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Machine Learning approach in Electric Motor Torque Prediction via state-of-the-art algorithms: LGBM + EDA

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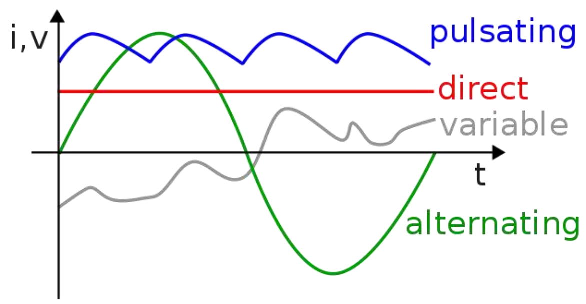
Abstract: *An electric motor converts electrical energy into mechanical energy to create a mechanical force called torque and spin the motor. An electric motor with great performance and efficiency will be used in various machinery, including electric vehicles, robots, and unmanned aerial vehicles. Carbon emission vehicles are going to be superseded by electric and fuel cell vehicles in order to remove greenhouse gases that cause climate change. Robots and drones (unmanned aerial vehicles) are important in society to assist or replace human labor to perform harsh work, especially industrial, military, medicine, space, search and rescue, transportation, agriculture, and domestic appliances. High speeds, high torque, and great efficiency of motors for battery savings are very important for their great performance achieved by using machine learning algorithms to predict the data of the torque from their emerging components. The Light Gradient Boosted Machine regression model is least likely to have any errors with the lowest mean absolute error 0.5419 and root mean square error 1.0567 out of all machine learning models. An electric current from the 'q' component provides greater torque than all other components in the data feature importance score; speed and torque are generated by regulating a supply of a more active current and voltage. This will result in more advanced machinery that serves individuals and society in a variety of ways, such as robots with high torque to service their activities in a variety of applications and driving drone propellers at high speeds to keep them running smoothly.*

Introduction

Background

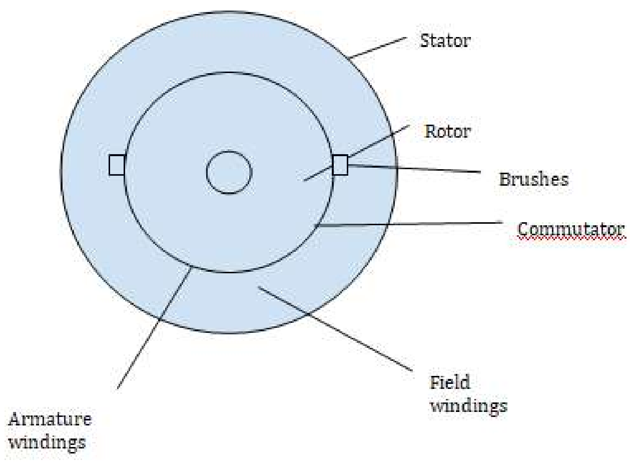
An electric motor is an electric machine that converts electrical energy into mechanical energy. An electric current transporting in a loop of wire present in a magnetic field creates a mechanical force and this force creates torque and spins the motor[1].

Two types of electric currents, direct current (DC) and alternating current (AC) are applied in motors. DC motors are powered by a direct current that flows only in one direction with a constant voltage and is generated from batteries and commutators. AC motors are powered by an alternating current that periodically changes its flow of charge and its voltage and is generated from alternators to power home applications[2].



