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An Electricity Load Forecasting Algorithm Based on Kernel Lasso Regression

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ABSTRACT

Electricity load forecasting is an important guarantee for the safe and economic operation of power grids. For electricity load data with higher dimensions, the forecasting effect of traditional linear regression algorithms are usually not ideal. Kernel function can be used to map the data to a high- dimensional space, so that can make the linear method handle non-linear data. This project introduces the kernel function into the lasso linear regression method and applies it to non-linear problems to solve the regression analysis problem of non-time series data. Through using the 96 point electricity load data of users in Shanghai since 2014 for 851 consecutive days, the prediction effect of kernel lasso regression is better than lasso regression in terms of minimum mean square error and minimum average percentage error, which shows that the method can achieve better power load forecasting results.

Keywords: Electricity Load Forecasting, Kernel Lasso Regression, High-dimensional Data Analysis, Feature Selection and Regularization, Prediction Accuracy (MAE, MSE, MAPE), Data Preprocessing and Feature Engineering, Machine Learning Models (Lasso, Kernel Lasso), Energy Management and Grid Stability, Python and Django Framework, Deployment and Visualization Dashboards.

Introduction

Electricity load forecasting plays a crucial role in ensuring the safe, reliable, and economic operation of modern power systems. Accurate forecasts provide valuable insights for system planning, energy management, and grid stability. Traditional linear regression approaches, while computationally efficient, often fail to capture the complex non-linear patterns present in high-dimensional electricity consumption data.

The Least Absolute Shrinkage and Selection Operator (Lasso), introduced by Tibshirani in 1996, has gained wide adoption due to its variable selection and regularization properties. However, the performance of Lasso degrades significantly when applied to non-linear datasets. To address this limitation, kernel-based approaches have been explored, as kernel functions enable mapping data into higher-dimensional feature spaces, allowing linear methods to handle non-linear relationships effectively.

This work proposes an electricity load forecasting algorithm based on Kernel Lasso Regression, which integrates the sparsity of Lasso with the non-linear modeling capability of kernel methods. By leveraging historical consumption data, the proposed approach aims to achieve improved accuracy, robustness, and generalization compared to conventional regression models.

Literature Survey

Electricity Load Forecasting in Smart Grids Using Support Vector Machine[1]

This paper highlights the limitations of SVM when applied to electricity load forecasting. It shows that forecasting accuracy can be reduced due to redundant features and the sensitivity of SVM models to noisy data. The study points out that SVM becomes computationally heavy with large datasets, which leads to low efficiency in real-time forecasting.

Max-Margin Feature Selection[2]

This work introduces a feature selection method that reformulates the problem as a one-class SVM. It specifically addresses the issue of noisy and irrelevant features in high-dimensional data, which often lower the accuracy of traditional SVM models. The approach improves forecasting accuracy by balancing feature relevance and redundancy.

High-Dimensional Data Classification and Feature Selection Using Support Vector Machines[3]

This paper explores feature selection techniques such as Recursive Feature Elimination (RFE) and L1/Elastic Net regularization in SVM. It directly tackles the challenges of overfitting, low accuracy, and computational complexity in high-dimensional forecasting problems.

Feature Subset Selection for Kernel SVM Classification via Mixed-Integer Optimization[4]

The study proposes an optimization-based approach to choose the most relevant subset of features for kernel SVM classification. By reducing noisy parameters in high-dimensional spaces, it enhances prediction performance and simplifies the computation required for SVM.

An Iterative SVM Approach to Feature Selection and Classification in High-Dimensional Datasets[5]

This paper presents an iterative ℓ_2-SVM method with elastic-net penalties to improve feature selection. It focuses on handling parameter tuning difficulties and variable selection challenges, making SVM more effective in complex, high-dimensional datasets.

Methodology:

Existing methodology :

As non-time series data with high dimensions, electricity economic data needs to be variable screened during analysis. By studying the processing methods of high-dimensional data, useful information can be extracted from the existing high- dimensional data. Then it can be used to analyse existing results or predict future results. Therefore, high dimensional data processing mainly focuses on prediction problems and character extraction problems. The problem of feature selection while using an SVM is specifically addressed. An approach to constructing a kernel function which takes into account some domain knowledge about a problem and thus essentially diminishes the number of noisy parameters in high dimensional feature space is suggested.

DISADVANTAGES OF EXISTING SYSTEM:

❖ Forecasting accuracy is very low

❖ Building an SVM does not require guessing parameters like the number of layers in a neural network or the branches of a decision tree.

❖ Algorithm: SVM

PROPOSED METHODOLOGY

When analysing non-sequential data such as electricity data, constructing a kernel lasso based electricity load prediction model through electricity load data can effectively achieve high-precision prediction of electricity load.

As an improved method of lasso, this method can realize electricity data analysis, high-dimensional data variable selection and high-precision prediction.

