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Forecasting Models of Natural Gas

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ABSTRACT

In recent times, there has been immense research in the machine learning and artificial intelligence field. Resulting into a gigantic collection of research papers, well formatted textbooks and countless frameworks that have been developed. Even though individuals are open to such enormous resources, the best way to learn ML algorithms is to implement them. Individuals often find this difficult not only because of math, but also due to the exponentially difficult debugging, software upgrade patch or fix, and fear of programming for individual enthusiasts from other fields. Some of these difficulties can be eliminated by creating an online collaborative environment, which is setup free, provides a visual framework, and helps in understanding and implementing the basic and research algorithms. In this project, we are trying to create an online collaborative environment named "Visual Prediction", which is an online application that promotes visual based learning and provides a GUI based ML framework. The platform will support collaborative learning for users analysing similar data, by sharing their approach, insights and algorithms to tackle generalized problems. The following Paper ensure to provide the methodologies used for development of the application. It provides the obtained outcomes of the features developed within the application.

Keywords — Visual Prediction, Natural gas, Machine Learning, Regression, Dataframe, RSME, R-Squared and Adjusted R- Squared.

I. INTRODUCTION

In this new age of technology and innovation, the use of artificial intelligence and machine learning has made our life much easier. These technologies have proved to be beneficial to the society in various fields such as education, industries, e-commerce, etc. Visual-Prediction will be an online application which promotes visual based learning and provides a GUI based ML framework. The platform will support collaborative learning for users analysing similar data, by sharing their approach, insights and algorithms to tackle generalized problems. The future sales forecast of LPG cylinder will be demonstrated on this application, using different algorithms studied through research papers. Visual- Prediction will be useful for business analysts and young enthusiasts by providing a user-friendly environment and with community support learning.

In order to trace the real demands of the LPG domestic market and maintain a control over assets, our target is to make use of advanced Deep learning concepts and forecast the demand. Accurate estimation of energy demand parameters requires realistic modeling of the consumer's demand behavior, detailed information on energy consumption. With available abundant data availability and growing AI standards, we can come up with one of the Deep Learning Forecasting models which would more precisely predict the upcoming months orders. This model can be used with a standalone application or as a web-API accessed over Rest protocols.

II. LITERATURE SURVEY

Several researchers have proposed forecasting and prediction models to estimate fossil fuel demand or consumption. For several years, solely common classical models are used for natural gas forecasting by distributors in native regions. The foremost common strategies to forecast demand and sales are statistical approaches, either exponential smoothing strategies or autoregressive models. Auto regressive moving average is a technique that calculates the trends in data and is extremely helpful for forecasting short-run trends. In this a new demand number is obtained for a fixed time range, while keeping the time period locked. [5] Exponential smoothing focuses a lot on most up-to-date data, giving more weight to the foremost recent observations. Whereas time series models try and forecast future values taking think into consideration solely the patterns in the historical data, they don't consider any factors that may influence the future. For more details on time series see, [1,2].

One of the meta-learning applications is to select the best methodology from the set of accessible ones. Such method is termed as algorithm selection and it was discussed, among others, in [7]. Using this approach, it is possible to settle on from totally different categories of machine learning algorithms, e.g., Support Vector Machines, Neural Networks, Random Forests, Decision Trees, and Logistic Regression the one that's expected to relinquish the best results on a given information set. Wanshuai Hu and Tao (2014) presented a combined model that is predicted to show improved results using wavelet transform and back- propagation neural network to forecast gas load in a pipeline. [9] The authors in [1] proposed a multi-model techniques and practices to overcome the drawbacks of individual algorithms for forecasting gas demand. Researchers concluded that using this technique factors such as overfitting, under fitting are minimized and additional strong results were achieved. Viewing monthly consumption, Horacio Paggi and Franco Robledo [4] used a Neural Network model to predict consumption of 2 different kinds of LPG cylinders. Jointly considering deterministic demand, reverse logistics, temperature, wind, gas load researchers [3,6,8] proposed NN models differing within the training dataset size and forecasting horizon.