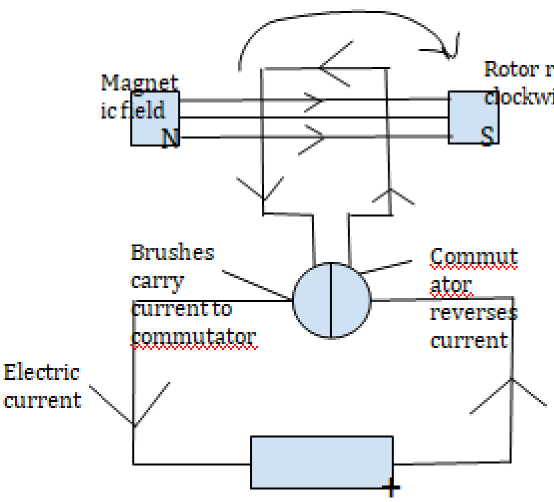
<Figure 1> Direct and Alternating current

Parts of the motor include a stator, a rotor, a commutator, armature and field windings, and brushes. A stator is the stationary magnetic part of the motor. A rotor is a rotating axle with a mounted coil inside of the stator. A commutator is the copper ring around the rotor that delivers electric current to armature windings. Armature windings are copper wires around the rotor to energize its static magnetic field. Field windings are copper wires in the stator to energize its static magnetic field. Brushes are carbon components between the commutator and the rotor that deliver electrical energy from the circuit to the rotor[3].

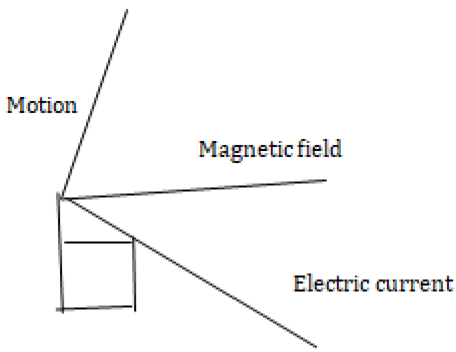


<Figure 2> Parts of an electric motor

According to Fleming's left-hand rule, as the electric current flows from the positive to the negative terminal of the battery, the magnetic field flows from the North to the South pole, and the wire moves in the opposite direction of the flowing current. In the motor, the electric current from the battery flows into brushes and it is transported to the commutator. And then, the coil rotates continuously in the same direction. To increase the torque of the motor, the permanent magnet must be more powerful, the electric current must be increased, or the rotor coil must have more loops of wire. Motors are used in a wide range of applications, such as home and industrial appliances, electric vehicles, and unmanned aerial vehicles[4].



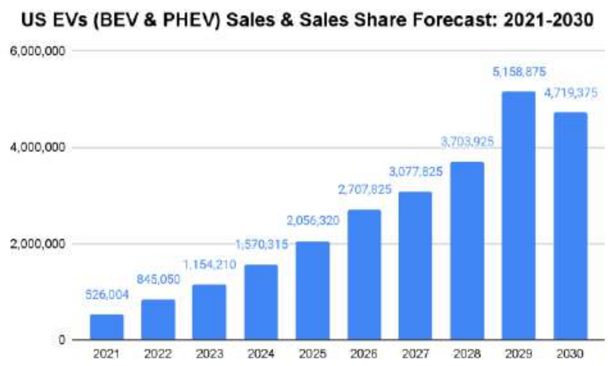
<Figure 3> Electric motor operation



<Figure 4> Fleming's left-hand rule

Objective

This research is to build electric motors with great performance and efficiency, so these will be used in electric vehicles and drones. Electric vehicles are very important vehicles in modern society because these vehicles emit no greenhouse gases, unlike internal combustion vehicles. Electric motors are primarily engines powered by batteries, solar panels, and fuel cells for electric vehicles. Drones (Unmanned aerial vehicles) are also very important for various areas, such as military, law enforcement, search and rescue, shipping and delivery, transportation, and agriculture. Four motors in a drone drive propellers in order to fly in the air. In order to make a great performance, motors must have high speeds, high torque, and great efficiency for battery savings. Therefore, this research is to make better performance by predicting the torque. Furthermore, the graph below, shows that EVs sales and sales share will increase gradually till 2030 and the number of sales in 2030 would be about nine times higher than in 2021, which means that research about electric vehicles is vital for the upcoming future[5].



