Convolutional Neural Network Enactment Layer based Ambient Temperature Prediction of Electric Motor

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Abstract: As we know that Plan temperature evaluations apply to the most smoking spot inside the motor's windings, not how much of that warm is exchanged to the motor's surface. The warm exchange will change incredibly from engine to engine based on outline measure and mass, whether the outline is smooth or ribbed, whether open or completely encased, and other cooling variables. Indeed the productivity of the engine may have small impact on the surface temperature. An exact torque assess leads to more exact and satisfactory control of the engine, diminishing control misfortunes and in the long run heat build-up. In this venture, the machine learning strategies were utilized for the expectation of surrounding temperature of Electric engine. The forecast of ambient temperature of Electric engine are accomplished in four ways. With this context, we have utilized Electric motor temperature dataset extracted from UCI Machine Learning repository for predicting the ambient temperature prediction. The forecasting of ambient temperature are achieved in four ways. Firstly, the data set is preprocessed with Feature Scaling and missing values. Secondly, empirical feature examination is done and the relation of motor speed and ambient temperature of the motor is visualized. Thirdly, the fresh data set is fitted to all the regressors and the execution is dismembered before and after scaling. Fourth, the raw data set is subjected to Convolutional neural network Conv1D with various activation layers like Relu, Sigmoid, softmax, Softplus, Softsign, Tanh, Selu, Elu and exponential layers. The performance is analyzed with EVS, MAE, MSE, RScore and Step loss of the Convolutional neural network. The execution is done using python language under Spyder platform with Anaconda Navigator. Experimental results shows that the Conv1D-Softsign activation layer tends to reach the RScore of 99.842 with the step loss of 0.0001155.

Keywords: Machine learning, feature scaling, neural network, activation layer, step loss

1. Introduction

The foremost curiously target highlights are rotor temperature ("pm"), stator temperatures ("stator_*") and torque. Particularly rotor temperature and torque are not dependably and financially quantifiable in a commercial vehicle. Being able to have solid estimators for the rotor temperature makes a difference the car industry to fabricate engines with less fabric and empowers control methodologies to utilize the engine to its greatest capability. A premium-efficiency engine, in spite of the fact that its inner temperature will be cooler as a result of lower misfortunes, may not have lower surface temperatures, since the ventilation fan will likely be littler to diminish windage misfortunes. Motor's surface isn't the way to judge working temperature, a motor's winding temperature is critical. The concern, of course, is for the astuteness of the engine stator's separator framework. Its work is to partitioned electrical components from each other, avoiding brief circuits and, hence, winding burnout and disappointment.

2. Background

A dataset is considered having genuine time information of surrounding temperature, coolant temperature, coordinate pivot and quadrature hub voltage and current, burden temperature, rotor temperature and stator temperature for forecast of engine speed and torque. This dataset is collected from the test seat of College of Paderbon research facility. Different machine learning models have been connected on the dataset. The result appears that Fine Tree is the finest show for forecast of both speed and torque of the changeless magnet synchronous engine having most reduced RMSE of 0.029224 and 0.052538 for expectation of speed and torque individually [1]. Lifted temperatures constrain the top execution of frameworks since of visit mediations by warm throttling. Non-uniform warm states over framework hubs moreover cause execution variety inside apparently comparable hubs driving to significant debasement of in general execution. In this paper we display a system for making a lightweight warm prediction system reasonable for run-time administration choices. We seek after two roads to investigate optimized lightweight warm indicators. First, we utilize highlight choice calculations to progress the execution of already planned machine learning strategies. Moment, we develop elective strategies utilizing neural arrange and straight regression-based strategies to perform a comprehensive comparative study of expectation strategies [2]. The precise assessment and forecast of stator winding temperature is of incredible centrality to the security and unwavering quality of PMSMs. In arrange to ponder the impacting components of stator winding temperature and avoid engine cover maturing, separator burning, lasting magnet demagnetization and other deficiencies caused by tall stator winding temperature, we propose a computer show for PMSM temperature forecast. Surrounding temperature, coolant temperature, direct-axis voltage, quadrature-axis voltage, engine speed, torque, direct-axis current, quadrature-axis current, changeless magnet surface temperature, stator burden temperature, and stator tooth temperature are taken as the input, whereas the stator winding temperature is taken as the yield. A profound neural organize (DNN) show for PMSM temperature forecast was developed. The exploratory comes about appeared the forecast blunder (MAE) was 0.1515, the RMSE was 0.2368, the goodness of fit (R2) was 0.9439 and the goodness of fit [3].

