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Predicting the Carbon Dioxide Emissions Using Machine Learning

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***Abstract*—There are severe impacts and consequences to humans, societies, and the environment due to global warming. Though there are various activities that contributes to global warming, the major contributor is carbon dioxide (CO_2) emissions. Human activities release large amounts of carbon dioxide from the burning of fossil fuels, such as oil, gas, or coal in producing energy. Net zero is the new ambition of industries in balancing the CO_2 emissions in environment. Thus, this study finds the best predictive model for CO_2 emissions using machine learning model with the dataset of CO_2 emissions from 1991 until 2020. Machine Learning techniques is an efficient approach to study the CO_2 emissions prediction and has been very appealing to few research. The dataset is split into a train-test (estimation-validation) set with 80% train set and 20% test set (80:20) proportion. The predictive model was developed using Random Forest, Support Vector Machine and Artificial Neural Network algorithms with different parameters to get the outcome. The predictive model's performance was evaluated based on the error measurement metric of Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Its reveals that Support Vector Machine with linear kernel function is the best model among others which produces 65.7254 Mean Absolute Error (MAE), 112.2196 Root Mean Square Error (RMSE) and 0.2279% Mean Absolute Percentage Error (MAPE) from the train set. For industries committed to net zero carbon emissions, this analysis will be an advising factor on the prediction system to find the CO_2 emissions and how much fossil fuels' reduction is required in achieving net zero carbon emission by 2050.**

***Keywords*—Carbon dioxide, machine learning, error measurement, support vector machine, random forest, artificial neural network**

I. INTRODUCTION

Carbon dioxide (CO_2) emissions and its danger to earth and humans are widely researched in recent years. Many organizations are combating in prevention of carbon emissions. As early as in primary education, students are taught about the danger of carbon dioxide emissions into the atmosphere and ways to reduce the emissions (Mahat *et al*., 2017; Wong *et al*., 2017). In recent years, there have been a growing number of initiatives to promote net-zero carbon dioxide (CO_2) emissions (Programmes & Gustafsson, 2000). Net-zero carbon emissions refers to carbon neutrality, which describes the balancing of CO_2 emissions in the environment. Stated in National Grid (2021), net zero is achievable when the amount of CO_2 emissions is lesser than the amount removed from the atmosphere. The produced greenhouse gas is balanced with net zero carbon emissions.

Human activities emit 60 or more times the amount of carbon dioxide released by volcanoes each year (Climate.gov, 2021). CO_2 is produced through human activities such as deforestation and burning of fossil fuels for energy production. CO_2 is produced from both renewable and non-renewable energy production. However, renewable sources produce negligible to almost zero carbon emissions. The Lancet Planetary Health (2021) further emphasised that we need to rapidly reduce CO_2 emissions in order to prevent increasingly dangerous climate changes.

Carbon emissions are extensively produced with fossil fuels used for power production. This includes carbon

produced through the consumption of solid, gas fuels, liquid and gas flaring from oil, coal and gas in combustion related activities. Economic development and carbon dioxide emissions are closely related. The economic growth has increased the demand for fuel in recent years. China has the largest base of carbon dioxide emissions which could be related to China's population and the vast economic growth of the country. China is facing unprecedented international pressure due to the large emissions produced (Z. Qiao *et al*., 2021). This has resulted in an increase in China's average temperature and sea levels rise faster than the global average, according to a 2020 report from China's National Climate Center (Council Foreign Relations, 2021).

In the year 2020, the world pandemic of Covid-19 has resulted in a significant drop in oil demand. This was due to the industries being closed and a reduction in the use of petrol and diesel for vehicles. Economic development also slowed down during the intense pandemic period. When the economy rises, the demand for fossil fuels rises as well. Accordingly, the Covid-19 crisis in 2020 triggered the largest annual drop in global energy-related carbon dioxide emissions since the Second World War (International Energy Agency, 2021).

The CO_2 Human Emission (2017) published that 87% of CO_2 emissions comes from burning of fossil fuels like oil, natural gas and coal, 9% from deforestation and other use of land and 4% comes from some industrial processes such as cement manufacturing. The prediction of CO_2 emissions from fossil consumptions has motivated the current research as fossil fuels are produced from oil and gas industries.

