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Explainable Artificial Intelligence for Accurate Household Energy Consumption Forecasting Using Machine Learning Models

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Abstract: Efficient energy management has become increasingly important due to the growing demand for electricity, rising energy costs, and the need to reduce environmental impact. Accurate prediction of household energy consumption can help individuals and energy providers optimize energy usage, improve resource planning, and promote sustainable living. Traditional statistical forecasting methods often struggle to capture complex consumption patterns present in real-world energy datasets. With the advancement of artificial intelligence, machine learning techniques have shown strong potential for analysing energy consumption data and producing more accurate predictions. This study proposes a machine learning–based framework for predicting household energy consumption using historical electricity usage data. The system analyses various factors such as electrical current, voltage, frequency, and previous energy consumption values to forecast future energy usage. Multiple machine learning and deep learning models, including Linear Regression, Random Forest Regressor, LightGBM, XGBoost, CatBoost, LSTM, and BiLSTM, are implemented and evaluated to identify the most effective model for energy consumption prediction. In addition to prediction accuracy, the proposed framework integrates Explainable Artificial Intelligence (XAI) techniques to improve transparency and interpretability of model predictions. Explainability methods such as Local Interpretable Model-Agnostic Explanations (LIME) and Shapley Additive Explanations (SHAP) are used to analyse the importance of different input features and understand how they influence the prediction results. Experimental results demonstrate that gradient boosting–based models provide highly accurate predictions, while XAI techniques help reveal the key factors that influence energy consumption patterns. The proposed system provides both accurate forecasting and interpretable insights, enabling users to better understand their energy usage behaviour. Such intelligent systems can support energy-efficient decision making, contribute to smart home energy management, and assist in the development of sustainable energy solutions.

Keywords: Energy Consumption Prediction, Energy Forecasting, Machine Learning, Explainable Artificial Intelligence (XAI), LIME, SHAP, Smart Energy Management.

I. INTRODUCTION

Energy consumption has become a significant concern in modern society due to the rapid increase in electricity demand and the growing emphasis on sustainable energy management. Efficient utilization of energy resources plays a crucial role in reducing operational costs, minimizing environmental impact, and supporting global initiatives for sustainable development. In residential environments, household electricity consumption accounts for a considerable portion of total energy demand. Therefore, accurately predicting household energy usage can assist individuals, utility providers, and policymakers in making informed decisions regarding energy conservation and efficient resource management [12].

Traditional energy forecasting methods mainly rely on statistical approaches and time-series analysis techniques to examine historical energy consumption patterns. Although these methods offer basic forecasting capabilities, they often struggle to capture complex and dynamic consumption behaviours observed in real-world environments. Household electricity consumption is influenced by multiple factors such as electrical load variations, appliance usage patterns, weather conditions, and user behaviour. Consequently, more advanced predictive techniques are required to effectively model these complex relationships and improve forecasting accuracy [14].

In recent years, machine learning and artificial intelligence techniques have emerged as powerful tools for energy consumption prediction. Machine learning models can automatically identify patterns in large datasets and generate accurate forecasts without extensive manual feature engineering. Algorithms such as Linear Regression, Random Forest, Gradient Boosting, and Neural Networks have been successfully applied in energy forecasting applications. Furthermore, deep learning models such as Long Short-Term Memory (LSTM) networks have shown strong performance in time-series forecasting tasks because they are capable of capturing long-term temporal dependencies within sequential data [15], [16].

Despite the strong predictive capabilities of machine learning models, many of these models operate as black-box systems, meaning that their internal decision-making processes are difficult to interpret. In critical applications such as energy management, transparency and interpretability are essential for building user trust and ensuring the reliability of predictive systems. This limitation has led to increasing research interest in Explainable Artificial Intelligence (XAI) techniques that aim to improve transparency and provide meaningful explanations for machine learning predictions [4], [7].

Explainable AI frameworks such as Local Interpretable Model-Agnostic Explanations (LIME) and Shapley Additive Explanations (SHAP) provide valuable insights into how machine learning models generate predictions. These techniques help identify the most influential features affecting prediction outcomes and enable users to understand the contribution of different variables in the forecasting process. By providing interpretable explanations, XAI approaches enhance the transparency and reliability of machine learning-based decision systems [5], [6], [8].