Temperature expectation based on twofold input of three-dimensional shaping machine control system. Temperature criticism slack of three-dimensional shaping machine leads the protest adhere to the hot bed and shaping fabric stream issue in progress, the three-dimensional shaping machine control framework was analyzed, and put forward a kind of input control calculation of double temperature forecast based on slightest squares bolster vector machine (LSSVM) [4]. The essential thought of the present proposed warm circuit is to utilize as it were two warm resistances to show the electric motor: one proportionate to the full conduction and other for convection. It is vital to know a few previous data approximately a known stack condition and the comparing temperature rise within the winding. In this way, the number of input parameters is radically diminished and overcomes the challenges related to geometric and physical parameter determination. The validation of the warm circuit was done with the help of tests of two engines in numerous stack conditions. [5].

The encased nature of the LIM essential as well as the or maybe huge crevice between the LIM essential and the LIM auxiliary together disconnect the LIM essential from its auxiliary side so that the auxiliary warm does not influence the essential temperature. On brief trains indeed a single drive disappointment can fundamentally moderate the RT prepare and subsequently the whole framework. In such cases the prepare must be evacuated from benefit, but some time recently it is done, to anticipate system-wide plan delays, it is common to boost LIM current supplied from the impetus inverter to attain the execution of a "healthy". The expanded current definitely produces much more serious than typical warm cycling driving to higher temperatures of DC supply cables, line inductors and the footing engine. Beneath the circumstances it is of basic significance to absolutely track the temperature of those components to anticipate consequent warm disappointments and to supply legitimate criticism for the LIM controlling calculation [6]. The proposed method may be a third-order warm show which permits the expectation of three temperature spots. It comprises of warm resistances, warm capacitances, and warm sources. The warm resistances are related to the warm exchange between two spots and depend on the warm conductance of the materials and the length and zone of the components. The warm capacitances are related to the warm amassed and depend on the warm capacity of the components and their volumes. The particular meaning and values of the demonstrate parameters depend on the particular chosen spots. In our case, the chosen spots are the rotor bars, the stator winding, and the engine frame. The warm resistances are gotten from the steady-state operation. For this condition, the warm capacitances gotten to be open circuited, and the circuit show is diminished to the straightforward circuit [7].

This paper proposes a Standard IGBTs in a multilayer structure. The temperature changes of diverse materials with jumbled Coefficients of Warm Development (CTE) may cause a detachment within the contact regions and lead to disappointment of the IGBTs such as bond wire lift-off and patch layer weakness. This paper has displayed a strategy to foresee the lifetime of IGBTs amid a long-term driving cycle by considering numerous impact variables, such as the encompassing temperature, the driving cycle, and the debasement of warm resistance. At that point the impact components on lifetime forecast are talked about in detail to progress the precision of lifetime expectation [8]. This paper presents a demonstrate based strategy of anticipating the greatest control capability of a battery, to be utilized for real-time electric engine control inside car powertrains. As this is often profoundly subordinate on battery state, the strategy comprises of a pack level state eyewitness coupled with a expectation calculation based on a energetic battery show. Approval comes about appear that exact SoC estimation is gotten with this calculation, with SoC estimation mistakes beneath 3% for person cells. Reenactment thinks about appear the significance and potential of following the greatest and least SoC values in strings of arrangement associated cells, prepared with detached adjusting frameworks, for exact control expectation. The battery state appraise is utilized to decide the battery demonstrate parameters to be utilized by the control expectation calculation [9]. This paper will present the method 2-D transitory FEA to calculate electromagnetic misfortunes, test estimation for the SLL, misfortune blend between calculation and estimation, 3-D consistent computational liquid flow (CFD), and exploratory verification. CFD has been performed over a whole demonstrate of TEAAC engine, as in and incompressible unfaltering administering equations continuity, energy, and energy were discretized based on finite-volume strategy. Non-inertial reference outline was actualized for turning discuss locale encasing rotor components counting centrifugal fans. [10].