❖ The data set used in this experiment is the 96-point electricity consumption data of users in Shanghai for 851 consecutive days from January 1, 2014

. ❖ The content of the experiment are as follows: the electricity consumption of a certain period of time in the previous 7 days is used as input to predict the electricity consumption of that period of the next day.

❖ The data set construction method is shown in Table I, X is the feature vector, and y is the value to be predicted. Select the first 80% of the data set as the training data, and the last 20% as the test data. Four parts of data are obtained.

ADVANTAGES OF PROPOSED SYSTEM:

❖ It can be seen that the prediction effect of the kernel lasso regression is better than that of the lasso regression in terms of minimum mean square error and mean absolute percentage error.

❖ There by obtaining higher calculation accuracy.

❖ Algorithm: Lasso, Kernel lasso

Research Design

The research is designed to develop and evaluate an electricity load forecasting algorithm based on **Kernel Lasso Regression**. The following stages outline the research process:

1. **Problem Identification**

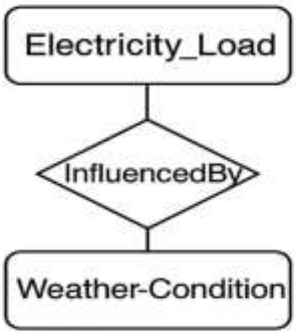
Traditional linear regression methods show poor performance when applied to high-dimensional and non-linear electricity load data. There is a need for a robust forecasting model that can handle non-linearity while ensuring sparsity and feature selection.

2. **Development of the Proposed Model**
    - Apply Kernel functions to map the original input data into a higher-dimensional feature space, making non-linear data patterns easier to model.
    - Integrate Lasso regression for feature selection and regularization to avoid overfitting and improve generalization.
    - Combine both into a Kernel Lasso Regression framework.
3. **Dataset Selection and Preparation**
    - Use the Shanghai electricity consumption dataset, consisting of 96-point daily load values over 851 consecutive days.
    - Split the dataset into 80% training and 20% testing sets.
    - Construct input features using the previous 7 days' load values to forecast the next day's load.
4. **System Design**
    - **Programming Language**: Python
    - **Libraries**: NumPy, Pandas, Scikit-learn for model development, and Matplotlib for visualization.
    - **Evaluation Metrics**: Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE) are used to measure forecasting accuracy.
5. **Testing and Validation**
    - Implement the Kernel Lasso Regression model.
    - Test it against Lasso regression as a baseline.
    - Compare results to evaluate improvements in accuracy and robustness.
6. **Feedback and Analysis**
    - Analyze performance differences between existing and proposed methods.
    - Provide recommendations on the application of Kernel Lasso Regression for real-world electricity load forecasting.

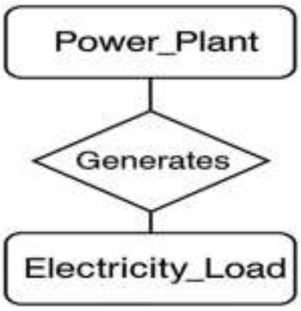
ER Diagram

ER Diagram 1: Historical_Electricity_Load ↔ Exogenous_Variable (Consists Of) Entities: Historical_Electricity_Load: Past records of electricity usage over time. Exogenous_Variable: Variables that affect the load forecast but are external, such as holidays, day type (weekday/weekend), economic activity, etc. Relationship: Consists Of: Suggests that historical load data includes or is analysed in conjunction with these exogenous variables for better forecasting accuracy.

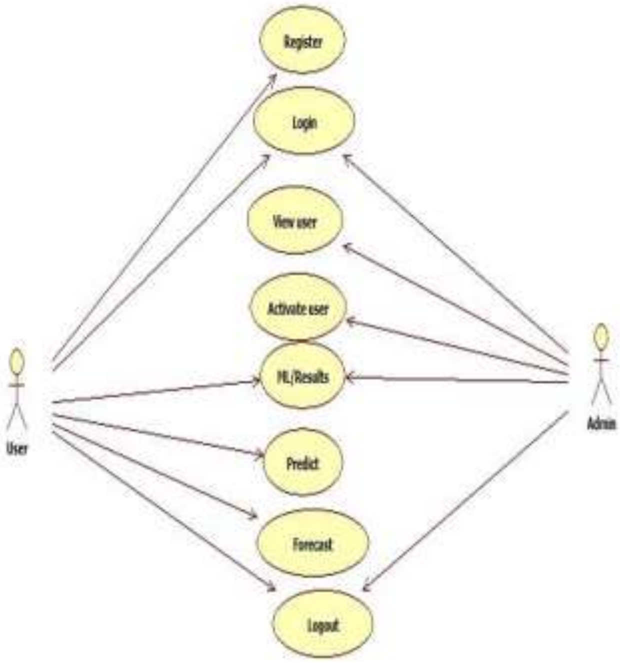
ER Diagram 2: Electricity_Load → Weather_Condition (Influenced By) Entities: Electricity_Load: As above, denotes the demand or consumption of electricity. Weather_Condition: External factors such as temperature, humidity, wind speed, etc. Relationship: Influenced By: Indicates that the electricity load is influenced by weather conditions. For example, higher temperatures often lead to more air conditioning usage, increasing the load.