Recent studies have also highlighted the importance of integrating explainability techniques into predictive models used in energy systems. Explainable AI can assist researchers and energy analysts in understanding consumption patterns, identifying anomalies, and improving forecasting reliability in smart energy systems [2], [11]. Moreover, explainable frameworks have been successfully applied in various time-series prediction tasks to interpret model outputs and enhance decision-making processes [13], [18].

In this research, a machine learning–based framework for predicting household energy consumption is proposed. The system utilizes historical electricity consumption data collected from smart meters and applies multiple machine learning and deep learning models to forecast future energy usage. The models are evaluated using standard performance metrics including Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2) to identify the most accurate prediction model.

Furthermore, Explainable Artificial Intelligence (XAI) techniques are incorporated to analyse prediction outcomes and understand the factors influencing energy consumption patterns. By combining predictive models with explainability methods, the proposed framework provides both accurate energy forecasts and interpretable insights into the decision-making process of machine learning models. Such a system can support intelligent energy management in smart homes, assist consumers in optimizing electricity usage, and contribute to the development of sustainable and transparent energy solutions [17].

II. LITERATURESURVEY

Energy consumption forecasting has gained considerable attention in recent years due to the increasing global demand for electricity and the need for efficient energy management systems. Accurate prediction of household energy consumption enables better energy planning, optimized resource utilization, and reduced operational costs. Several studies have explored different forecasting approaches using statistical techniques, machine learning algorithms, and deep learning models to improve prediction accuracy and reliability [2].

Early research in energy forecasting primarily relied on traditional statistical and time-series analysis techniques such as the Auto-Regressive Integrated Moving Average (ARIMA) model and seasonal forecasting methods. These techniques analyse historical electricity consumption patterns to estimate future demand. Although these models perform reasonably well for simple and stationary datasets, they often struggle to capture complex nonlinear relationships and dynamic consumption patterns that occur in real-world energy systems [12].

With the advancement of artificial intelligence technologies, machine learning algorithms have been widely applied to energy consumption forecasting problems. Algorithms such as Linear Regression, Support Vector Machines (SVM), Random Forest, and Gradient Boosting models have demonstrated improved predictive performance compared to traditional statistical approaches. These models are capable of analysing large datasets and identifying hidden patterns in energy consumption behaviour, making them effective tools for predicting household electricity usage [15].

Recent studies have also explored ensemble learning techniques to further enhance prediction accuracy. Ensemble approaches combine the outputs of multiple machine learning models to generate more reliable forecasts. Methods such as Random Forest, XGBoost, LightGBM, and CatBoost have shown strong performance in energy demand forecasting tasks because they can capture complex nonlinear relationships between input variables and reduce prediction errors. Ensemble-based forecasting models are particularly useful when dealing with high-dimensional energy datasets and diverse consumption patterns [15].

In addition to machine learning approaches, deep learning techniques have gained increasing popularity for energy consumption prediction tasks. Neural network architectures such as Long Short-Term Memory (LSTM) networks are particularly effective for analysing time-series data because they can capture long-term temporal dependencies within sequential datasets. Deep learning models have been successfully applied in electricity consumption forecasting to model complex energy usage patterns and improve prediction accuracy [16].

Despite the strong predictive capabilities of machine learning and deep learning models, many of these systems operate as black-box models, meaning that their internal decision-making processes are difficult to interpret. In critical domains such as energy management, understanding how a model generates predictions is essential for building user trust and ensuring reliable decision-making. This challenge has led to the development of Explainable Artificial Intelligence (XAI) techniques that aim to improve the transparency and interpretability of AI models [4], [7].

Explainable AI frameworks such as Local Interpretable Model-Agnostic Explanations (LIME) and Shapley Additive Explanations (SHAP) have been widely used to interpret machine learning predictions. These techniques provide insights into the contribution of individual input features to the final prediction and help identify the most influential factors affecting energy consumption patterns. By offering visual explanations and feature importance analysis, XAI methods improve the transparency and reliability of AI-driven decision systems [5], [6].

