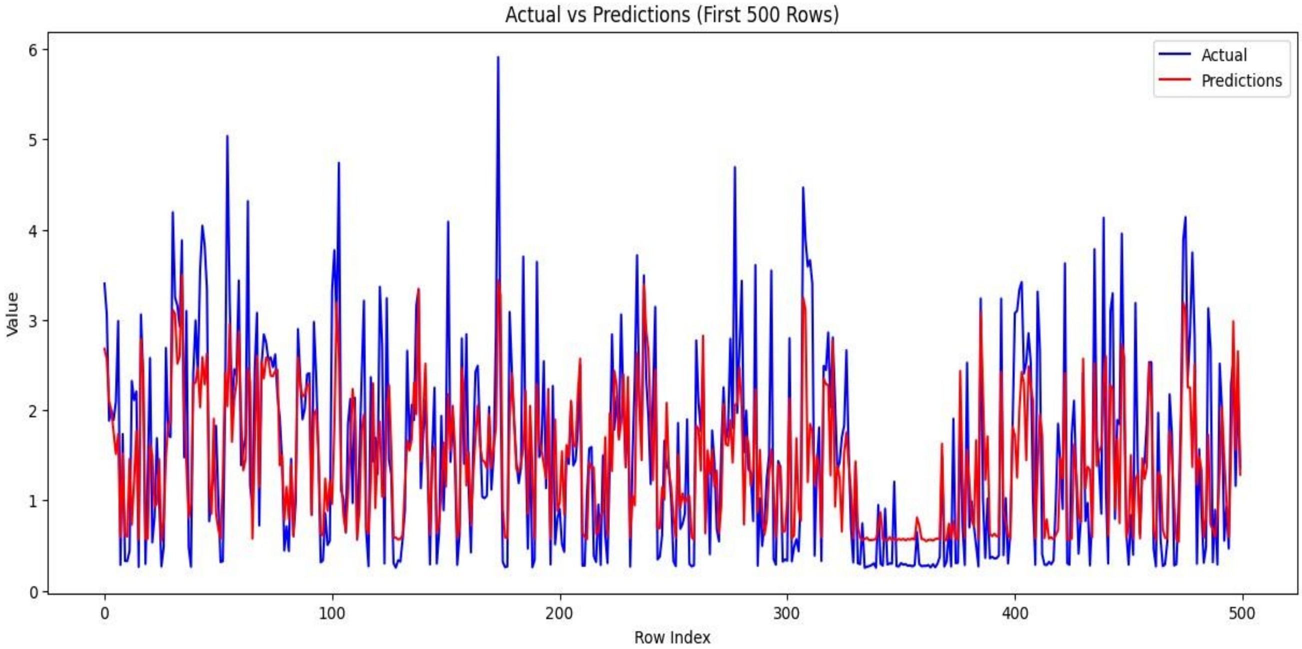

Figure 8 LSTM with K-fold model Prediction

Figure 9 illustrates the prediction results of the CNN model using K-fold cross-validation. The graph shows how well the model captures patterns across different data folds, with predicted values closely matching the actual data, indicating good generalization performance.