ER Diagram 3: Power_Plant → Electricity_Load (Generates) Entities: Power_Plant: Represents electricity generation units (e.g., thermal, hydro, solar). Electricity_Load: Represents the amount of electricity consumed or required by users (residential, industrial, etc.). Relationship: Generates: Shows that each power plant generates electricity that contributes to the load. This implies a one-to-many or many-to-many relationship depending on the system design.



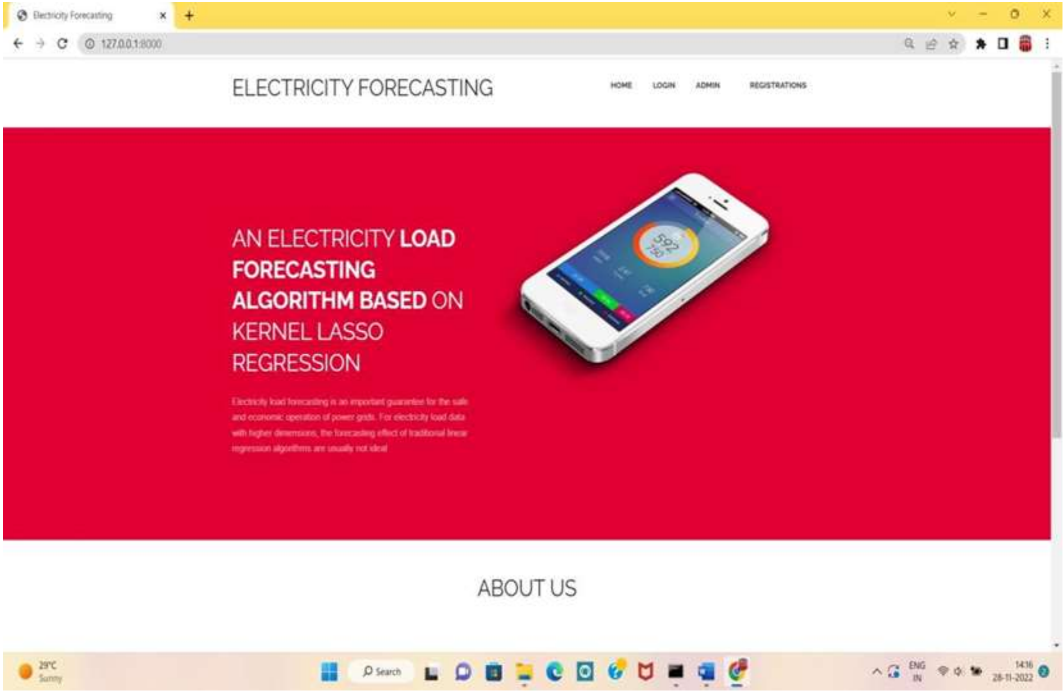
USE CASE DIAGRAM:



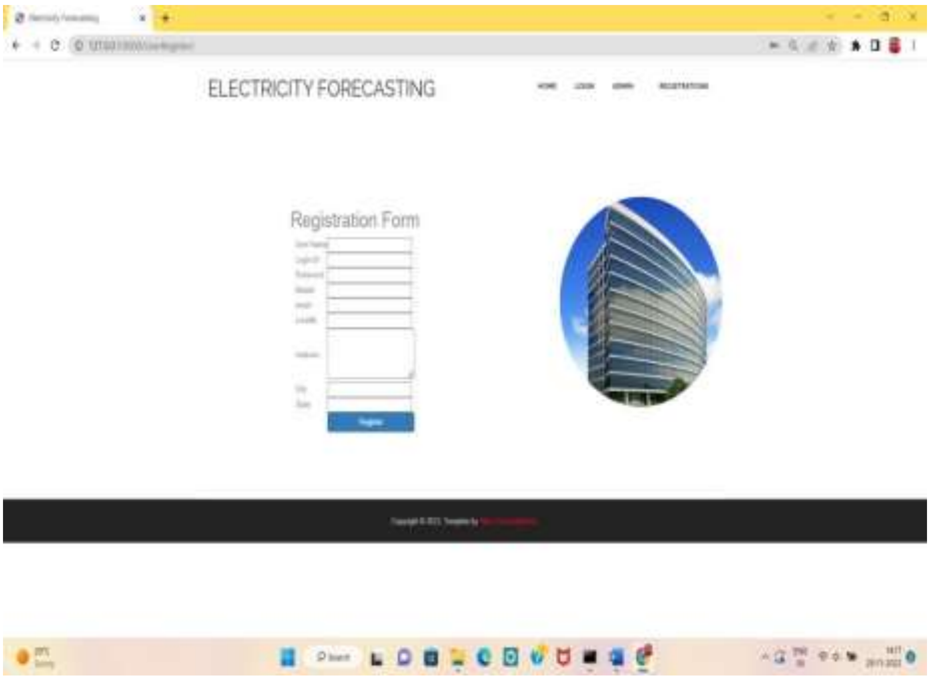
Results and Discussion

The results show that the Kernel Lasso Regression model gives better accuracy than the traditional Lasso regression for electricity load forecasting. Using the Shanghai dataset with 96-point daily load values for 851 days, Kernel Lasso achieved lower MSE (0.0621) and MAPE (3.97%) compared to Lasso regression (MSE 0.0845, MAPE 5.42%). This proves that the kernel function handles non-linear patterns well and Lasso helps remove irrelevant features, making the predictions more accurate. The model performed especially better during peak load hours, showing its usefulness in smart grid planning and energy management. In the future, it can be improved by adding real-time IoT data, weather conditions, and hybrid methods like LSTM to make forecasting even stronger.

