Application of Hybrid Ensemble Machine Learning Approach For Prediction of Residential Natural Gas Demand and Consumption

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Abstract:- The only byproducts of burning natural gas are carbon dioxide, water vapor, and very little amounts of nitrogen oxide, making it the cleanest fossil fuel on the planet. A wide range of consumer products, such as stoves, dryers, fireplaces, and furnaces, are also powered by natural gas. At least one of your appliances undoubtedly runs on natural gas. In this work, the demand for residential natural gas was forecasted using a hybrid ensemble regression machine learning approach. Accurate forecasting of the demand for natural gas is crucial for effective energy management and resource allocation. The hybrid ensemble approach mixes a number of regression algorithms, including linear regression (LR), decision tree regression (DTR), support vector regression (SVR), and K-nearest neighbor (KNN), to take advantage of the benefits of each unique model and improve prediction performance. The hybrid ensemble regression model's process has two steps. In the first stage, distinct regression models are trained on the dataset. The second stage involves evaluating each model's predictions. To evaluate the effectiveness of the hybrid ensemble model, a range of measures, including mean absolute error (MAE), mean squared error (MSE), coefficient of determination (R-squared), and accuracy, are generated and compared to those of individual regression models. The anticipated accuracy of the model is further assessed using cross-validation techniques to ensure resilience. The results of the experiment demonstrated that the hybrid ensemble regression technique routinely outperformed individual regression models in terms of prediction accuracy. Combining numerous models enables the collection of the various correlations and patterns contained in the data, enhancing the model's overall performance.

Keywords:- *Ensemble, Hybrid, Machine Learning, Natural Gas, Prediction.*

I. INTRODUCTION

Natural gas has long been used in all aspects of human endeavor, but particularly in home construction. Natural gas is the cleanest fossil fuel on earth because the only byproducts of burning it are carbon dioxide, water vapor, and very little amounts of nitrogen oxide. Natural gas is also used to power a sizable variety of consumer goods, including stoves, dryers, fireplaces, and furnaces. At least one of your appliances undoubtedly runs on natural gas. Like almost all other energy sources, natural gas can be dangerous if used improperly. A few simple safety measures and knowledge on what to do in the event of a gas leak can help you protect yourself and those you love. Therefore, a well-designed forecasting model is crucial to managing energy policy successfully by providing energy diversity and energy requirements that adapt to the dynamic structure of a country, region, or the entire world, in line with previously unheard-of increases in energy demand (Faruk et al., 2019).

As a fossil fuel, natural gas is one of them. It is environmentally friendly to use natural gas to supply energy requirements for industry, transportation, and other uses. Between a fifth and a third of the energy used worldwide is consumed by buildings. Natural gas accounts for more than a third of the energy used in European residential buildings (Then et al., 2020). The strategic growth of nations' economies and societies depends on energy. The basic purpose of data mining is to create models using preprocessed or existing data to find patterns that the data set's attributes have shown. Energy plays a crucial role in the strategic development of society and economies. To uncover patterns that the data set's features have revealed, data mining's fundamental goal is to build models utilizing preprocessed or existing data. Because they show how the attributes are related to one another, some of the patterns act as explanations. According to the most recent statistics, other modes forecast prospective values for specific attributes. In data mining, four different types of patterns are commonly sought after association patterns, prediction patterns, clustering patterns, and sequencing patterns (Chen & Zhang, 2022).

The need to predict how much natural gas demand and consumption is required for residential addresses is of paramount important as it will help in planning and scheduling activities including making a sound decision (Driven et al., 2019). In some countries, the demand for natural gas depend on seasons, like in Algeria for example the demand is higher during holidays and special days (Laib et al., 2019). Likewise in Nigeria the demand for natural gas particularly premium motor spirit is higher most often during the last quarter of the year.

Many researchers have gone in to it (Šebalj, 2019), such as (Liu et al., 2022) who acknowledged that the impact of climate change may be lessened, people's living conditions could be improved and reasonable and appropriate private and governmental policies could be influenced with accurate predictions of natural gas demand and consumption in both residential and commercial structures. The reminder of the paper is organized as follows: Section II present the existing relevant literature review, in section III the methodology employed was stated. Section IV provides the results obtained and discussion. Finally, conclusion was drawn in section V.