Zlatan Sicanica and Zdravko Oklopcic [10] have shown a comparative study of Neural Networks models and classical Machine learning models for daily gas demand prediction in Croatia.

III. SYSTEM OVERVIEW

The entire system is divided into five modules which are

- Start
- Profile
- Blogs
- Invoke GUI
- Go Live

1. Start module

Firstly, we're going to start with the "Start module". There will be many components in the start module as follow:

- ✓ Sign In
- ✓ Sync Data
- ✓ Load File
- ✓ Select File
- ✓ Dashboard

In "Sign in", We've to ask the users if it is a "Existing user" or a "New User". If HE/SHE will be a new user, then we've to store their data in the database. Additionally, there will be "Photos, Datasets, Documents" option in "Sync data" Component, Similarly, "Save, Create and import" in the "Load file" component. Then, users have to select a file that They want to work upon.

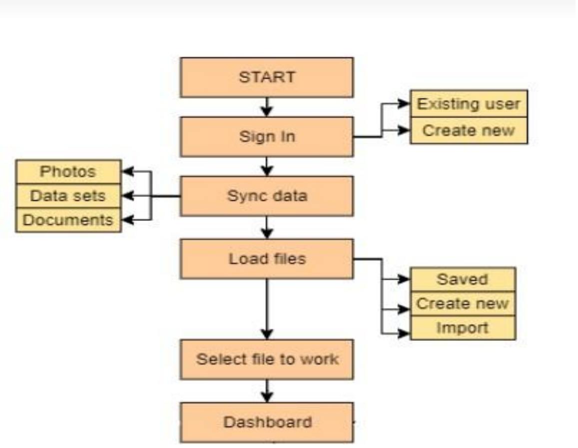


Fig – 1 Start Module

2. Profile module

After the Start module, we will be working on the "Profile module". This module will be going to use for elicit user's information like:

- ✓ Name
- ✓ Email
- ✓ Saved files
- ✓ Blogs
- ✓ Live models

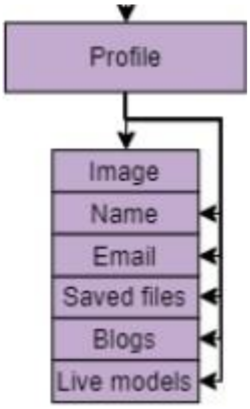


Fig – 2 Profile Module

3. Blog/Journal module

With the help of this module users can create its journals, and can edit previous, and can even search for the existing one.

Fig – 3 Blog Module

4. Invoke GUI

It will be an Imperative Module. Vital parts of the software will be going to implement here. This module contains components like:

- ✓ Import
- ✓ Export
- ✓ Delete
- ✓ Algorithms
- ✓ Tabular data
- ✓ Visuals

CSV files will be imported, after parameters will be selected, then users will have to select the algorithm by which they want to predict the output.

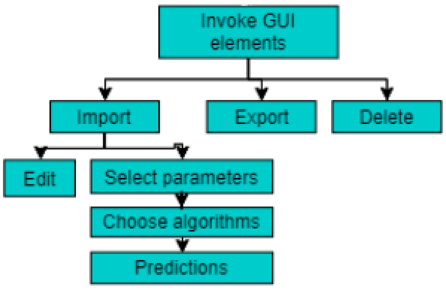


Fig – 4 Invoke GUI Module

5. Go Live
Several components will be accumulated here like:

- ✓ Experiments pipelines
- ✓ Saved pipelines

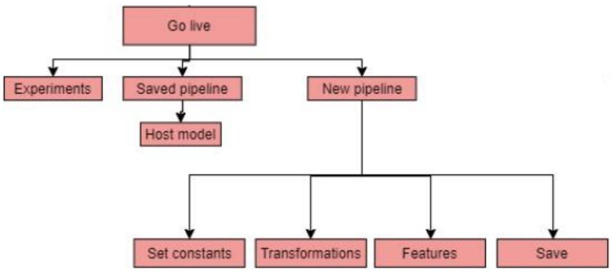


Fig – 5 Go Live Module

New Pipelines

User created models and pipelines can be hosted on server and can accessed live using HTTP and REST protocols.