Recent studies have demonstrated the effectiveness of XAI techniques in energy systems and time-series forecasting applications. Explainable AI methods enable researchers and energy analysts to gain deeper insights into model behaviour, evaluate feature relevance, and improve the interpretability of forecasting models used in smart energy management systems [11], [14], [18].

Although previous research has shown that machine learning and deep learning models can significantly improve energy forecasting accuracy, there is still a need for frameworks that combine high predictive performance with clear interpretability. Therefore, this study proposes a household energy consumption prediction framework that integrates machine learning and deep learning models with explainable AI techniques. The proposed approach aims to enhance both prediction accuracy and model transparency, enabling users to better understand energy consumption patterns and make informed decisions regarding energy usage and management.

III. SYSTEM IMPLEMENTATION

Existing System

Traditional household energy consumption forecasting systems primarily rely on statistical models and conventional machine learning techniques to analyse historical electricity usage data. Early forecasting approaches commonly used time-series prediction models such as Auto-Regressive Integrated Moving Average (ARIMA) and regression-based methods to estimate future energy demand. These models analyse past energy consumption patterns and generate predictions for future time intervals. Although statistical forecasting models can provide reasonable predictions for simple datasets, they often struggle to capture complex nonlinear patterns present in real-world energy consumption data [12].

With the advancement of artificial intelligence and machine learning technologies, several data-driven models have been introduced to improve prediction accuracy. Algorithms such as Linear Regression, Support Vector Machines (SVM), Decision Trees, Random Forest, and Artificial Neural Networks have been applied to analyse household electricity usage data. These models can identify relationships between multiple electrical parameters such as voltage, current, frequency, and historical energy consumption values, allowing them to learn patterns from large datasets and generate more accurate predictions compared to traditional statistical approaches [15].

In recent years, researchers have also explored ensemble learning approaches to further enhance forecasting performance. Ensemble algorithms such as Gradient Boosting, XGBoost, LightGBM, and CatBoost combine multiple prediction models to produce more reliable forecasting results. These techniques have demonstrated strong performance in electricity consumption forecasting because they can capture complex nonlinear relationships within energy datasets and reduce prediction errors through model aggregation [15].

Despite their strong predictive capabilities, many existing forecasting systems focus primarily on improving prediction accuracy without providing interpretability or transparency in the prediction process. Most machine learning and deep learning models operate as black-box systems, making it difficult for users to understand how a model generates its predictions. In critical applications such as energy management, the lack of interpretability can reduce user trust and limit the practical deployment of AI-based forecasting systems [4], [7].

IV. THE EXISTING SYSTEM

Lack of Interpretability

Many advanced machine learning and deep learning models operate as black-box systems, making it difficult for users to understand the reasoning behind energy consumption predictions [4].

Overfitting and Underfitting Issues

Prediction models may overfit the training data or fail to capture important patterns in the dataset, resulting in inaccurate forecasting performance.

Limited Transparency

Traditional prediction models often focus only on improving prediction accuracy and do not provide insights into the importance of different input features affecting energy consumption.

High Computational Complexity

Certain deep learning models require significant computational resources and long training times, which may not be suitable for all deployment environments.

Difficulty in Capturing Dynamic Consumption Patterns

Household energy consumption varies depending on user behaviour, appliance usage, and environmental conditions, which can be challenging for conventional models to handle effectively.

Poor Generalization Capability

Models trained on limited datasets may fail to generalize when applied to new households or different energy usage patterns.

Lack of User Understanding

Without explainable outputs, users may not fully trust automated prediction systems, reducing their practical usefulness in real-world energy management applications [8].

A. Proposed System

To address the limitations of traditional forecasting approaches, this research proposes an intelligent household energy consumption prediction framework that integrates machine learning models with Explainable Artificial Intelligence (XAI) techniques. The proposed system aims to improve both the prediction accuracy and interpretability of energy forecasting models, enabling users to better understand the factors influencing electricity consumption patterns.