II. RELATED WORK

The recent research, which ranges from the last four years, were examined in this study, and is reviewed in this section. There are a lot of studies in the literature. Machine learning algorithms were employed in the work by (Faruk et al., 2019) to forecast the consumption of natural gas in the province of Istanbul. The results demonstrate that the support vector regression (SVR) technique is much superior to the artificial neural network (ANN) technique for time series forecasting of natural gas consumption, providing more reliable and accurate results in terms of fewer prediction errors. This study may very likely be used as a useful benchmarking study for many developing nations because of the data format, customer consumption frequency, and consumption behavior over multiple time periods.

(Šebalj et al., 2019) suggests analyzing methodologies and procedures for predicting the consumption of natural gas. The paper offers a comprehensive synthesis and analysis of the most recent research on natural gas consumption projections for residential and commercial use. The results show that while neural networks are the most popular, genetic algorithms, support vector machines, and Adaptive Network-based Fuzzy Inference System (ANFIS) are the best accurate approaches for estimating natural gas demand. The two most frequently used input variables are past natural gas consumption data and meteorological data, and predictions are most frequently generated on a daily and annual level on a nation area level.

Natural gas is one of the main sources of energy in the entire world, according to a study by (Laib et al., 2019). By creating a Multi Layered Perceptron (MLP) neural network as a nonlinear predicting monitor, it presents a novel hybrid prediction model that addresses the weakness of the two-stage method. The approach offers a fresh, useful functionality. The results of the forecast performance were significantly improved by its estimates of the next day's consumption profile, especially during seasons with strong client demand and consumption.

In their study (Bala and Shuaibu, 2022), the authors employed machine learning and hybrid techniques to forecast the energy consumption of the United Kingdom. However, machine learning techniques like neural networks and support vector regression outperformed dynamic regression models, while the seasonal hybrid model outperformed time series and machine learning models, even though combination forecasts underperformed other models.

Energy consumption modeling for the residential and commercial sectors was also measured using machine learning. These models are developed based on a number of factors, including population, natural gas and electricity costs, gross domestic product, and the share of renewable energy sources in total energy consumption. The results of the three machine learning algorithms show that by 2040, Iranian residential and commercial energy consumption will be 76.97, 96.42, and 128.09 Mtoe, respectively. According to the findings, Iran must develop and implement new policies to increase the share of renewable energy sources in overall energy consumption (Nabavi et al., 2020).

Using certain hybrid algorithms inspired by nature, (Qiao et al., 2020) predicted the monthly natural gas usage. According to the study, the invasive weed optimization (IWO) can be a more accurate predictive network when compared to other hybridization strategies for enhancing the MLP method's error performance. According to the anticipated outcomes, combining optimization techniques could increase prediction precision and boost the multi-layer perceptron's (MLP) productivity.

Artificial neural networks (ANN) were also used to forecast ultimate natural gas usage. Speculate about how natural gas will be used in the future. For Myanmar, actual recorded consumption data from 1990 to 2015 are used. The most recent five years' worth of data (2011-2015) are combined with the prior years' data for testing. The years (1990–2010) are used for instruction. Data on the population, GDP, and other factors that influence the final use of natural gas are used to develop the model. The training model is reliable (MSE) with a minimum error rate of 0.005 Mean Squared Error. Myanmar's yearly natural gas consumption is projected using the created ANN model (Yin & Htay, 2021).

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Then et al., (2020) modeled a decline in gas demand in 57 metropolitan German distribution grids to examine the effects of various distribution network operator (DNO) strategies and grid-specific factors on grid charges. By analyzing the entire operating costs and related grid charges for various scenarios and strategies, the implications on DNO business models are calculated. Depending on the DNO's policy and the pattern of consumers leaving the grid, grid prices could increase as a result of the substitution of gas-bound equipment, which could generate a self-reinforcing feedback loop and lead to grid defection.

Data mining techniques are first used to uncover and gather the hidden patterns of electricity usage in the data. The cluster centers are used to divide the level of electricity usage after the clustering analysis has been submitted to the particle swarm optimization-K-means algorithm. Finally, a workable, effective classification model is proposed (Cai et al., 2019), which uses a support vector machine as the core framework for optimization. The results demonstrate that the accuracy and F-measure of the novel model, which both significantly outperform conventional methods, reach 96.8% and 97.4%, respectively.