<Figure 5> US EVs Sales & Sales Share Forecast from 2021 to 2030

Related Works

Mukherjee et al. tried to model the best prediction for the speed and the torque of the permanent magnet synchronous motor, one of two types of AC motors along with an induction motor through using various machine learning models. In this disquisition, a system dataset consisting of direct and quadrature axis voltage and current, and frame, rotor, and stator temperature, and a coupla generated synthetic data using multivariate distributional marginal and respective density functions. Machine learning is deployed in the domain of the motor, creating a film tree-based regression model with large feature space-based datasets to provide better data forecasting than statistical forecasting methodologies. Related to the optimization results obtained from the machine learning algorithms, the top three regression models on the basis of root-mean-square-error value display two conditions: speed and torque of the permanent magnet synchronous motor[6].

Another research is to measure the temperature of windings and enclosures, the rotational speed, and the current of brushless DC motors. This measurement has a purpose to find out that the higher motor temperatures cause its parts' damages. From the percentage survey of individual failures in induction motors, more than 40% of failures are caused by bearing failures and 38% are stator problems. In this subject, an independent variable of a graph system is the time and its dependent variables are winding and enclosure temperature, rotational speed, and current. Machine learning algorithms for regression predict the value of the target variable based on features and then modify its own linear regression model structure to minimize errors. The maximum accuracy of the model is achieved through hyperparameter tuning with parameters that influence the algorithm behavior and are not optimized in the learning process. The evaluation of the motor winding temperature efficiency was carried out on the basis of root mean squared error, mean absolute percentage error, and coefficient of determination[7].

More research is to estimate the temperature of windings, stator, rotor, and exterior of the permanent magnet synchronous motor through various temperature estimating techniques. Lumped parameter thermal networks are circuit diagrams of inner heat transfer based on thermodynamic theory and incorporating experimentally measured data. Recurrent and convolutional neural networks model architectures in various domains and sequence learning tasks. Temporal convolutional networks inherit advances in applications on sequential data but are distilled to a simpler form. In the result data, the found optimal for recurrent neural networks and temporal convolutional networks achieve a state of architecture on the task of estimating temperature for the stator and the rotor[8].

Additional research is to estimate the torque of an induction motor throughout the multi-motor drive system with the mechanical power provided by several motors. Supervised machine learning in the data estimates the flux and the torque and the artificial neural network utilizes the voltage, current, and speed data. A hybrid machine learning observer is presented to estimate torque with the stator voltage and the current as of the domain. A basic observer based on the current model in rotor flux components is utilized for comparisons. For the operating result, the nominal torque is linked to 1% of a root mean square torque estimation error. In the comparison, the magnetic flux with a standard open-loop current model resulted in 4.6% of a root mean square torque error[9].

Materials and Methodologies

Data Description

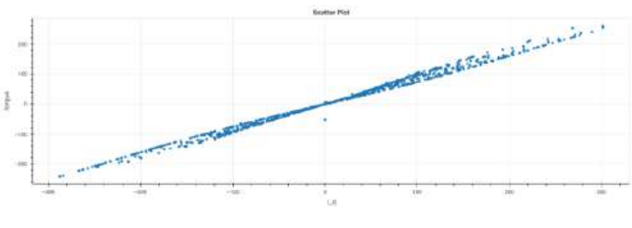
The data set is collected from the Kaggle website, whose address is https://www.kaggle.com/wkirgsn/electric-motor-temperature[10]. It was recorded at 2 Hz and consists of multiple measurements that are able to be recognized from each other by column "profile_id" between one and six hours long. The motor turns with a high power by driving cycles indicating a reference motor speed and torque. Currents and voltage from i_d and i_q and u_d and u_q coordinates are results from a standard strategy of controlling speed and torque. This strategy derives from set currents and voltages to speed and torque. Most driving cycles are random walks in the speed-torque-plane in order to imitate a more accurate degree than constant excitations and ramp-ups and downs[8].