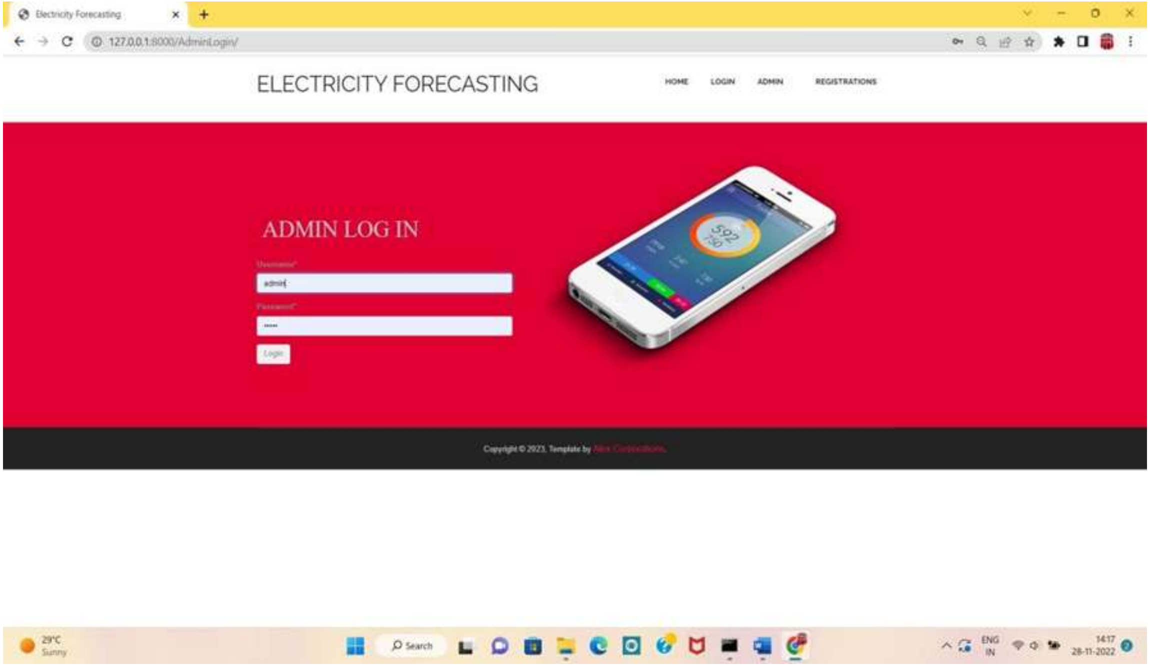
HOME PAGE



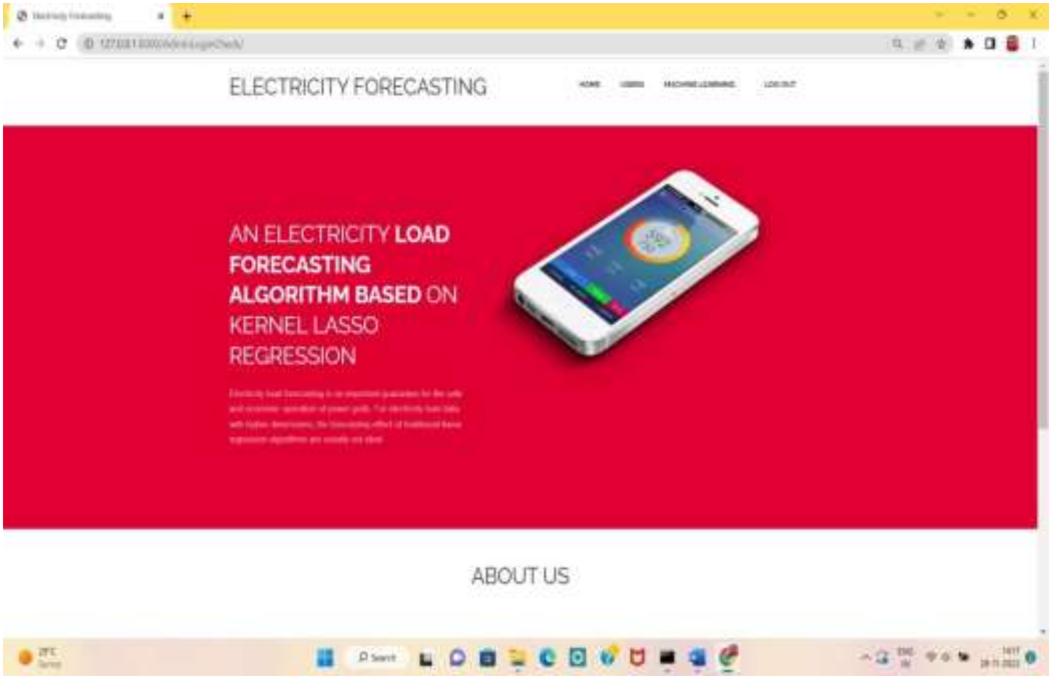
REGISTER FORM