This study aims to address the problems raised by (Shapi et al., 2020), who built a prediction model for energy utilization in the cloud-based machine learning platform of Microsoft Azure. A case study involving two tenants of a business building is utilized to highlight real-world applications in Malaysia. The obtained data is evaluated and prepared prior to being used for training and testing models. To compare the potency of each strategy, RMSE, NRMSE, and MAPE metrics are used. The experiment's findings show that the distribution of energy use differs depending on the renter.

It was possible to accurately predict the consumption of natural gas in Istanbul's Bahçeşehir by using a range of powerful machine learning techniques. Final performance evaluations showed that XGBoost outperformed MLP, Forest Regression, and Linear Regression by 0.04 Mean Absolute Error each. Because it is highly scalable, efficiently cuts down on compute time, and makes best use of memory, XGBoost performs better at prediction (Ahmed et al., 2021). Accurate forecasts prevent economic loss and keep supply and demand in balance.

The amount of natural gas used by data centers was calculated by (Liu et al., 2022). Under the premise that electricity and gas are employed as energy suppliers of energy supply and energy consumption from two viewpoints, the data center energy scheduling model is built by taking into account the service level of the data center. The lowest model is the scheduling calculation model used in the data center. The best model is the data center energy supply scheduling model. The particle swarm approach is used to mimic the timetable. The results show that, while accounting for the degree of data center service delay, using natural gas as an additional energy source can significantly reduce the data center's overall energy consumption.

A consistent intraday load forecasting technique for the natural gas flow state space model is presented in the work by Chen and Zhang (2022). The trials' findings show that the model's load forecasting accuracy and relative error both reached 0.026 and 98.5%, respectively, solving the problem of processing the long-term collected historical data of gas intra-day load. The calculation's data input was also reduced by 33.6%, which promoted qualitative research and the quantification of factors influencing intraday load.

Machine learning was picked after looking through the models that were available. In particular, a genetic algorithm (GA) and artificial neural networks (ANN) were coupled. Their suggested models were put to use in a real-world testbed. They made advantage of CompactRIO to put ANNs into practice. To train and validate the given models, real-world data from a PV system and SB electrical appliances is used. Despite the model's modest prediction accuracy, which is brought on by the small size of the data set (Bourhnane et al., 2020), the model is highly advised as a blueprint for researchers willing to deploy real-world SB testbeds and investigate machine learning as a promising venue for energy consumption prediction and scheduling.

Investigate data-driven prediction models for predicting natural gas prices based on well-known machine learning techniques, such as Gaussian process regression, support vector machines (SVM), and artificial neural networks (ANN) (GPR) (Driven et al., 2019). For evaluation and the cross-validation method of model training, we use monthly Henry Hub natural gas spot pricing data from January 2001 to October 2018. The results show that these four machine learning methods perform differently when attempting to forecast natural gas prices. SVM, GBM, and GPR all perform predictions less accurately than ANN does generally. This has proven that machine learning classifiers can accurately predict outcomes for many tasks.

The research could be used to considerably enhance natural gas consumption forecast systems, despite its limitations due to the small number of articles it looked at. For supply-demand equilibrium and investment purposes, accurate predictions of natural gas consumption are crucial. Accurate and exact forecasts prevent economic loss and keep supply and demand in equilibrium.

III. METHODOLOGY

The suggested model system, which is represented in the accompanying picture, will forecast natural gas demand and consumption from both residential and commercial components using two separate datasets and will be implemented using a machine learning technique-based data mining approach. The model would attempt to fix the issue identified with the current system. The addition of a strategy for noise reduction in the dataset is due to the fact that noisy data will lead to biased predictions, which could lead to inaccurate performance accuracy. Two datasets would be developed from different sources in order to further ensure good and reliable performance.