	u_q	coolant	stator_winding	u_d	stator_tooth	motor_speed	i_d	i_q	pm	stator_yoke	ambient	torque	profile_id
0	-0.450682	18.805172	19.086670	-0.350055	18.293219	0.002866	0.004419	0.000328	24.554214	18.316547	19.850691	0.187101	17
1	-0.325737	18.818571	19.092390	-0.305803	18.294807	0.000257	0.000606	-0.000785	24.538078	18.314955	19.850672	0.245417	17
2	-0.440864	18.828770	19.089380	-0.372503	18.294094	0.002355	0.001290	0.000386	24.544693	18.326307	19.850657	0.176615	17
3	-0.327026	18.835567	19.083031	-0.316199	18.292542	0.006105	0.000026	0.002046	24.554018	18.330833	19.850647	0.238303	17
4	-0.471150	18.857033	19.082525	-0.332272	18.291428	0.003133	-0.064317	0.037184	24.565307	18.326662	19.850639	0.208197	17
5	-0.538973	18.901548	19.077168	0.009147	18.290628	0.000636	-0.613635	0.336747	24.573601	18.323682	19.850634	0.476218	17
6	-0.653148	18.941711	19.076583	0.238890	18.292524	0.001337	-1.005647	0.554211	24.576578	18.321938	19.850630	0.670015	17
7	-0.758392	18.960861	19.082499	0.395099	18.294041	0.001422	-1.288384	0.706370	24.574949	18.314655	19.850628	0.782036	17
8	-0.727128	18.973546	19.085533	0.546623	18.291064	0.000577	-1.490530	0.817339	24.587080	18.308925	19.850626	0.816541	17
9	-0.874307	18.987812	19.076025	0.578944	18.287233	-0.001248	-1.634055	0.898013	24.553242	18.301733	19.850624	0.926010	17

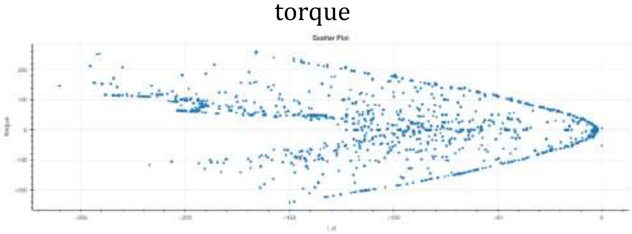
<Figure 6> Overall contents from the dataset

Exploratory Data Analysis

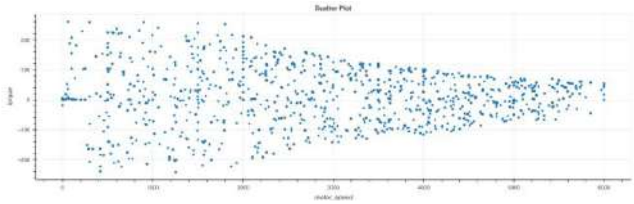
With the torque as the y-axis and comparing it to other variables with a scatter plot, the positive relation of i_q appears, while i_d, motor speed, u_d, and stator tooth do not yield a clear correlation with torque. From this result, it can be inferred that i_q would be the most influential feature in the dataset.



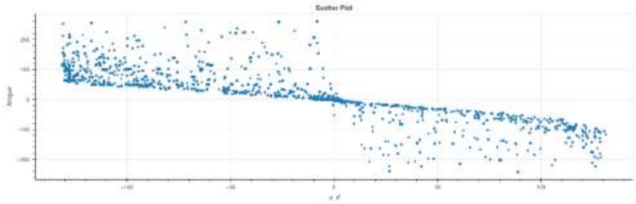
<Figure 7> Graph of relationship between i_q and torque