Net-zero carbon emissions refers to carbon neutrality, which describes the balancing of CO_2 emissions in the environment. Net-zero or carbon emission balanced energy flow can be attained through on-site renewable energy generation by applying energy conservation measures (Wills *et al*., 2021). In reaching net-zero, the carbon footprint and energy consumption of industrial, commercials and residential buildings are to be minimized. Net-zero carbon emissions indicates that carbon emissions and their removals from the atmosphere should be equalized.

The amount of carbon emission is different in each country. The energy consumption and CO_2 emissions show an increasing trend yearly in 2025 in Iran (Mirzaei & Bekri, 2017). As early as in 2009, China became the world's major CO_2 emitter (C. Zhang & Zhou, 2016). The contributing factor may impact the carbon emissions trend in each country. According to Mardani *et al*., (2020), the most efficient approach for studying the interrelationships among CO_2 emissions, economic growth and energy consumption is using Machine Learning.

Machine Learning (ML) is one of the most technical fields that sits at the intersection of statistics and computer science and lies at the core of data science and artificial intelligence. ML and artificial intelligence are widely used nowadays, and it is proven to be powerful tools in technology and data analysis (Shalaby *et al*., 2021). ML is about training computers to produce results without explicit programming. ML is the foundation for artificial intelligence, and it is the ways we 'teach' a computer model to make prediction and draw conclusions from data.

The presence of a carbon emission predictive model based on ML techniques has been very appealing to researchers. The most used ML algorithm to develop a predictive model in carbon emission prediction is the Neural Network and Support Vector Machine (SVM). In predicting the CO_2 emissions in industries and residential consumption, SVM provides the required evidence to a policy on CO_2 emissions reduction (Sun & Liu, 2016). Mardani *et al.* (2020) stated that combining Adaptive Neuro-Fuzzy Inference System (ANFIS), Artificial Neural Network (ANN), Self-Organizing Maps (SOM) and Singular Value Decomposition (SVD) techniques, provides a better result in predicting CO_2 emissions. In serving different types of applications models, a wide range of neural network architectures are presented, and Artificial Neural Network (ANN) works in a typical feed-forward model comprising an input layer, hidden layers, and finally an output layer (Shalaby *et al*., 2021).

Sajid, M. J. (2020) specified that predicting non-linear relations is much sturdy with artificial neural networks. In forecasting CO_2 emissions, Wen & Yuan (2020) detailed that the Back Propagation of Neural Network (BPNN) is better than SVM and the Random Forest (RF). Furthermore, Chiroma, H (2015) also stated that the accuracy is improved with speed for predicting the Organization of the Petroleum Exporting Countries (OPEC) CO_2 emissions built on ANN. With the prosperities of artificial intelligent techniques and their propositions, traditional neural networks offer a new means of CO_2 emission prediction (Sun & Sun, 2017). The Least Square SVM analysis model is the best structure to determine the prediction result as a normal distribution (Daryayehsalameh *et al*., 2021; Saleh *et al*., 2016).

Ehteram *et al*., 2021 also confirms that SVM with seagull optimization algorithm outperforms ANN. However, they used ANN with one hidden layer and one output layer which is not sufficient to conclude ANN's effectiveness. In this study, ANN with 5, 10 and 15 hidden layers are used to compare the models. Ma *et al*., 2021 who proposed Gaussian process regression method for CO_2 emissions analysis in China did not make a comparison with another ML algorithm.

This paper aims on predicting the CO_2 emissions with various ML algorithm and the algorithm assessment is based on error rate measurements. The methods are Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). These are some of the error rate measurements used to observe the performance of the ML methods in prediction the carbon dioxide emissions.

II. METHODOLOGY

In this study, the prediction model performance in terms of different learning strategies is observed. The selection of worldwide countries is uncommon based on the previous studies. Qiao *et al.* (2021) used the same dataset source to forecast CO_2 emissions in APEC countries. Benalcazar *et al*., (2017) used the dataset from the same source as this study to study the coal consumptions and not the overall fossil fuels. There is a need to accurately predict the CO_2 emissions worldwide to reduce the global warming impact. The use of ML techniques in carbon emissions predictions that focuses on

overall worldwide countries is still lacking. The more prediction of CO_2 emissions, the better and accurate decision on reducing of CO_2 emissions can be engaged.