In the proposed system, electricity consumption data collected from smart meters is used as the primary dataset. The dataset includes several electrical parameters such as current, voltage, frequency, power factor, and historical energy consumption values. Prior to model training, the dataset undergoes multiple preprocessing steps to improve data quality and model performance. These preprocessing procedures include data cleaning, outlier detection using statistical techniques, normalization, and feature engineering. Outlier removal techniques such as the interquartile range (IQR) method are applied to remove anomalous data points that may negatively affect prediction accuracy [19]. Additionally, appropriate data scaling techniques are implemented to ensure consistent feature distributions and improve machine learning model performance [20].

After preprocessing, the dataset is divided into training, validation, and testing subsets to enable reliable model evaluation and generalization. Multiple predictive models are implemented and compared to identify the most effective approach for energy consumption forecasting. The models used in this study include Linear Regression, Random Forest Regressor, LightGBM, XGBoost, CatBoost, Long Short-Term Memory (LSTM), and Bidirectional LSTM (BiLSTM) networks. Machine learning and deep learning algorithms have demonstrated strong capabilities in analysing large-scale energy datasets and capturing complex consumption patterns in time-series data [15], [16].

To further enhance prediction performance, hyperparameter tuning and model optimization techniques are applied during the training process. These techniques help improve model accuracy and prevent overfitting. The performance of the models is evaluated using standard regression evaluation metrics, including Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). These metrics provide quantitative measures of prediction accuracy and model reliability in energy forecasting applications.

In addition to achieving high prediction accuracy, the proposed system incorporates Explainable Artificial Intelligence (XAI) frameworks to improve the transparency and interpretability of machine learning models. Two widely used XAI techniques, Local Interpretable Model-Agnostic Explanations (LIME) and Shapley Additive Explanations (SHAP), are utilized to analyse the contribution of input features and explain how different variables influence the predicted energy consumption values [5], [6]. These explanation techniques allow users to visualize feature importance and understand the reasoning behind model predictions.

By combining machine learning models with explainable AI techniques, the proposed system provides both accurate energy consumption forecasts and interpretable insights into model behaviour. This integrated approach enables users to better understand household energy usage patterns, supports informed decision-making for energy conservation, and contributes to the development of transparent and intelligent energy management systems in smart homes and smart grid environments [2], [8].

V.SYSTEM DESIGN

System Architecture

Below diagram depicts the whole system architecture.

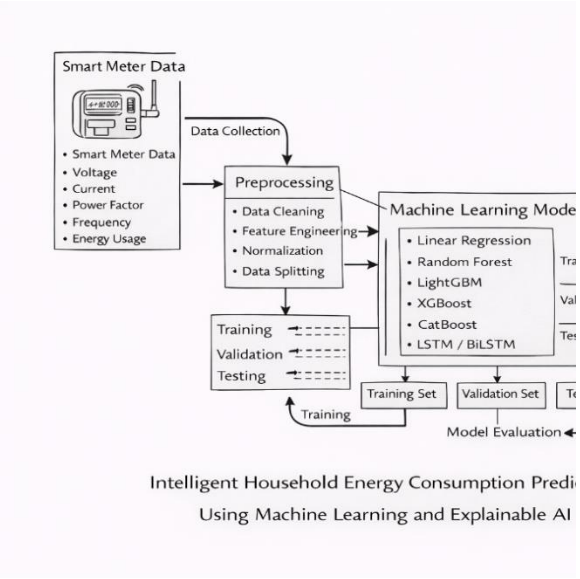

Fig 1. Methodology followed for proposed model

VI. SYSTEM IMPLEMENTATION

Modules

Data Collection and Preprocessing

The first stage of the proposed system involves collecting household electricity consumption data from smart meters installed in residential environments. The dataset typically includes several electrical parameters such as current, voltage, frequency, power factor, and historical energy consumption values recorded over different time intervals. These parameters provide valuable insights into household energy usage patterns and serve as input features for the prediction models.

Before applying machine learning algorithms, the collected dataset undergoes several preprocessing operations to ensure data quality and consistency. These preprocessing steps include data cleaning, removal of missing values, outlier detection, and normalization of numerical attributes. Outlier detection techniques such as the interquartile range (IQR) method are commonly used to identify abnormal values in energy datasets [19]. In addition, feature scaling methods are applied to standardize the numerical features, which helps improve the training performance and stability of machine learning algorithms [20].