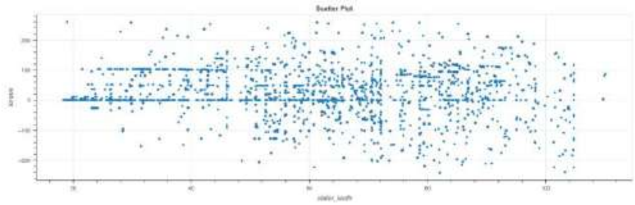
<Figure 8> Graph of relationship between i_d and torque



<Figure 9> Graph of relationship between motor_speed and torque

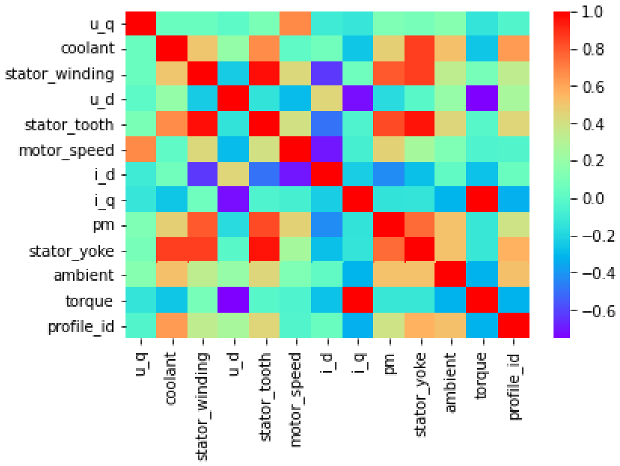


<Figure 10> Graph of relationship between u_d and torque



<Figure 11> Graph of relationship between stator tooth and torque

This figure below shows the correlation between the torque and various variables. The correlation is high when the spectrum color of the relationship between them is red and it is low when its color is violet. In the column of the torque, the u_d has the lowest negative correlation since its color is purple and the i_q is the highest positive correlation since its color red.



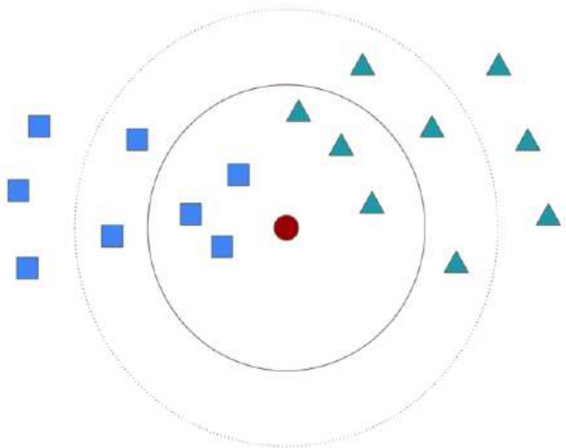
<Figure 12> Heatmap of correlation coefficients between the features

K-Nearest Neighbors

K-nearest neighbors(KNN) belong to the supervised learning of the machine learning field, and they can be used for both classification and regression. As the name suggests, KNN utilizes the K number of neighbors for the prediction. For a particular training data input x, K observations with x_i in close vicinity are considered, and the average of the responses of those K independent variables yields $\hat{y}$ [11]. In order to determine the nearest neighbors through two methods, which are Euclidean distance, and Manhattan distance. The Euclidean distance may be thought of as a straight line between two places. Manhattan distance, on the other hand, is the distance between two sites while going solely at a right angle instead of a diagonal line[12]. However, Jiang et al. suggested three major drawbacks of the KNN algorithm: 1) Using a standard Euclidean distance as a measuring, 2) Arbitrarily assigning neighborhood size as a model parameter, 3) Utilizing simple majority voting for the class probability estimation[13].