Three chosen ML algorithm for this study are Random Forest (RF), Support Vector Machine (SVM) and Artificial Neural Network (ANN). SVM algorithm has obvious advantages for model refinement with small data samples and high dimensionality (Chen *et al.*, 2021). The RF not only unite the classification and regression tree together, based on decision tree, but also welcomed by researchers in virtue of the characteristic of fast calculation speed and the ability of measuring the importance of variables in ML approach (Wei *et al*., 2018). Shalaby *et al*., (2021), concludes that ANN model gives the best results in terms of prediction performance compared to the other models where the accuracy was never below 98% and is the most recommended model to be used for predictions.

The evaluation and selection of the model uses three error rate performance measurement which are Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). In measuring a good forecast accuracy, MAE is a good KPI. It provides the measure of how far the predictions were from the actual output. RMSE is also defined as the square root of the average squared error measure of how spread out the residuals are from the regression line data points. In other words, it tells you how concentrated the data is around the line of best fit (Statistics How To, 2022a). MAPE provides the mean of the absolute percentage errors of prediction. MAPE promotes high weight to forecast errors when the demand is low. It measures the accuracy as a percentage and can be calculated as the average absolute percent error for each time period minus actual values divided by actual values (Statistics How To, 2022b).

Random Forest (RF) predictive model is developed in Alteryx Designer with several parameters such as target variable selection, predictor variable selection, number of trees to use for the model and specific number of variables to select between at each split (Forest Model Tool, 2021). The target variable for RF predictive model development for this study is CO_2 emissions and the predictive variables are all other variables.

RF is known as an ensemble supervised learning method based on decision tree where it can unite the classification and regression tree together through bagging algorithm (Wei *et al*., 2018). In RF, the number of estimators is an important parameter to control overfitting. The number of estimators represents the maximum deepness or number of trees that can be produced in the model. In previous study in predicting diffusivities in supercritical CO_2 systems, Aniceto *et al.* (2021) applied 5, 10, 15, 20, 30, 50, 100 and 150 as the number of estimators. Whereas Merchante *et al*., (2021) used 50 repetitions.

In this study, the number of trees used, and compared are 50, 100 and 150, representing small, medium, and large trees. In Alteryx Designer all other parameters are set to default value where the minimum five number of records allowed in a tree node, and 100% records used to create each tree. The model was built and fitted using the train set and evaluated using the test set. Each model is evaluated individually.

Support Vector Machine (SVM) predictive model is developed in Alteryx Designer with several parameters which are the target fields, predictor fields and the method of prediction either classification or regression (Support Vector Machine Tool, 2021). The target variable for SVM predictive model development for this study is CO_2 emissions and the predictive variables are the oil consumption, coal consumption and the gas consumption. Since the target variables are numeric type, regression is selected as the method of prediction. SVM is a popular ML tool for classification and regression (MathWorks, 2022).

SVM transforms the input space into high-dimensional spaces by using non-linear transformation defined in inner product and solves the generalized optimal classified plane (Sun & Liu, 2016). The selection of kernel functions is a key issue of SVM models, where different kernel functions lead to different generalization and learning ability of prediction models (W. Qiao *et al*., 2020). W. Qiao *et al.* (2020) further states that commonly used kernel functions are polynomial kernel function, linear kernel function, Sigmoid kernel function, and Radial Basis function (RBF). In previous studies, Khairalla *et al*., (2018) uses polynomial kernel function with C equals to 1, 2 exponents and 0.0001 epsilon. Chen *et al*., (2021) states that the prediction models based on RBF and Polynomial kernel are the ones with high accuracy.

Thus, in this study, four different kernel functions are compared. The kernel functions are polynomial kernel function, RBF, linear and sigmoid as the options available in Alteryx Designer. The Alteryx Machine tuned parameters is selected to provide a range of parameters and computationally find the best parameters by searching a grid of possible values (Support Vector Machine Tool, 2021). The epsilon regression is used for all SVM model since the data are numerical. The range that has been set for the parameters for RBF is 1.0000 for the value of gamma.

Artificial Neural Network (ANN) predictive model is developed in Alteryx Designer with several parameters which are the target variable, predictor variables, and number of nodes in hidden layer (Neural Network Tool, 2021). The target variable for ANN predictive model development for this study is CO_2 emissions and the predictive variables are all other variables.