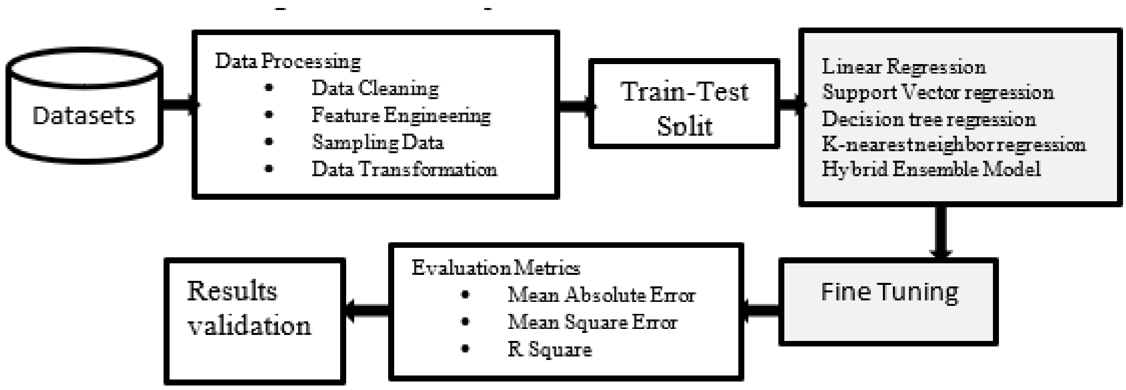

Fig 1. Architecture of the Proposed Model

A. *Natural Gas Dataset*

Dataset will be collected from kaggle.com which is the largest community of data scientist (https://www.kaggle.com/datasets).

B. *Data Preprocessing*

Data modifications done on it before feeding it to the algorithm are referred to as pre-processing. Data preprocessing is a method for transforming unclean data into clean data sets. In other words, anytime data is acquired from various sources, it is done so in a raw manner that makes analysis impossible. Data cleaning, dimensionality reduction, feature engineering, data sampling, data transformation, and imbalanced data are a few of the crucial data preprocessing approaches.

This crucial stage is utilized to improve the data's quality in order to encourage the extraction of valuable insights. To prevent overfitting or underfitting the suggested developed model, it is also important to make sure that there isn't too much noise in the dataset. Boost the model performance's accuracy and computational effectiveness to get the dataset ready for the right prediction.

C. *Feature Extraction*

In order to decrease dataset overfitting, increase prediction accuracy, and shorten model training time, feature extraction is crucial. The properties of the dataset that would be utilized to train the machine learning models have a significant impact on the algorithm's performance. Model performance may be negatively impacted by irrelevant, unsuitable, or only partially relevant features. In order to automatically choose the features in the dataset that contribute the most to the output or prediction variable that interests us, feature selection will be applied to the data. Unrelated elements in the data might make models less accurate, especially those that use linear techniques like logistic and linear regression.

D. *Fine Tuning*

In order to enhance the performance of a machine learning model that has already been trained, fine-tuning often refers to the process of further training the model on a particular task or dataset. This is done to make use of the data-driven knowledge and information the model has previously gathered during the pre-training phase. It enables you to apply prior knowledge to a new assignment where you can continue to train and change the model to boost its effectiveness and accuracy.

These are the stages involved in fine tuning

- Loading the pre-trained model
- Freeze most if not all layers in the model to prevent them from further training
- Swap final layer or layers of the model with a new one that are specific to the tack
- Train the model on dataset using a lower learning rate than in the pre-trained phase
- Analyze the performance of the improved model and make any necessary hyper-parameter adjustments.

E. *Prediction Tools and Methods*

Throughout this study, the Python programming language would be used. To assist with the experiment, Sci-kit Learn libraries would be used. Prediction model-specific libraries and extensions are abundant in the Python programming language. One of the finest places to get machine learning algorithms is Sci-kit Learn (https://scikit-learn.org), where almost every form of algorithm is easily accessible and can be evaluated quickly and easily. The data will be handled using Numpy and Pandas. Jupyter Notebooks would be utilized for debugging and for its ability to present code elegantly.

F. *System Specification/Configuration*

A laptop computer with the following specifications would be used to perform and/or implement these research experiments: Intel(R) Core(TM) i5-2520M CPU @ 2.50GHz, RAM 4.00 GB, 64-bit operating system, x64-based processor.

G. *Performance Evaluation Technique*

Building a prediction model using machine learning techniques has as its main objective the generality of the training datasets. On real data, machine learning models should be able to perform fairly effectively. Training data and testing data will be separated into two groups. Testing data will be used to put machine learning classifiers to the test, whilst training data will be used to train classifiers.