Light Gradient Boosting Machine

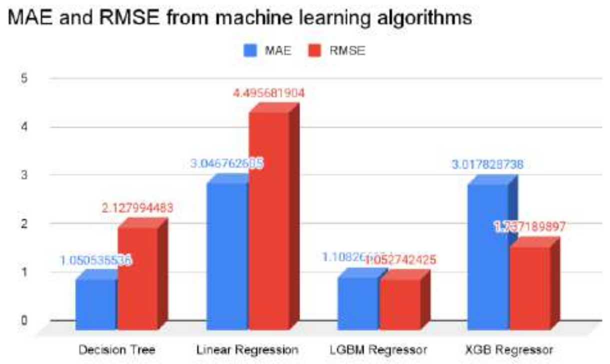
Because of its great performance and speed, the light gradient boosting machine (LGBM), which belongs to supervised learning in the machine learning sector, has been widely employed. LGBM is a cutting-edge algorithm that evolved from prior boosting methods. The LGBM's most notable features are gradient-based one-side-sampling (GOSS) and proprietary feature bundling (EFB). Both strive to reduce computation speed and memory utilization while maintaining good performance. GOSS's job is to delete data points with low gradients, while EFB's purpose is to bundle mutually exclusive features in order to reduce the dataset's dimension. Furthermore, LGBM provides GPU training, which has the potential to significantly reduce calculation time[14].



<Figure 13> Overall architecture of the K-Nearest Neighbors algorithm

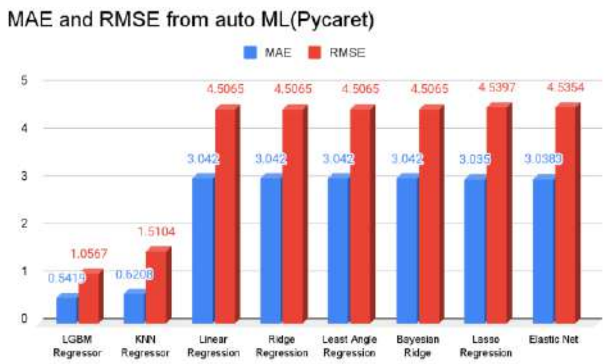
Result

In the graph below, the value of the mean absolute error from the decision tree model is 1.05 and the value of the root mean square error is 2.13. The linear regression model shows 3.05 of the mean absolute error and 4.5 of the root mean square error. 1.11 of the mean absolute error and 1.05 of the root mean square error appear from the LGBM regressor model, and 3.02 of the mean absolute error and 1.74 of the root mean square error is shown in the XGB regressor model.



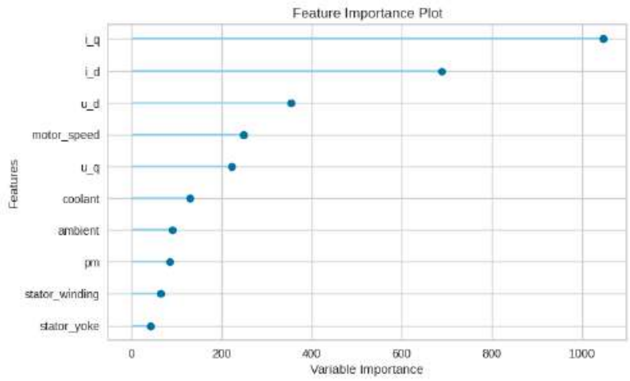
<Figure 14> MAE and RMSE from machine learning algorithms

In this graph below, the value of the mean absolute error from the LGBM regressor model is 0.54 and the value of the root mean square error is 1.06. The KNN regressor model shows 0.62 of the mean absolute error and 1.51 of the root mean square error. 3.04 of the mean absolute error and 4.51 of the root mean square error appeared from linear regression, ridge regression, least angle regression, and Bayesian ridge models. 3.04 of the mean absolute error and 4.54 of the root mean square error occurred in the lasso regression and elastic net models.