ANN is a highly interconnected network, generally consisting of an input layer, one or more hidden layers, and an output layer (Benalcazar *et al*., 2017). The ANN approaches often have an input layer, one or more hidden layer(s), and an output layer (Daryayehsalameh *et al*., 2021). In previous studies, Sun & Liu, (2016) uses two hidden layers. Whereas Shalaby *et al*., (2021), states that the hidden layer network with five neurons was able to give good predictions of the process outputs. Sajid, (2020), uses three hidden layers for his model.

Too few hidden neurons can cause underfitting and high statistical bias, where too many hidden neurons can result in overfitting (Tool Mastery Neural Network, 2021). In this study three different neural network structures are compared. The first with five hidden layers, the second with ten hidden layers and the third with 15 hidden layers.

A. Datasets

The sample dataset is from an oil and gas industry, annual figures collected from 1965 to 2020, based on Default CO_2 Emissions Factors for Combustion listed by the Intergovernmental Panel on Climate Change (IPCC) in its Guidelines for National Greenhouse Gas Inventories (2006).

There are lists of 92 countries. These countries are categorized into six continents with the total CO_2 emissions for each continent. The data includes the sum of all the countries as total world. The data also includes a summation for European Union countries, Commonwealth of Independent States (CIS), Organisation for Economic Co-operation and Development (OECD) and non-OECD countries. The data sums to a total of 57 columns and 103 rows of data in each dataset for oil consumptions, gas consumptions, coal consumptions and CO_2 emissions. To ease the integration of all datasets, an individual data cleaning was required. The unwanted and empty rows from the excel file were removed. The columns were renamed to differentiate the data and to select data from year 1991 until 2020 for integration. Therefore, to achieve this, individual dataset underwent some pre-processing to ensure common rows and columns for integration.

In this study, the train-test split ratio was 80:20, with 80% for the train set and 20% for the test set which follows the pareto principle. According to Pareto Principle, the general point is that 80% of the effects come from 20% of causes in most cases (Towards Data Science, 2020). The training set was used for learning and fitting the model, and the testing set was used to evaluate the fitted model after learning (Aniceto *et al*., 2021). The dataset was split into estimation and validation (train-test) set with 80% train set and 20% test set (80:20) proportion using "create samples tool" in Alteryx.

III. FINDINGS

The comparison between three different ML model performance with different parameters based on MAE, RMSE and MAPE are discussed in this section. Comparison is made to select the best model for CO_2 emissions prediction implementation. The performance measurement of Random Forest (RF), Support Vector Machine (SVM) and Artificial Neural Network (ANN) are listed in Table 1.

TABLE 1. PERFORMANCE MEASUREMENT COMPARISON FOR THREE MODELS

	Train set (80%)			Test set (20%)		
Model	**MAE**	**RMSE**	**MAPE**	**MAE**	**RMSE**	**MAPE**
RF Number of trees = 50	1313.5293	1569.4603	4.7342%	188.1493	325.0368	0.5985%
RF Number of trees = 100	1260.5370	1543.8909	4.5248%	197.3158	315.6018	0.6359%
RF Number of trees = 150	1232.4405	1509.1776	4.4210%	208.2872	347.0192	0.6560%
SVM Kernel Function = Radial	4639.5454	5521.0283	18.8998 %	4627.9711	4799.4792	16.7314 %
SVM Kernel Function = Linear	65.7254	112.2196	0.2279%	22.0630	36.3161	0.0736%
SVM Kernel Function = Polynomial	225.5026	451.0808	0.7829%	402.8854	487.2585	1.3365%
SVM Kernel Function = Sigmoid	4639.5876	5521.0695	18.9000 %	4627.9974	4799.5070	16.7315 %
ANN Hidden Layers = 5	1999.6914	2845.9293	7.7849%	183.7025	266.9995	0.6319%
ANN Hidden Layers = 10	852.3918	1223.7027	3.1204%	241.0493	326.3034	0.7664%
ANN Hidden Layers = 15	1644.3127	2316.2464	6.4266%	802.5869	961.6670	2.6741%

An accurate prediction is the one with the lowest error rate for MAE and RMSE (Saleh *et al*., 2016). Whereas, for MAPE the highest percentage of error rate is the accurate prediction. Looking into the number of trees comparison in RF model, the predictive model utilizing 150 number of trees fitted the model better for train set data which produced lower error measurement compared to the model utilizing 50 and 100 number of trees. However, for test set, predictive model utilizing 50 number of trees fitted the model better. The predictive model utilizing 150 number of trees achieve highest performance for train set, with 1509.1776 for RMSE, 1232.4405 for MAE, and 4.421% for MAPE for the train set. As for the test set, the highest performance predictive model is the model utilizing 50 number of trees, where the RMSE value is 325.0368, for MAE is 188.1493, and 0.5985% for MAPE for the best performance accuracy.