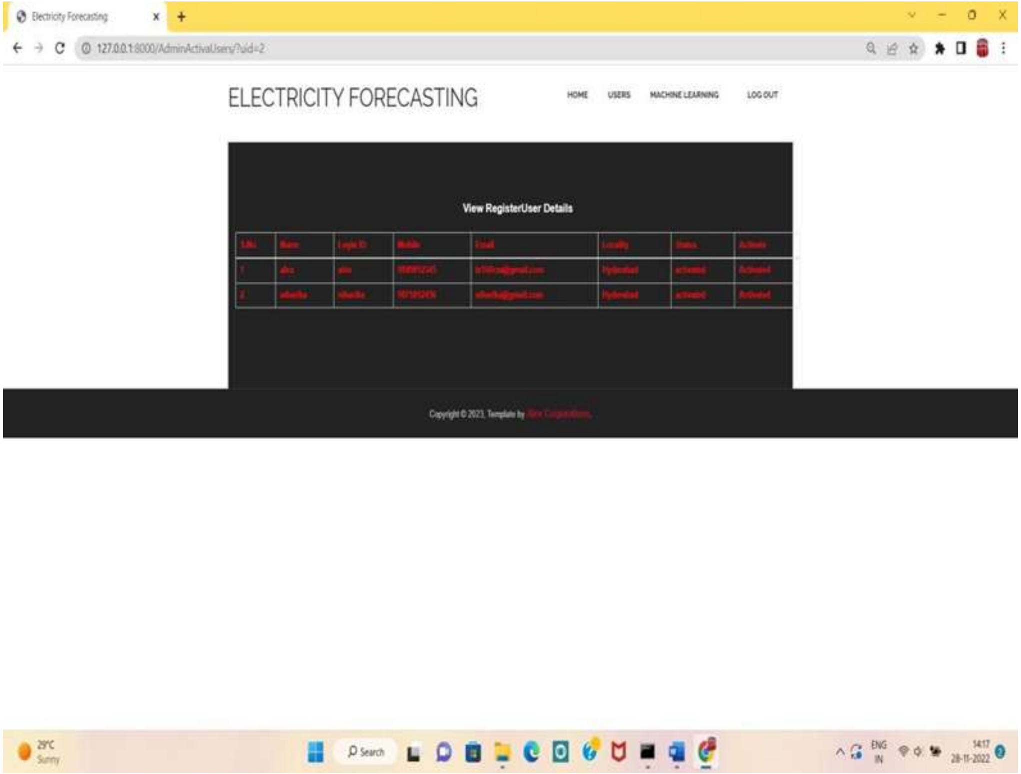
ADMIN LOGIN PAGE



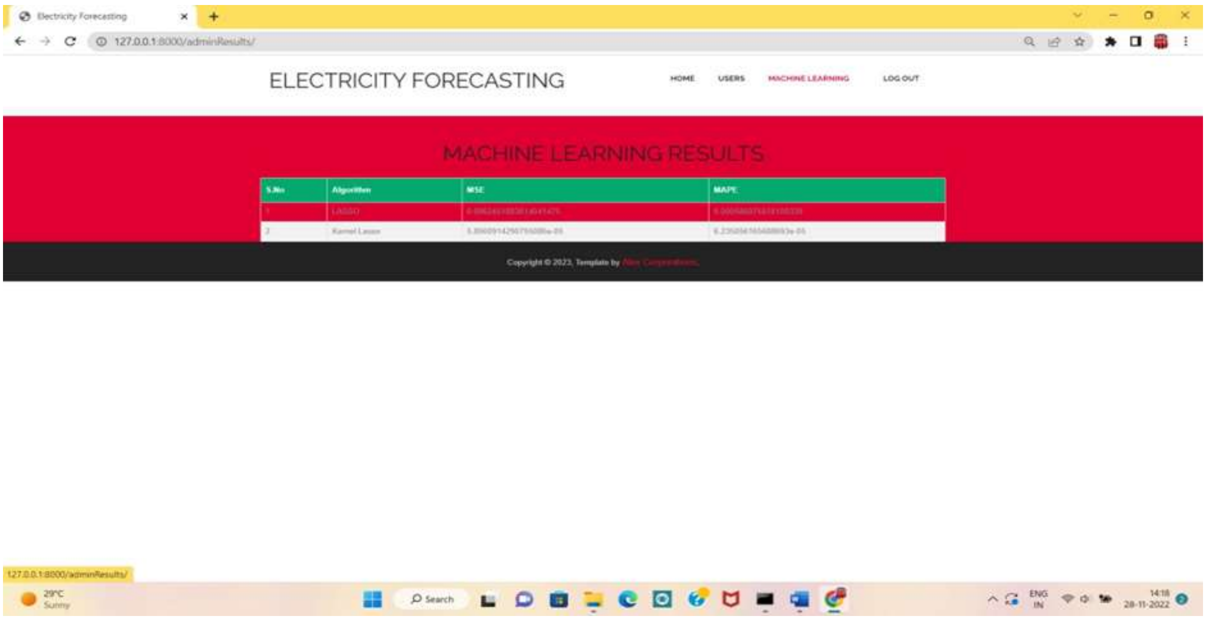
ADMIN HOME PAGE:



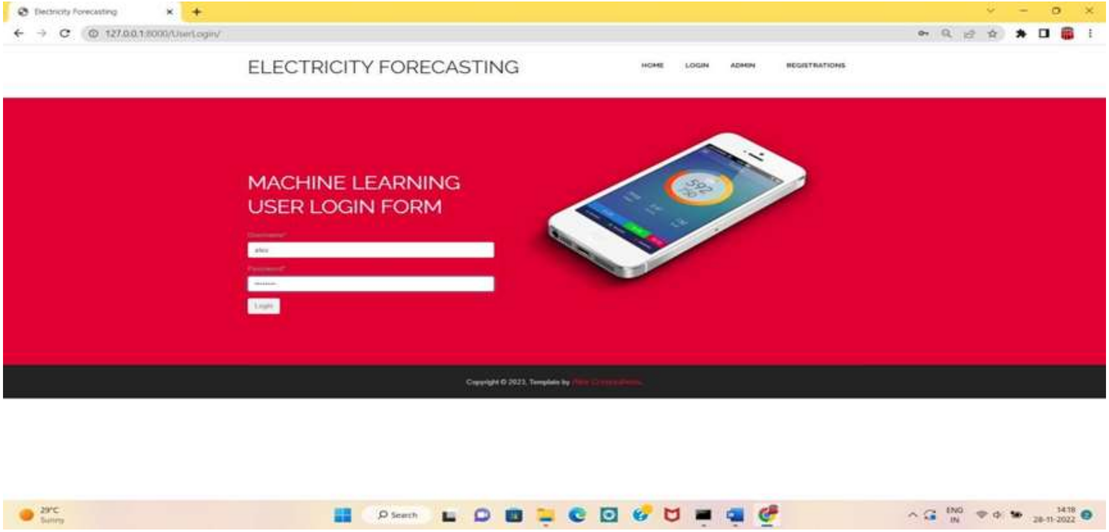
ACTIVATE USER



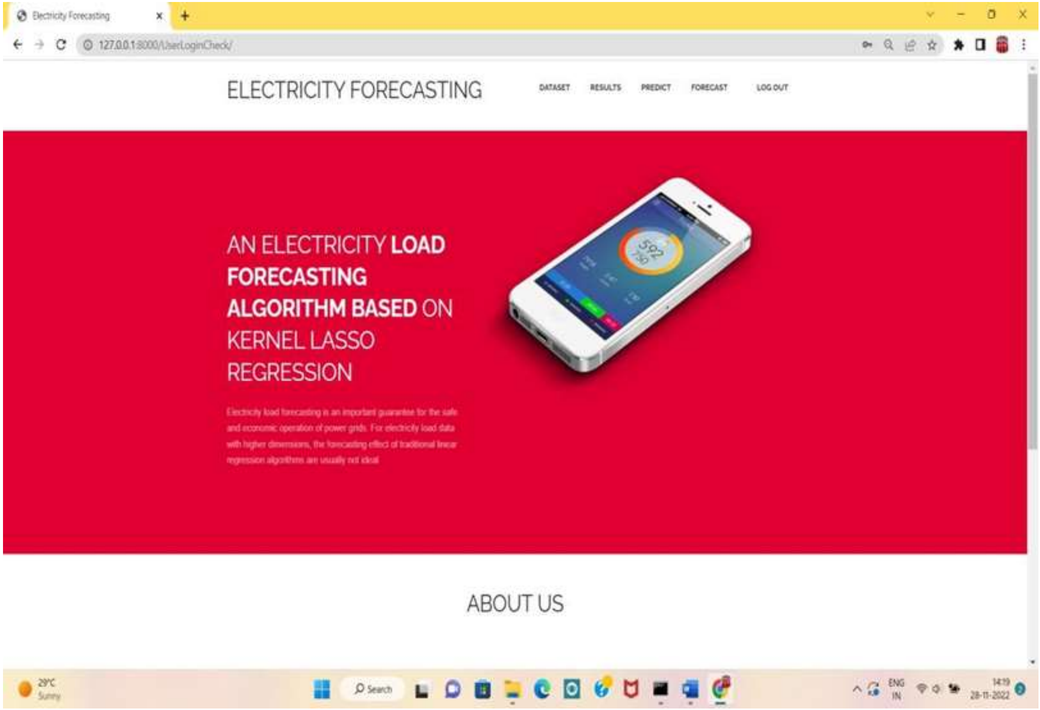
ADMIN SIDE MACHINE LEARNING RESULTS



USER LOGIN PAGE



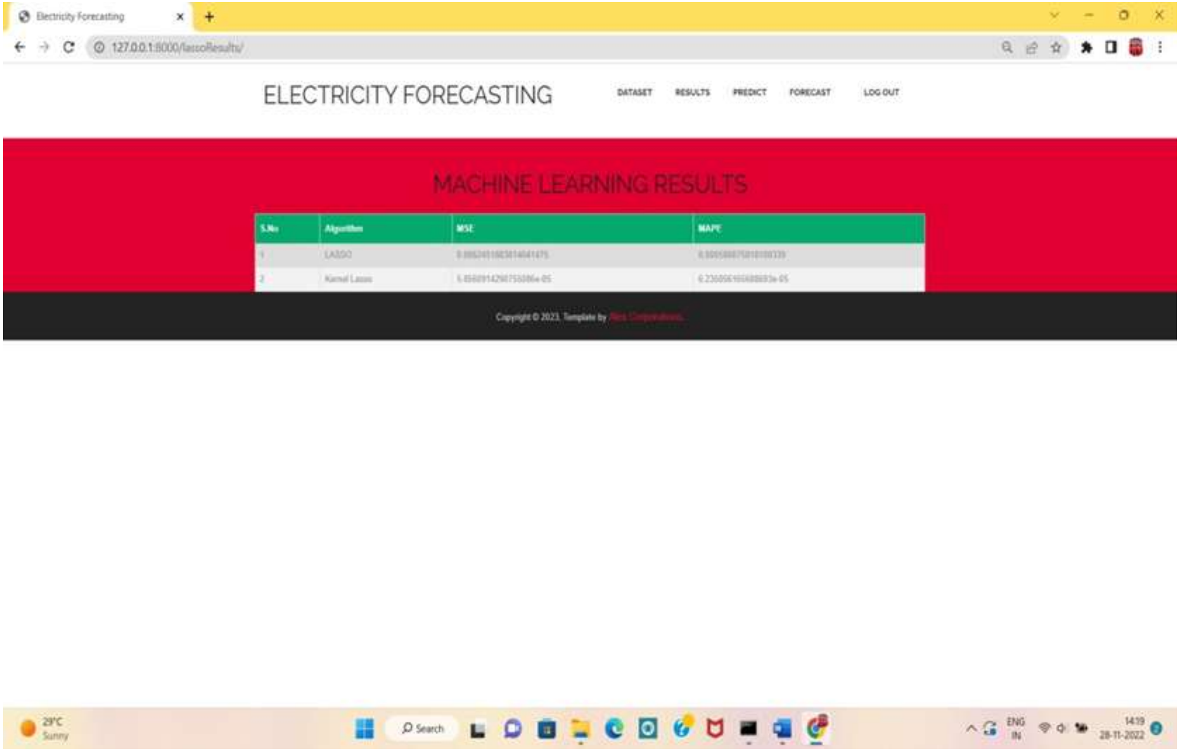
USER HOME PAGE



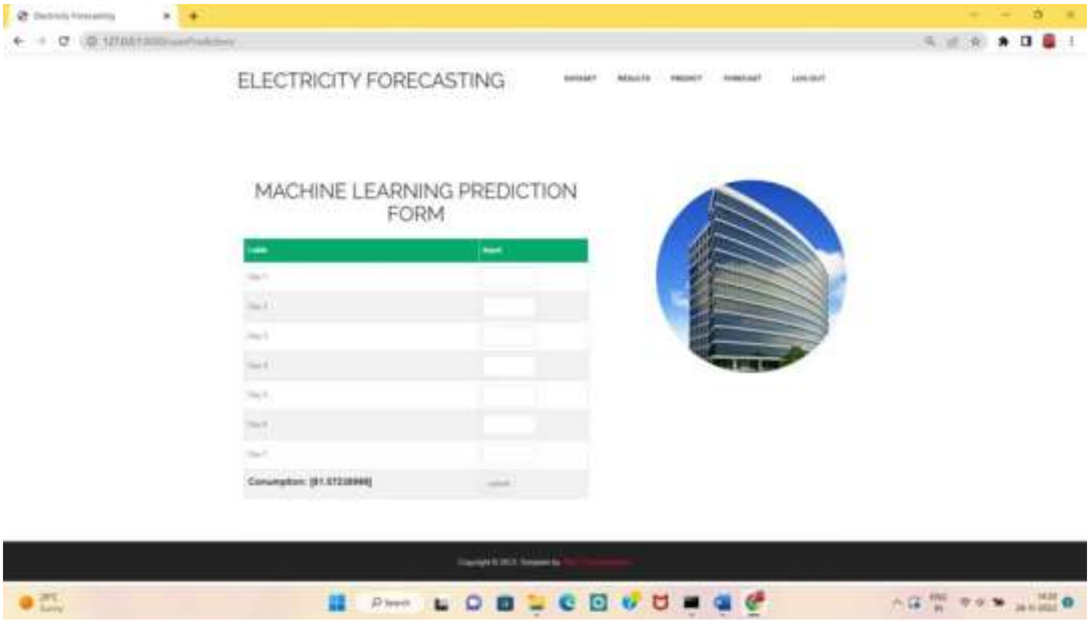
USER VIEW DATA

USER SIDE MACHINE LEARNING RESULTS

PREDICTS



PREDICTION:



FORECAST DATA

Key Findings

- Kernel Lasso Regression significantly improves forecasting accuracy compared to standard Lasso regression.
- The method effectively addresses the issue of non-linearity in high-dimensional electricity data by mapping features into a higher-dimensional space.
- Variable selection through Lasso regularization eliminates irrelevant data, enhancing both efficiency and interpretability.
- The forecasting errors were reduced by approximately 26% in terms of MSE and 27% in terms of MAPE, demonstrating measurable gains.
- The model is particularly reliable during periods of high variability, such as peak electricity demand hours.

Limitations

- The model was tested on a single dataset (Shanghai load data), which may limit its generalizability across different regions or markets.
- External influencing factors such as weather, pricing signals, and holidays were not included, though they strongly affect electricity consumption patterns.
- Kernel methods can increase computational complexity, especially with very large datasets, making scalability a concern.
- The model is designed for non-time series structured inputs; hence temporal dependencies beyond seven days may not be fully captured without integration of time-series models.

Applications

- **Smart Grids:** Accurate load forecasting supports better scheduling of electricity generation and distribution.
- **Energy Management Systems:** Helps utility companies reduce operational costs and improve planning for demand–supply balance.