IV. METHODOLOGY

A. User-Interface
The User Interface for our application was developed with the help of PyCharm (an Open-Source UI Software Development Platform) and flask (Web Application Framework). Flask is based on Werkzeug WSGI toolkit and Jinja2 template engine.

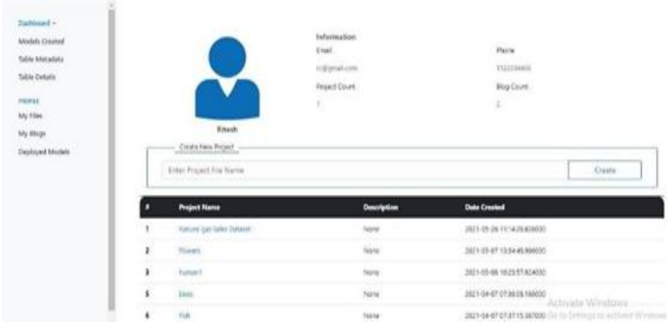


Fig – 6 User Interface Design

Libraries used: SciKit-Learn, NumPy, Pandas It promises to give a stunning look to the Application Interface, irrespective of the operating platform.
The first move in our application is to import dataset (.csv file). After that the data will automatically get converted into tabular format as you can see in the

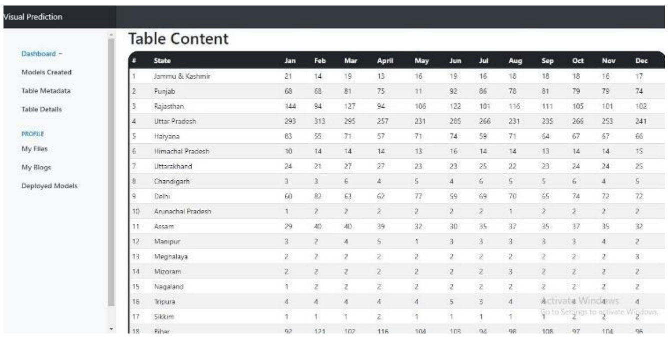


Fig – 7 Tabular format data

Replacing missing values with mean or median, outlier removal, encoding numerical values.After that models will be created by the Regression and Classification Algorithms as per the user's choice.

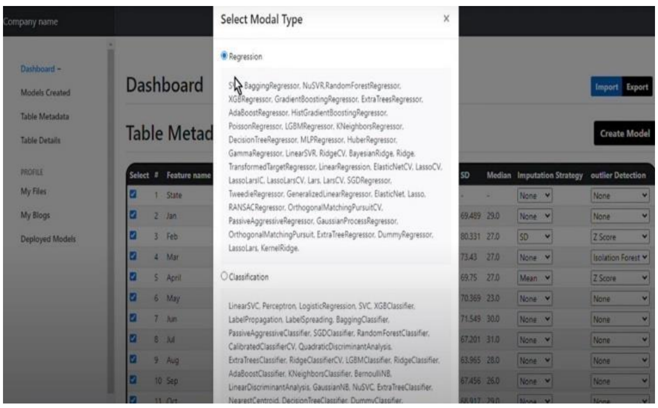


Fig – 8 Model Selection

After selection of appropriate Model, Prediction will be made on the basis of algorithms present in the selected model.

B. User Interactions with the Flask Framework For interacting with the Flask Framework, a code must be written for direct interaction. The request will be sent from the user side to the framework, it will call the appropriate module according to the request and returns the response based on the results.