Table 1 also shows the comparison between using four different parameters on the SVM models. For the train set, the smallest error measurement with linear kernel function SVM model. In the kernel functions comparison, the predictive model utilizing linear kernel function fitted the model better and produced the lowest error measurement compared to the model utilizing polynomial, radial and sigmoid kernel functions. It reveals that linear kernel function fits the model and reduces the biasness. The predictive model utilizing linear kernel functions achieved both highest performance for train and test set, with 36.3161 for RMSE, 22.0630 for MAE, and 0.0736 for MAPE for the test set and for the train set, the RMSE value is 112.2196, MAE is 65.7254, and 0.2279% for MAPE for the best performance accuracy.

Finally, the comparison among ANN models using three different hidden layers was also shown in Table 1 above. From the table, it is observed that as the number of hidden layers increases, the value of RMSE increases as well. This indicates that the model performance is reduced with higher hidden layers. ANN model with five hidden layers performs better compared to 10 and 15 hidden layers. This is in line with what Shalaby *et al*., (2021) has stated, that the hidden layer network with 5 neurons was able to give good predictions of the process outputs. However, for the train set, ANN with 10 hidden layers performs better. The ANN with 5 hidden layers produces RMSE of 266.9995, MAE of 183.7025 and MAPE of 0.6319 for test set. The ANN with 10 hidden layers produces RMSE of 1223.7027, MAE of 852.3918 and MAPE of 3.1204% for train set.

By comparing all three algorithms, RF, SVM and ANN, the SVM model with parameters of linear kernel function is the most suitable model for predicting CO_2 emissions. The SVM with linear kernel function model fitted in both train and test set validation produces the lowest performance error.

IV. MODEL IMPLEMENTATION

The best ML predictive model for CO_2 emissions has been selected as SVM with linear kernel function. This section explains the process and results using the selected predictive model to predict the test set (20% from total records) of CO_2 emissions. Overall, comparing all three algorithms, RF, SVM and ANN, the SVM model with parameters of linear kernel function is the most suitable model for predicting CO_2 emissions. The SVM with linear kernel function model fitted in both train and test set validation produces the lowest performance error. The test set consists of 24 CO_2 emissions data. Fig. 1 shows the Alteryx Designer workflow to execute the process which involves several steps.

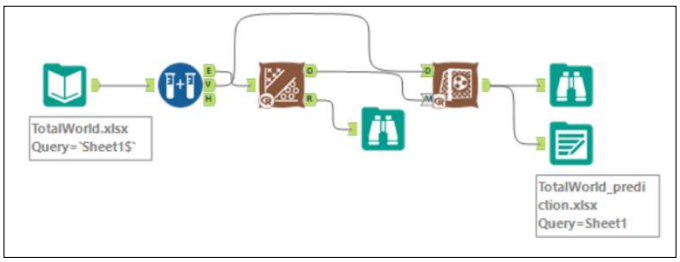

Fig. 1. Alteryx workflow for SVM with Linear Kernel Function

In the workflow, the SVM model with Linear Kernel Function is trained and the test set was produced. The workflow starts with inputting the data in canvas and is split into train and test set with 80:20 proportion. Then, "score tool" is used to predict the test set.

The model development starts by importing the original integrated excel file dataset of 'TotalWorld' as used to derive the data in Table 1, into the canvas using the "input tool". Then, the dataset is split into estimation and validation (train-test) set with 80% train set and 20% test set (80:20) proportion using "create samples tool". Lastly, the score is extracted into excel worksheet.

V. VISUALIZATION

CO_2 emissions prediction result produced by Alteryx workflow in Fig. 1 is plotted in Microsoft Excel to illustrate the prediction descriptive analysis and compare the test set. The actual and predicted CO_2 emissions' scatterplot is shown in Fig. 2. The scatterplot shows a linear trend between actual and predicted CO_2 emissions indicating the SVM linear kernel function performs well. However, since R^2 equals to 0.999979 and can be said that it is equals to one, there is not much differences between the actual and predicted CO_2 emissions.