H. *Choice of Evaluation Metrics*

Evaluation metrics are employed to measure the magnitude of mistakes in the performance of the prediction models. It aids in properly determining which of the results acquired is more accurate and reliable for application and

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further research. Regression, in contrast to classification, entails making predictions about a continuous or quantitative variable. Mean Absolute Error (MAE), Mean Squared Error (MSE), and R Square (R2) Metric are the three (3) primary metrics for assessing predictions on regression machine learning issues. Although there are many of these tools available, this study will examine the best and most widely used measures for assessing each model's success. These measurements or indices aid in determining how accurate the models being utilized are (Qiao et al., 2020). The values of the parameters used in the equations are calculated as follows:

x_i = Actual value

y_i = Predicted value

n = Number of data points/rows

$\bar{y}_i$ = Mean of all actual values

- *Mean Absolute Error (MAE)*

The sum of the absolute differences between the expected and actual values is known as the mean absolute error, or MAE. It illustrates just how inaccurate the projections were. The metric provides a notion of the error's size but not its direction, such as over prediction or under prediction.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|x_i - y_i| \quad - \quad - \quad - \qquad i$$

- *Mean Square Error (MSE)*

Similar to the mean absolute error in that it gives a broad idea of the extent of error, the mean square error (MSE), sometimes known as the root mean square error (RMSE), is a measure of error. The units are returned to the output variable's original units when the mean squared error is taken into account, which might be significant for explanation and presentation. The calculation of mean squared error is illustrated in the formula below.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2 \quad - \quad - \quad - \qquad ii$$

- *R Square (R^2)*

Usually, regression models employ this metric. It provides a measurement of how well a collection of predictions fits the data. The coefficient of determination is the statistical name for this measurement. For no-fit and perfect fit, it is a value between zero (0) and one (1). This formula is used to determine the mean R2 given a group of predictions.

$$R2 = 1 - \frac{\sum_i (x_i - y_i)^2}{\sum_i (x_i - \bar{y}_i)^2} \quad - \quad - \quad - \qquad iii$$

IV. RESULT AND DISCUSSION

The longest period dataset in the literature was gathered from the Kaggle machine learning repository. It contains monthly figures of natural gas usage from January 1997 to August 2020, as presented in Figure 2 below.

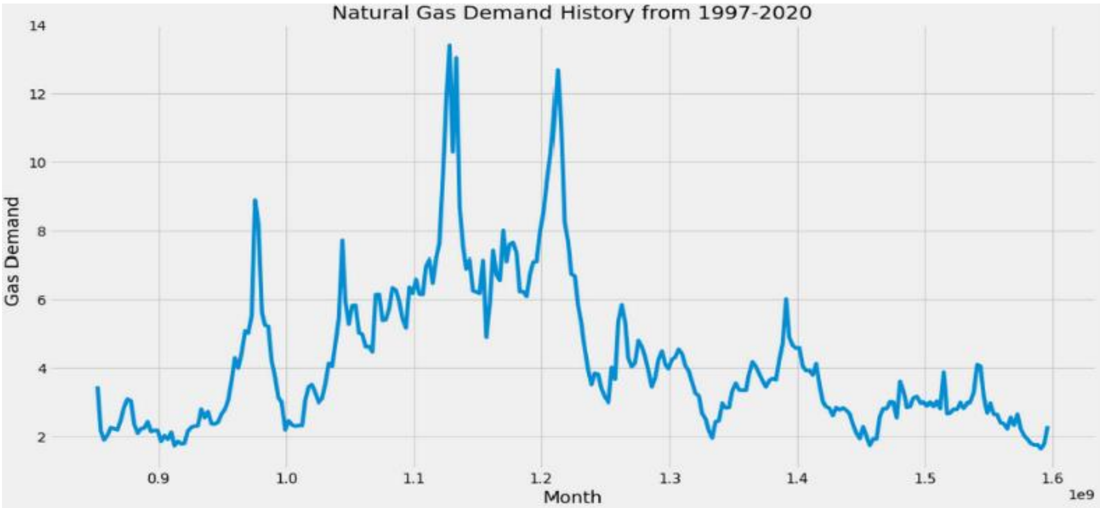

Fig 2: Natural Gas Demand History

TABLE I. COMPARISON OF PREDICTION MODELS PERFORMANCE

Model	MSE	MAE	R^2 score	Accuracy
LR	5.517869605	1.692801814	0.017428471	95.38447525
DTR	0.570523256	0.487209302	0.89840646	59.0135889
SVR	2.448486661	0.995936355	0.89840646	60.49370316
KNN	0.489458884	0.444046512	0.912841658	92.4553162
HE	1.164821453	0.721612403	0.792579296	97.48707913