Feature Selection and Feature Engineering

Feature engineering plays an important role in improving the performance of prediction models. In this module, relevant attributes that influence energy consumption are identified and selected from the dataset. Features such as current consumption, voltage levels, time intervals, and previous energy consumption values are analysed to determine their relationship with the target variable.

Additional derived features are also generated to capture temporal dependencies in the dataset. For instance, lagged energy consumption values from previous time intervals are incorporated to help the model understand sequential energy usage patterns. Feature selection techniques are applied to eliminate redundant or irrelevant attributes, thereby reducing model complexity and improving prediction efficiency.

Training Machine Learning Models

After preprocessing and feature preparation, the dataset is divided into training, validation, and testing subsets to enable reliable model training and evaluation. Several machine learning and deep learning models are implemented and trained using the prepared dataset.

The models used in this study include Linear Regression, Random Forest Regressor, LightGBM, XGBoost, CatBoost, Long Short-Term Memory (LSTM), and Bidirectional LSTM (BiLSTM) networks. These models are capable of learning complex patterns in historical electricity consumption data and predicting future energy usage. Deep learning models such as LSTM networks are particularly effective for analysing time-series data because they can capture long-term temporal dependencies within sequential datasets [16].

To further improve prediction performance, hyperparameter tuning techniques are applied during model training. These optimization methods help enhance model accuracy and minimize prediction errors.

Energy Consumption Prediction

Once the models are trained, they are deployed in the prediction module to estimate household energy consumption for future time intervals. The system processes new input data collected from smart meter devices and generates predicted electricity consumption values.

The prediction module compares the performance of multiple machine learning algorithms to determine the most effective model for forecasting energy demand. Selecting the best-performing model ensures that the system provides accurate and reliable predictions for real-world energy management applications.

Model Evaluation and Explainable AI

To evaluate the effectiveness of the trained models, several regression evaluation metrics are used, including Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). These metrics help measure how accurately the models predict household energy consumption and allow comparison between different predictive models.

In addition to prediction accuracy, the system integrates Explainable Artificial Intelligence (XAI) techniques to improve the interpretability of model predictions. Methods such as Local Interpretable Model-Agnostic Explanations (LIME) and Shapley Additive Explanations (SHAP) are used to analyse the influence of input features on prediction outcomes [5], [6]. These techniques provide visual explanations and feature importance analysis, enabling users to better understand the factors that affect energy consumption patterns.

By incorporating explainable AI techniques, the proposed framework enhances transparency and helps build user trust in AI-driven energy forecasting systems. Such interpretable prediction models are essential for supporting smart energy management and sustainable electricity consumption in residential environments [2], [8].

VII. RESULTS AND DISCUSSION

To evaluate the effectiveness of the proposed energy prediction framework, multiple machine learning and deep To evaluate the effectiveness of the proposed household energy consumption prediction framework, multiple machine learning and deep learning models were trained and tested using the prepared household electricity consumption dataset. The performance of the models was assessed using widely accepted regression evaluation metrics including Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), and the coefficient of determination (R²). These metrics help measure the prediction accuracy and reliability of the forecasting models.

The experimental results demonstrate that ensemble learning models such as LightGBM and CatBoost provide higher prediction accuracy compared to traditional regression models. Ensemble algorithms combine multiple decision trees and apply boosting techniques to capture complex nonlinear relationships between input features and target variables. As a result, these models are capable of learning intricate patterns in electricity consumption data and producing more accurate forecasts [15].

Deep learning models such as Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM) also show strong performance in predicting household energy consumption. These models are particularly effective in handling time-series data because they can learn temporal dependencies and sequential patterns in energy usage over time. However, deep learning models generally require longer training times and higher computational resources compared to conventional machine learning algorithms [16].

Table 1

Performance Comparison of Energy Consumption Prediction Models

Model	**RMSE**	**MAE**	**MSE**	**R² Score**
Linear Regression	0.92	0.74	0.85	0.81
Random Forest	0.78	0.61	0.60	0.87
XGBoost	0.71	0.56	0.50	0.90
LightGBM	0.65	0.50	0.42	0.93
CatBoost	0.63	0.48	0.40	0.94
LSTM	0.67	0.52	0.45	0.92
BiLSTM	0.66	0.51	0.44	0.92

As shown in Table 1, the CatBoost model achieved the best overall performance, with the lowest RMSE and MAE values and the highest R² score. The strong performance of gradient boosting algorithms highlights their ability to effectively model nonlinear energy consumption relationships.