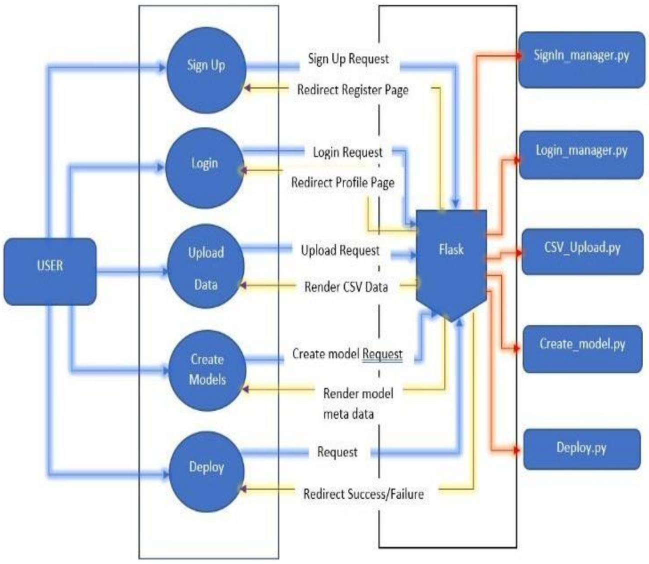


Fig – 9 User Interaction with the Flask Framework

V. RESULT

We have implemented our Login and Sign-Up page using Flask Framework and MongoDB. The following Fig –10 shows the Login/Sign-Up page of Visual Prediction.

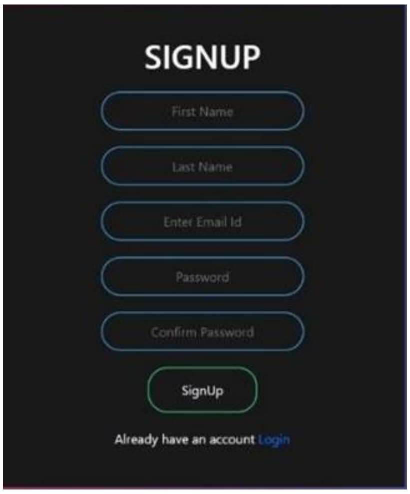


Fig – 10 Login/Sign-Up Page

For testing the models, the regression models are fetched from the Sklearn library to a list variable. The data set is passed through a pipeline, where at each pipe: preprocessing of data, training model and validation is carried out. The results at each pipe are added to a dataframe object and the final object is sorted as per the decreasing performance i.e., RSME value. The pre-processing step involves transformation of the dataset i.e., generalization, replacing missing values with mean or median, outlier removal, encoding numerical values. At training phase, the processed data in the earlier phase is now separated into training and testing dataset, followed by fitting the training set to the models list fetched from Sklearn library. In validation phase the trained model is tested against the testing data set and performance parameters like RSME, R-Squared and Adjusted R-Squared are calculated. The results or validation data of each model is added to a dataframe object. In the end, the dataframe object contains performance details of each models and is sorted in the increasing order of RSME. Fig-11 shows the Logic Diagram.