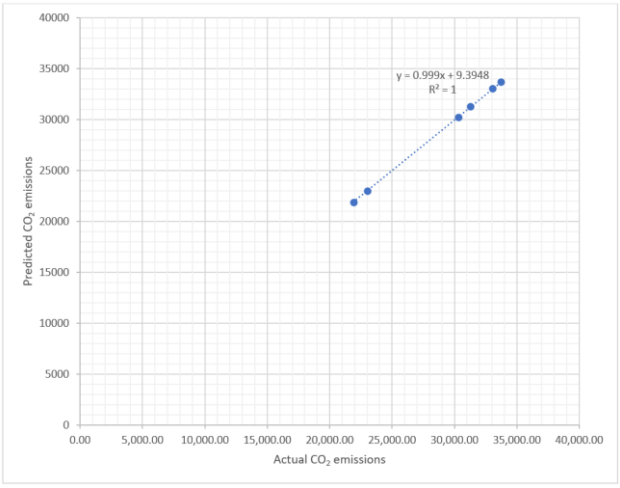

Fig. 2. Actual vs predicted CO_2 emissions

Fig, 3 is a column chart which shows comparison of average CO_2 emissions between actual and predicted CO_2 emissions worldwide. The average actual CO2 emissions is 28,894 million tonnes of CO_2 emissions and the average predicted CO_2 emissions is 28,874 million tonnes. Comparing both the values, the average predicted CO_2 emissions is slightly lower. Thus, this indicates the model tends to predict lower emissions than the actual emissions.

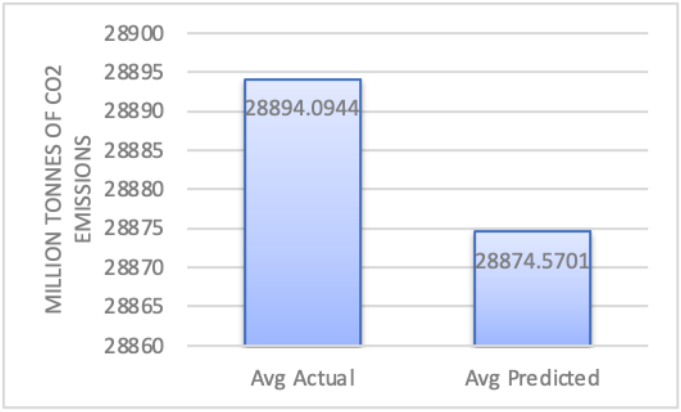

Fig. 3 Average actual and predicted

In summary, SVM with linear kernel functions model tend to predict slightly lower CO_2 emissions than the actual. Although prediction using SVM is not able to give results as accurate as the actual CO_2 emissions, the result is 99.9979% accurate. Therefore, the difference between the actual CO_2 emissions and CO_2 emissions is very small and it indicates an insignificant prediction error produced by the predictive model. This concludes that the SVM with linear kernel function prediction model is substantial to be used for CO_2 emissions prediction worldwide.

VI. CONCLUSION

Statistics regarding increasing CO_2 emissions and the danger to human and earth is shocking and worrying. CO_2 emissions are critical to be monitored since it is one of the leading causes of natural disaster and diseases to human. Further, in achieving net zero by 2050, the consumption of fossil fuels, especially coal in China and oil in major carbon emitting countries are to be reduced. This process has resulted in SVM with linear kernel function model to be selected as the best model among the others. The evaluation using MAE, RMSE and MAPE indicates that SVM with linear kernel function outperforms the other models. Thus, this study proposed SVM as the best ML model among Random Forest (RF), Support Vector Machine (SVM) and Artificial Neural Network (ANN) in evaluating the contributing factors in the increase of carbon dioxide emissions. The study to evaluate the ML model for carbon dioxide emissions for different based on Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) is achieved. SVM with linear kernel function model can be used to predict the CO_2 emissions with the fossil fuels consumptions over the years. Oil and gas industries should increase their effort in attaining vast use of renewable energy as an alternative to fossil fuels the soonest in order to achieve net zero by 2050.

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