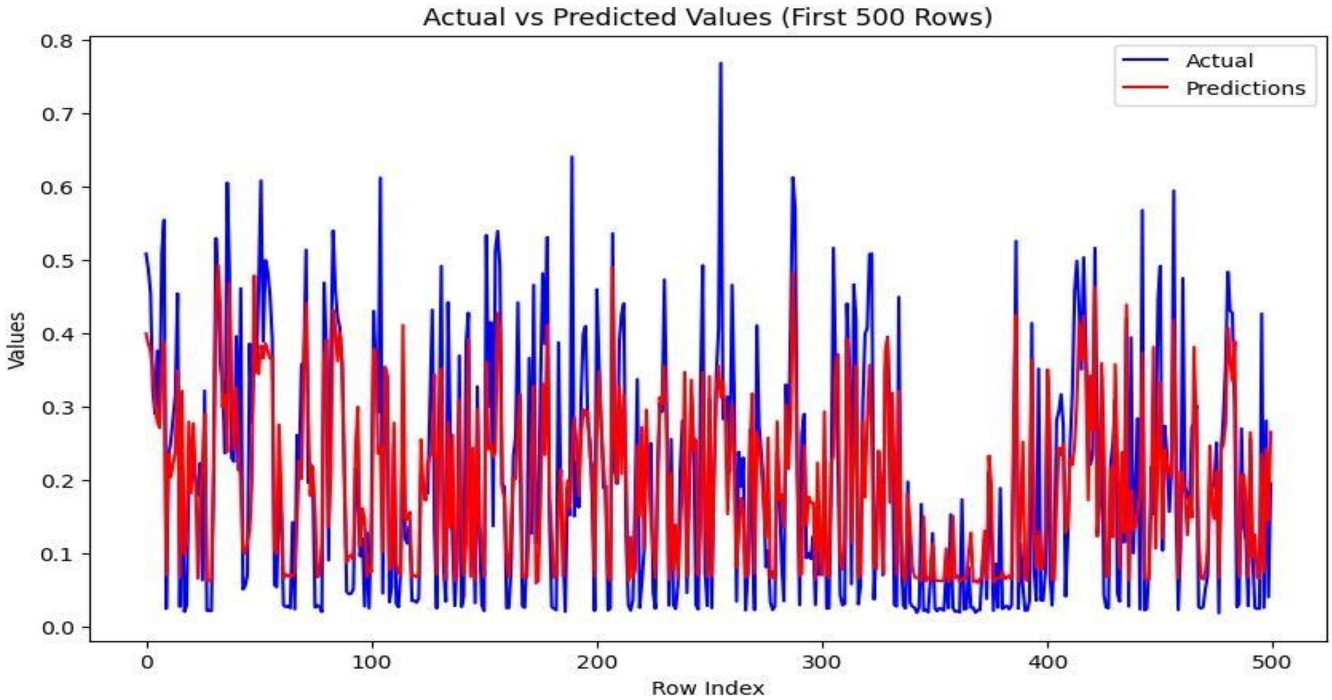

Figure 9 CNN with K-fold model Prediction

Figure 10 illustrates the prediction results of the hybrid LSTM-CNN model. The plot demonstrates the combined strength of temporal feature extraction from LSTM and spatial pattern recognition from CNN, resulting in predictions that closely align with the actual values and enhanced overall accuracy.

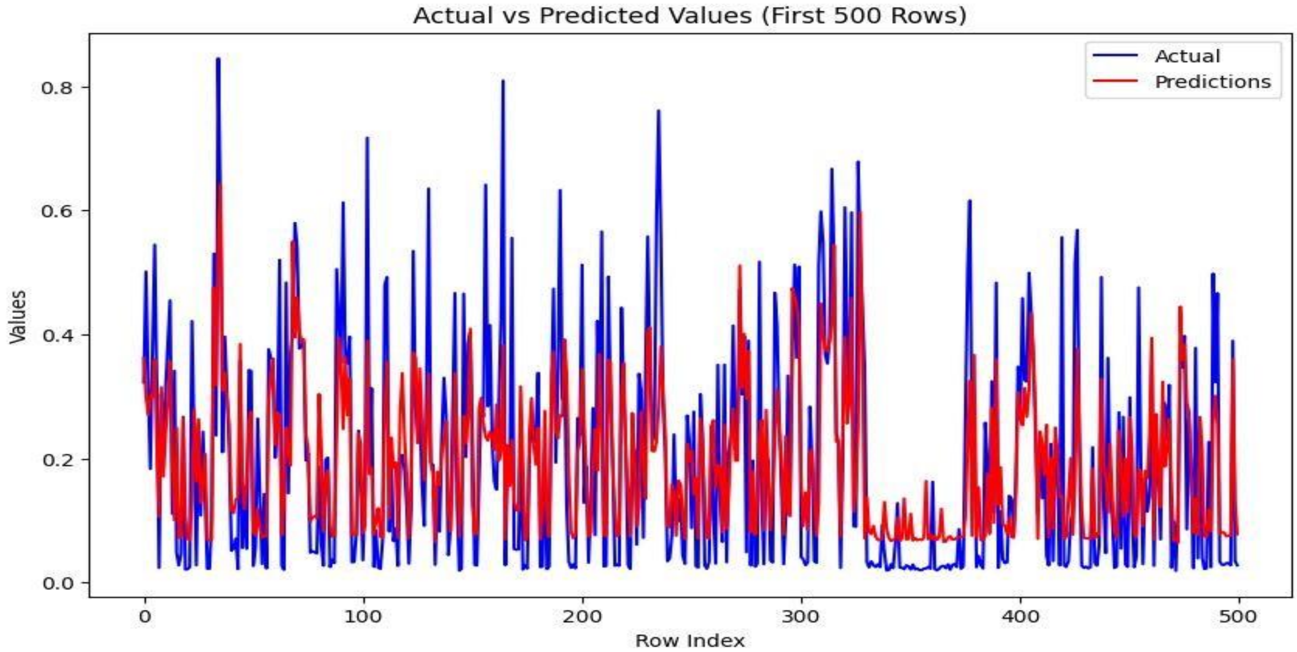

Figure 10 represents Hybrid of LSTM and CNN Model Prediction

Figure 11 depicts the prediction results of the LASSO regression model. The graph shows how the model captures the underlying trend in the data, with predicted values approximating the actual observations while enforcing sparsity to reduce overfitting and enhance model interpretability.