3. Proposed Work

The electric motor temperature dataset with 12 independent variables and 1 dependent variable with 9,98,8071 observations has been used for implementation. The prediction of electric motor temperature is done with the following contributions. Fig. 1. Shows the overall workflow of the system.

(i) Firstly, the data set is preprocessed with Feature Scaling and missing values.
(ii) Secondly, empirical feature examination is done and the relation of motor speed and ambient temperature of the motor is visualized.
(iii) Thirdly, the fresh data set is fitted to all the regressors and the execution is dismembered before and after scaling.
(iv) Fourth, the raw data set is subjected to Convolutional neural network Conv1D with various activation layers like Relu, Sigmoid, softmax,Softplus, Softsign, Tanh, Selu, Elu and exponential layers. The performance is analyzed with EVS, MAE, MSE, RScore and Step loss of the Convolutional neural network.

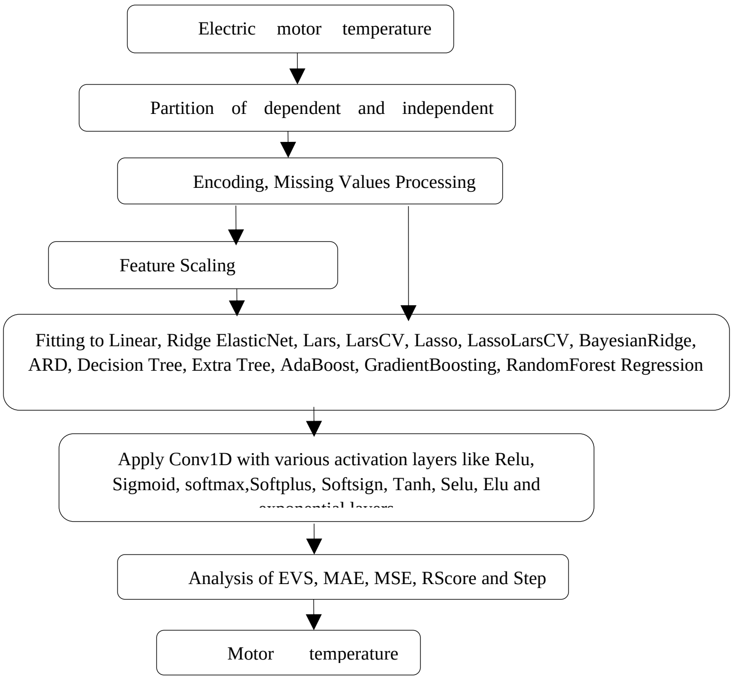

Fig.1. Overall workflow of the system.

4. Exploratory Data Analysis

The electric motor temperature dataset extricated from the UCI machine learning store is utilized for usage. The dataset comprises of 9,98,8071 information with following 12 autonomous highlights

(i) Ambient- Encompassing temperature as measured by a warm sensor found closely to the stator.
(ii) Coolant - Coolant temperature. The engine is water cooled. Estimation is taken at outflow.
(iii) U_d- Voltage d-component
(iv) U-q - Voltage q-component
(v) Motor speed
(vi) Torque - Torque induced by electricity.
(vii) I_d – electricity d component
(viii) I_q – electricity d component
(ix) stator_yoke - Stator yoke burden temperature measured with a warm sensor.
(x) stator_tooth - Stator tooth burden temperature measured with a warm sensor.
(xi) stator_winding - Stator wind burden temperature measured with a warm sensor.
(xii) Profile id – identifier of the electric motor machine

and 1 Target "Pm" which is Changeless Magnet surface temperature speaking to the rotor temperature. This was measured with an infrared. The code is implemented with python under Anaconda Navigator with Spyder IDE.