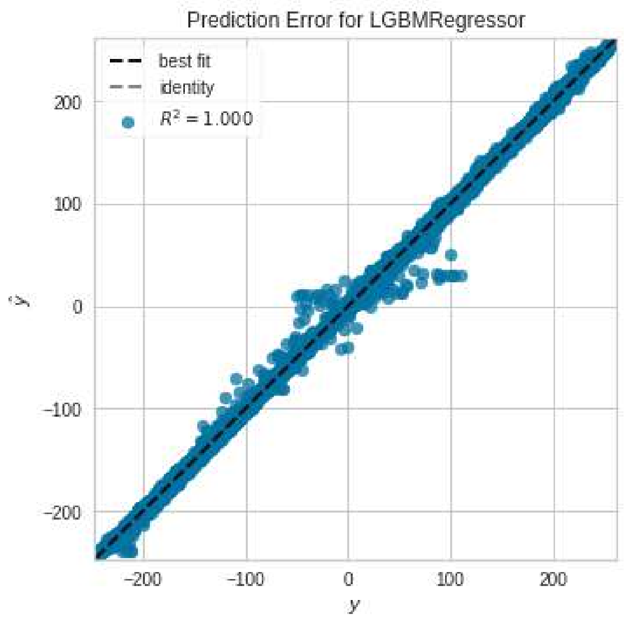
<Figure 15> MAE and RMSE from machine learning algorithms(Pycaret)

In the feature importance plot below, the row of i_q has the highest variable importance. It reveals which variable has the most impact on the accuracy of the LGBM regressor. The row of i_d has the second-highest importance and the row of u_d has the third-highest importance. The motor speed has the fourth-highest importance and the row of u_q has the fifth-highest importance. The least important row is the stator yoke. The second least important row is the stator winding and the third least important row is pm. The fourth least important row is ambient and the fifth least important row is coolant.



<Figure 16> Visualizing feature importance from LGBM

The axis of y represents the prediction value and the axis of x shows the real value of the torque, and these values are quite similar. And also, the value of R^2 is 1.00, which analyzes that this LGBM regression model below has a high correlation with the data.



<Figure 17> Visualizing prediction error from LGBM

Discussion

The major research of this paper is to predict the torque via various machine learning algorithms, since an exact torque predicts more accurate and efficient control of the motor, reducing power losses, and high temperature. The LGBM regression revealed 0.5419 of MAE and 1.0567 of RMSE. EDA via data visualization and correlation matrix of heatmap was conducted in order to scrutinize the patterns between multiple columns, and there exists a positive relationship between i_q and torque columns. Furthermore, the feature importance score was calculated and the result revealed that i_q has the highest one. I_q is an electric current at the q-component and it is the most important factor to torque throughout the data. It provides a more efficient current and voltage from this current to control the speed and torque of the motor in various situations. This research would be beneficial to create motors for electric vehicles that would replace all internal combustion fuel vehicles, which are harmful to the environment. For further research, this experimental result would be applied to implementing robotics technologies since all of these are driven by motors.

Limitations

The major limitation of this research is having no experimental data through the physical testing of motors with its actual electrical components because the whole data set comprises the regression analysis of several components from a permanent magnet synchronous motor.

For further research in the future, I'm going to apply this proposed model to different types of motors and their features in order to examine their great performance for battery savings.

Conclusion

The purpose of this report is to use machine learning algorithms to create data of the torque from emerging components of an electric motor that predicts the highest and lowest values from these components. The Light Gradient Boosted Machine (LGBM) regressor model has the lowest mean absolute error (MAE) 0.5419, and root mean square error(RMSE) 1.0567, out of all of these machine learning models, which means it has the least chance to get errors. An electric current from the 'q' component provides the highest torque out of all components from the data feature importance score; controlling the speed and torque of the motor with a supply of a more effective current and voltage. This result would improve various machinery to operate them without any malfunctions and provide the people and the social benefits in various ways, such as switching fossil fuel-powered cars into electric and fuel cell vehicles, driving propellers of drones with high speeds, and performing robots with high torque to perform their actions in industrial and other applications.

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