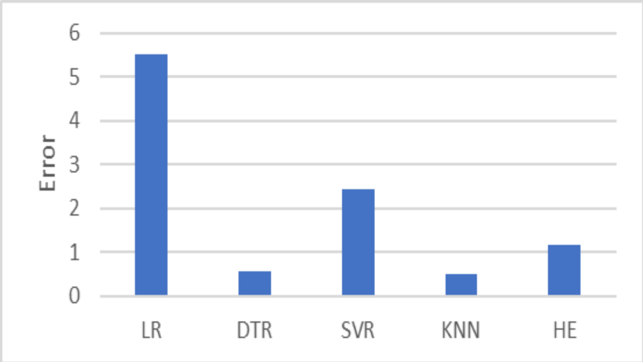

Fig 3: Mean Squared Error (MSE)

The mean square error (MSE), also known as the root mean square error (RMSE), is shown in Figure 3. It is similar to the mean absolute error in that it gives a general notion of the size of the error. The LR has a significant amount of prediction error, as depicted in the figure. SVR and Hybrid Ensemble (HE) come next.

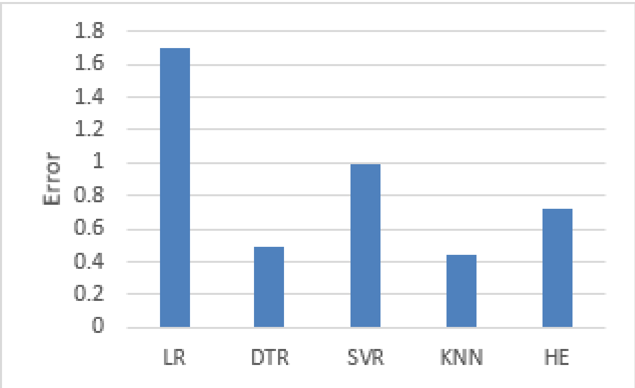

Fig 4: Mean Absolute Error (MAE)

Figure 4 above depicts the mean absolute error (MAE), which is used to illustrate how inaccurate the forecasts were. The MAE results produce similar performance for the various machine learning models as the MSE results did.

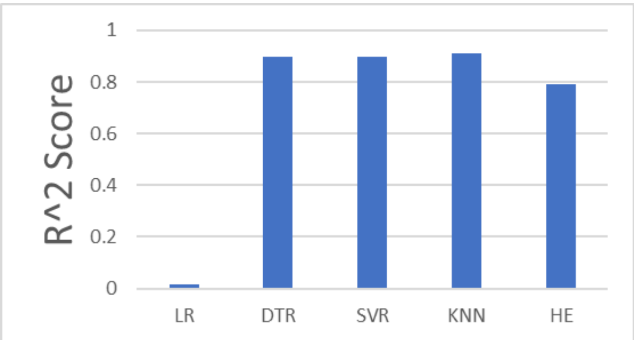

Fig 5: R^2 score

The outcomes of the r-square evaluation model for all models were reported, as seen in figure 5. It gives a hint as to how well a collection of predictions fits the data in terms of actual values. It is employed to further examine and guarantee the accuracy of the prediction performance results obtained from the created model.

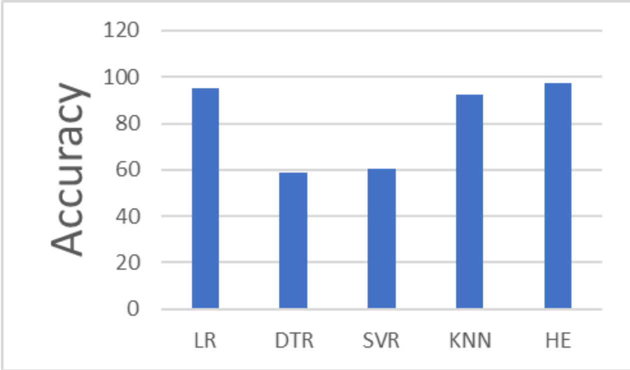

Fig 6: Accuracy Score

The accuracy performance measures are displayed in Figure 6 and show that the hybrid ensemble machine learning model has the highest accuracy, followed by linear regression and K-nearest neighbor.