The data set is splitted with 80:20 for training and testing dataset. Fig.2. shows the target feature analysis and relationship with motor speed and pm. The correlation of the features is shown in Fig. 3.

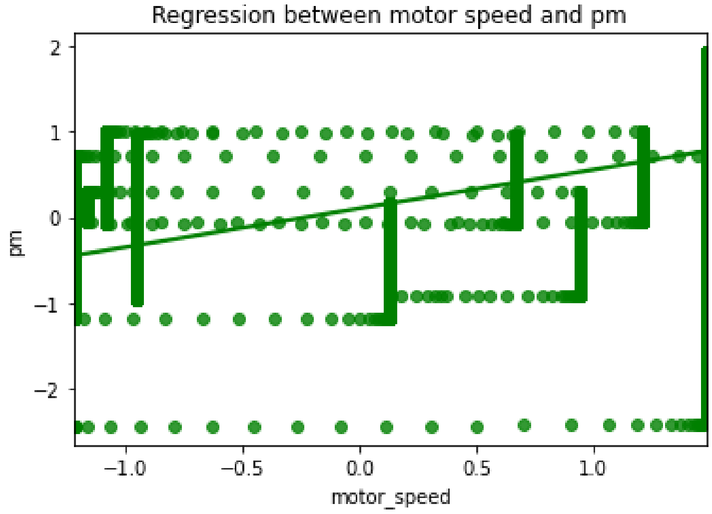

Fig.2. Target feature analysis with respect to Gender and Duration of the Exercise dataset

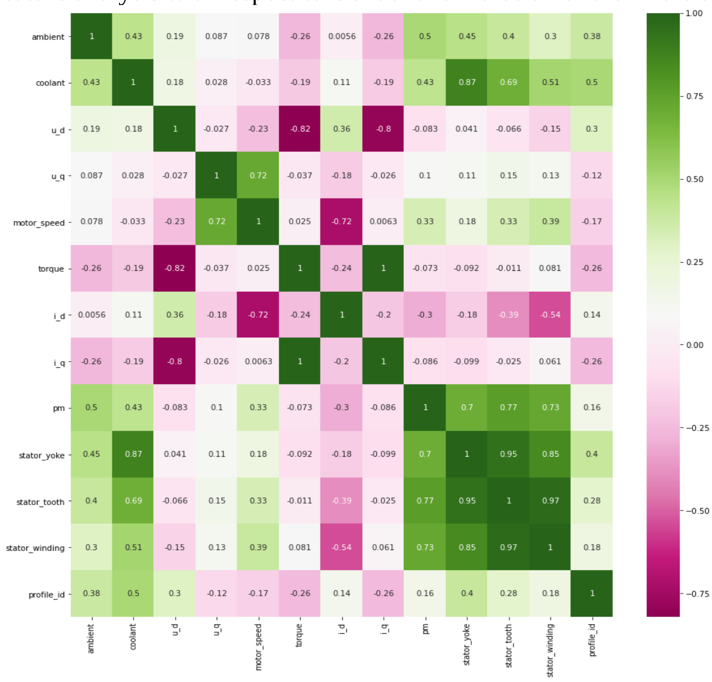

Fig.3. Feature Correlation of the Exercise dataset

5. Implementation and Discussion

The raw data set is fitted to all the regressors like Linear Regression, Ridge Regression, ElasticNet Regression, Lars Regression, LarsCV Regression, Lasso Regression, LassoLarsCV Regression, BayesianRidge, ARDRegression, Decision Tree Regression, Extra Tree Regression, AdaBoost Regression, GradientBoosting Regression and RandomForest Regression with and without the presence of feature scaling and performance is shown in Table 1 and Table 2, the RScore and the running time comparison is shown in Figure. 4 - 5.