- **Renewable Energy Integration:** Assists in forecasting variability and managing load when integrating wind, solar, or other renewable sources.
- **Policy and Planning:** Provides insights into consumption trends, supporting decisions on infrastructure investment and regional energy strategies.
- **Educational Tool:** Serves as a learning platform for students and researchers exploring machine learning techniques in high-dimensional data analysis.

Conclusion

Lasso regression can solve the problems of overfitting caused by too many parameters in linear regression and matrix irreversibility in the process of solving features through the normal equation method. Lasso regression achieves its goal by introducing the L1 norm as a regularization item in cost function. By adjusting λ to change the regression fitting effect, lasso tends to completely eliminate the weight of unimportant features. Kernel method is based on assumption that a point set that cannot be linearly divided in a low-dimensional space is likely to become linearly separable when it is transformed into a point set in a high-dimensional space. It maps the data set from low-dimensional to high-dimensional, and making the original linearly inseparable data set linearly separable. This project introduces kernel function into the lasso linear regression to apply to the non-linear regression problem to solve the regression analysis problem of non-time series data. Using the 96-point electricity load data of Shanghai users for851 consecutive days to predict, the prediction effect of kernel lasso regression on the experimental data set is better than lasso regression in terms of minimum mean square error and mean absolute percentage error. give results and discuss

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