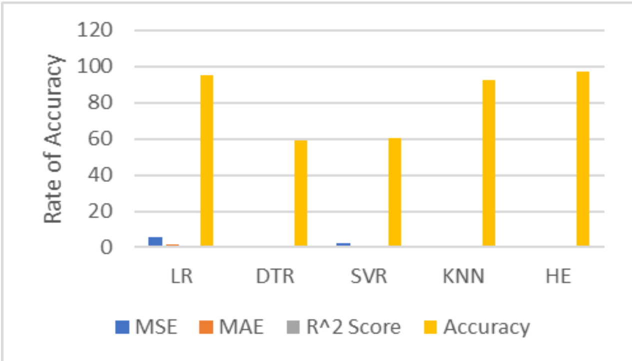

Fig 7: Comparison of Models Used

The figure 7 shows the comparison of all the various machine learning model used in the study as also shown in Table 1 above. As displayed in the figure above the hybrid ensemble have the highest prediction accuracy and minimum error errors. Therefore, for efficient energy management and decision-making, a precise forecast of residential natural gas demand is essential. For energy management organizations and regulators, the hybrid ensemble regression approach offers a potent tool for making well-informed decisions about resource allocation, infrastructure development, and energy-saving strategies. By assuring reliable and efficient natural gas transportation, energy companies may streamline their supply chains, reduce waste, and boost customer satisfaction.

➢ *Further Discussions*

A hybrid ensemble regression machine learning approach has some notable benefits and consequences for predicting residential natural gas demand and consumption. The discussion examines the approach's main principles and any potential field repercussions. When compared to individual regression models, the hybrid ensemble regression approach showed greater prediction accuracy. The method captures a wider range of patterns and correlations contained in the data by merging different algorithms, such as LR, SVR, DTR, and KNN. As a result, estimates of residential natural gas demand become more precise and trustworthy, which is very advantageous for energy management firms, decisionmakers, and energy providers when planning and maximizing resource allocation.

The usage of ensemble techniques improves the prediction model's resilience and generalization abilities. The hybrid ensemble strategy decreases the possibility of over-fitting and improves model stability by including a variety of regression models. This is crucial when predicting residential natural gas demand because the addition of numerous variables, such as socioeconomic and meteorological variables, might result in complex interactions. The hybrid ensemble approach makes sure the model can handle various situations and adjust to changes in the data.

The hybrid ensemble regression approach is flexible and able to be adjusted to a variety of prediction scenarios. The ensemble process' fusion techniques, including stacking or weighted averaging, allow for many combinations of separate models. Moreover, the hybrid ensemble approach can be easily extended to incorporate additional regression models or incorporate domain-specific knowledge, further enhancing its adaptability.

V. CONCLUSION

The study concludes that the hybrid ensemble regression machine learning methodology is an effective technique for precisely forecasting residential natural gas demand and consumption. The hybrid ensemble approach captures various patterns and correlations within the data and improves predictive performance by merging numerous regression models. The evaluation metrics repeatedly showed that the hybrid ensemble model was superior to individual regression models, including MAE, RMSE, and R-squared. The outcomes showed how effective this strategy could be at improving energy planning and resource management in the residential natural gas market. The results point to the potential value of the suggested hybrid ensemble technique as a tool for precise and dependable residential natural gas demand prediction, enabling more effective energy planning and resource management.

➢ *Future Research*

Though the hybrid ensemble regression method produces encouraging findings, there are still areas that could be applied. The model's forecasting skills can be improved by enlarging the dataset to incorporate a wider range of variables impacting natural gas demand, such as building attributes, energy saving measures, and customer behavior. To summarize, there are many benefits to forecasting residential natural gas consumption utilizing a hybrid ensemble regression machine learning approach, including improved prediction accuracy, robustness, flexibility, and practical application. The residential natural gas market could benefit from this strategy by optimizing resource allocation, supporting energy management techniques, and informing policy decisions. The subject can advance and goals for sustainable energy management can be attained with more study and application of the hybrid ensemble approach.

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