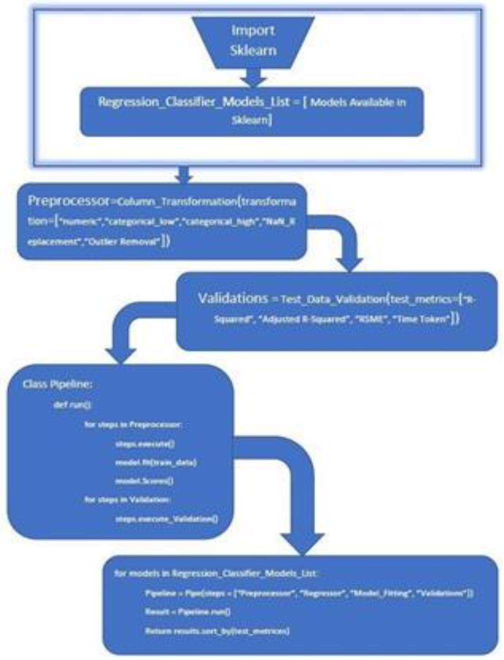
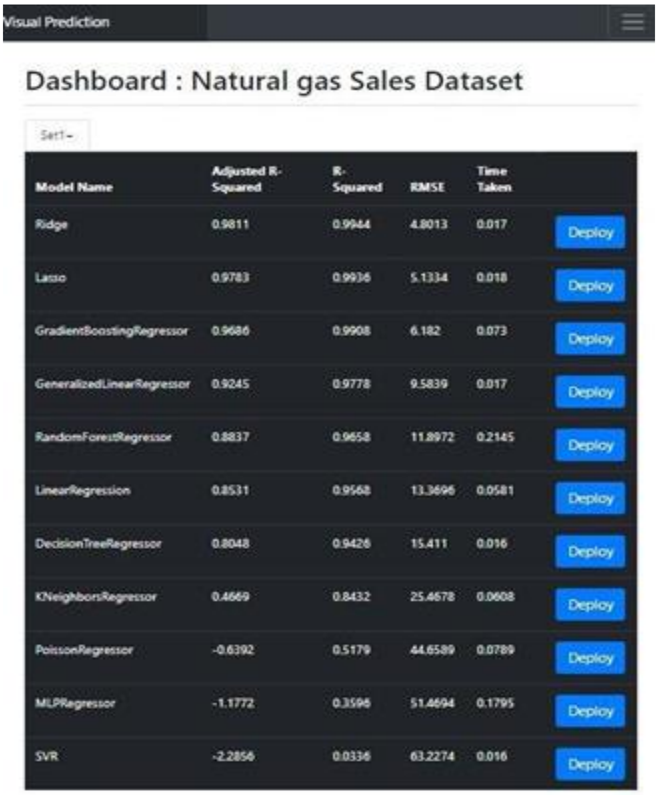


Fig – 11 Logic Diagram

Fig-12 shows the predicted data for dataset (Natural gas Sales). It shows results for different regression models. It shows the Adjusted R-Squared Value, R-squared Value, RMSE Value and Time Taken for the different models.


Visual Prediction

Dashboard : Natural gas Sales Dataset

Set1

Model Name	Adjusted R-Squared	R-Squared	RMSE	Time Taken	
Ridge	0.9811	0.9944	4.8013	0.017	Deploy
Lasso	0.9783	0.9936	5.1334	0.018	Deploy
GradientBoostingRegressor	0.9686	0.9908	6.182	0.073	Deploy
GeneralizedLinearRegressor	0.9245	0.9778	9.5839	0.017	Deploy
RandomForestRegressor	0.8837	0.9658	11.8972	0.2145	Deploy
LinearRegression	0.8531	0.9568	13.3696	0.0581	Deploy
DecisionTreeRegressor	0.8048	0.9426	15.411	0.016	Deploy
KNeighborsRegressor	0.4669	0.8432	25.4678	0.0608	Deploy
PoissonRegressor	-0.6392	0.5179	44.6589	0.0789	Deploy
MLPRegressor	-1.1772	0.3596	51.4694	0.1795	Deploy
SVR	-2.2856	0.0336	63.2274	0.016	Deploy

Fig – 12 Predicted Data

VI. CONCLUSION

In our Project the application, Visual Prediction, developed with the help of PyCharm and Flask Framework was able make prediction based on the Datasets (natural gas consumption). The pre-processing step, transformation of the dataset i.e., generalization, replacing missing values with mean or median, outlier removal, encoding numerical values were successfully carried out. The proposed system will be a user- friendly ML, DL based visual Framework. It will be used for analysts and young aspirants to analyse, create models and predict data. The process of analysis and estimation for a specific product can be shared among the community. The web application will include most of the available machine learning algorithms and techniques. The process of estimation/forecasting can be automated and be accessed every time using simple Rest Protocols.

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