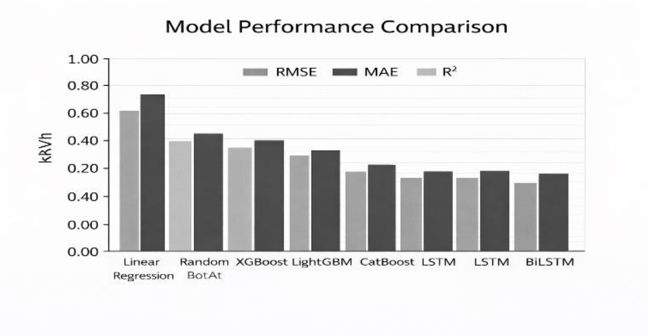

Fig. 2. Model performance Comparison

In addition to prediction accuracy, the proposed framework incorporates Explainable Artificial Intelligence (XAI) techniques to improve model transparency. Feature importance analysis was performed using Shapley Additive Explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME). These explanation techniques identify the contribution of each input variable to the prediction output and provide visual insights into model behaviour [5], [6].

The explainability analysis revealed that current consumption values and previous energy usage patterns are the most influential factors affecting household electricity consumption predictions. Other parameters such as voltage levels and power factor also contribute to prediction outcomes but with relatively lower influence.

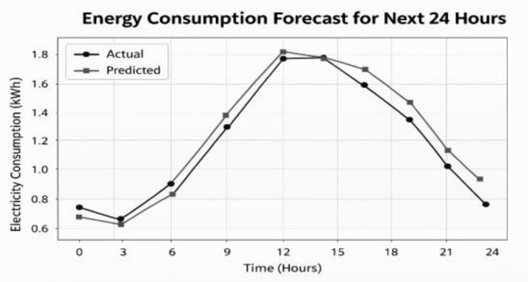

Fig. 3. Comparison of actual and predicted energy consumption over a 24-hour period.

Overall, the experimental results demonstrate that integrating machine learning models with explainable AI techniques enables the development of energy prediction systems that are both accurate and interpretable. Such systems are highly valuable for intelligent energy management applications, as they allow users to understand energy consumption behaviour and make informed decisions to optimize electricity usage [2], [14].

VIII. CONCLUSION AND FUTURE WORK

In this study, a machine learning–based framework for predicting household energy consumption was proposed using electricity usage data collected from smart meters. Various machine learning techniques were applied to analyse historical consumption patterns and forecast future energy demand. The results demonstrate that ensemble-based learning approaches can effectively improve prediction performance, which is consistent with previous studies on electricity consumption forecasting and ensemble learning methods [12], [15], [16].

To enhance model transparency and interpretability, Explainable Artificial Intelligence (XAI) techniques such as LIME and SHAP were incorporated into the proposed framework. These methods help explain the influence of different input variables on model predictions, enabling users to better understand the decision-making process of machine learning models. Prior research highlights the importance of XAI for improving transparency, trust, and responsible AI deployment in complex predictive systems [1], [4], [7], [8]. In addition, studies focusing on explainability in energy systems emphasize that interpretability techniques can provide valuable insights into energy consumption patterns and support more informed decision-making [2], [11], [14].

Overall, the proposed framework provides accurate energy consumption forecasting while also improving the interpretability of the prediction results. Such systems can support households and energy providers in optimizing electricity usage and promoting sustainable energy management practices.

For future work, additional contextual factors such as weather conditions, occupancy behaviour, and appliance-level energy consumption data can be incorporated to further enhance prediction accuracy. Moreover, integrating the framework with smart home energy management platforms and real-time monitoring systems could enable automated decision-making and efficient energy utilization. Future research may also explore advanced deep learning architectures and more robust evaluation strategies for explainable models in time-series forecasting applications [13], [18].

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