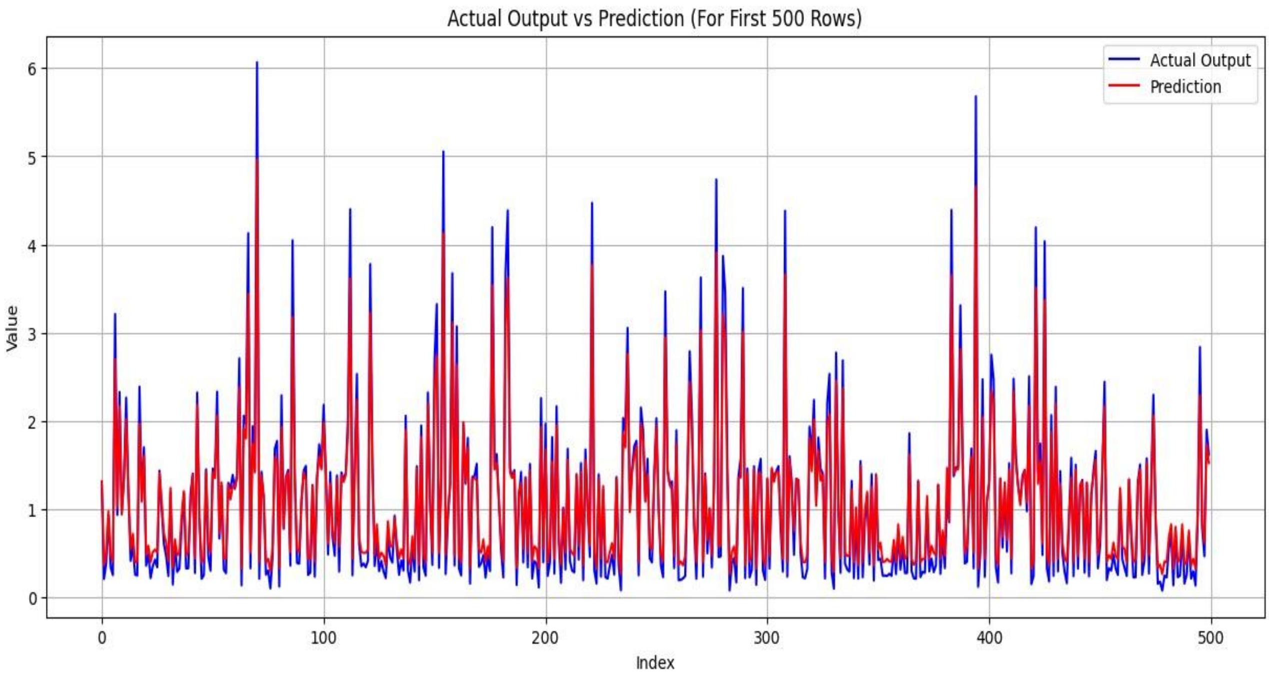

Figure 11 LASSO Regression Model Prediction

To sum up, the CNN model exhibits superior performance over the LSTM model in terms of RMSE. Combining CNN and LSTM doesn't yield substantial improvement compared to using CNN alone. Lasso regression shows competitive performance with neural network models in RMSE and significantly outperforms them in R2 score, suggesting a strong fit to the data. However, it's essential to weigh the interpretability of coefficients in Lasso regression against neural network models.

CONCLUSION

The research paper presents a comprehensive strategy to improve energy monitoring and consumption prediction by integrating RS485 to Ethernet TCP/IP converters with electricity meters, alongside employing machine learning algorithms. Energy use patterns are correctly forecasted based on real-time data from energy meters and are pre-processed for machine learning. Five of the machine learning methods used are Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and Lasso Regression, for prediction of energy usage. The techniques are evaluated under careful preprocessing and model training through the study of metrics such as RMSE and R^2 Score. The results show that although LSTM models suffer from some overfitting, CNN models show better performance than LSTM models as measured by RMSE, with the hybrid model of CNN-LSTM showing similar performance. Lasso Regression surprisingly shows competitive performance compared to neural network models, indicating its potential as an alternative and simpler yet efficient method for energy consumption prediction. Further, the design of the system is carefully developed to include hardware interfaces for data gathering, a frontend for easy data display, and a backend for processing and storing data.

Using state-of-the-art machine learning methods and powerful preprocessing, the suggested system provides rich insights into energy usage patterns, which will allow informed decision-making at the individual, organizational, and energy provider levels. The combination of IoT devices and sensor networks also makes the system even more accurate. In general, the research paper emphasizes the use of both traditional and sophisticated machine learning methods with IoT infrastructure as a means of transforming energy consumption and usage forecasts, leading towards more effective use of resources as well as better energy practices. The proposed energy consumption monitoring and forecasting system effectively integrates advanced IoT hardware with robust machine learning techniques to provide accurate and real-time insights into energy usage. The combination of precise data collection, comprehensive preprocessing, and predictive modeling enables better energy management and decision-making. Importantly, by facilitating optimized resource allocation and promoting energy conservation, this system contributes significantly to reducing environmental impact. The approach outlined in this research paves the way for smarter, more sustainable energy practices that benefit individuals, organizations, and energy providers alike.

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