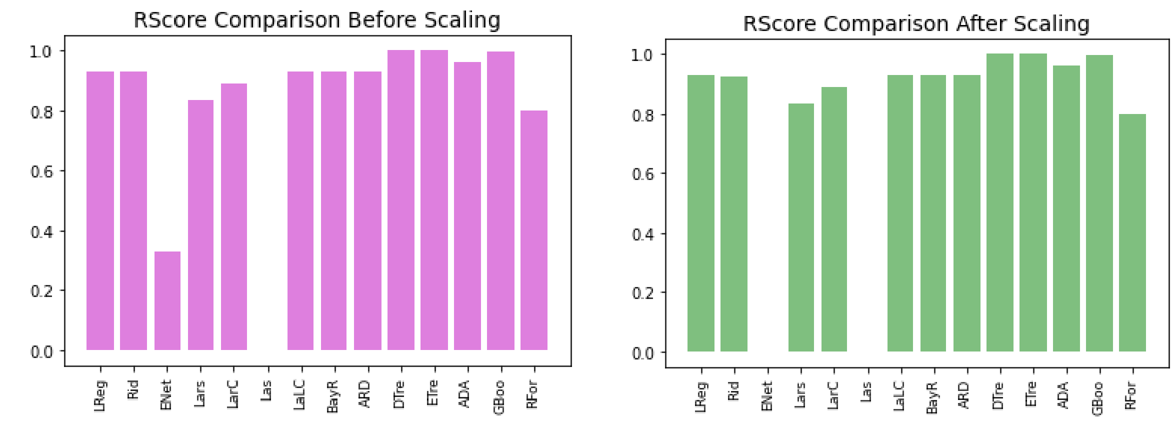

Fig.4. RScore Analysis of raw dataset before and after feature scaling

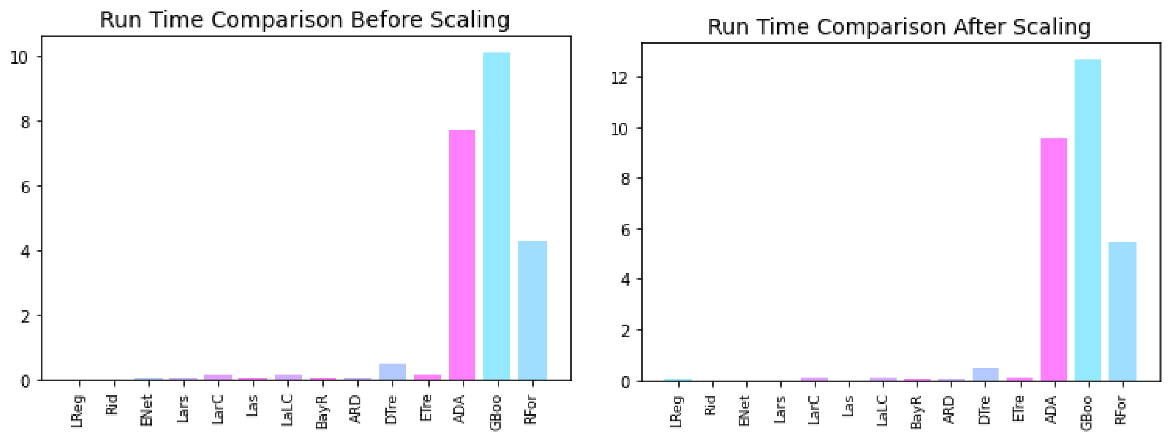

Fig.5. Response time analysis of raw dataset before and after feature scaling

Table 1. Regressor performance of the raw dataset before scaling

Regressor	**EVS**	**MSE**	**MAE**	**RScore**	**Running Time (ms)**
Linear	0.927315	0.056735	0.175612	0.927278	0.008356
Ridge	0.927192	0.05683	0.17589	0.927156	0.007014
ElasticNet	0.328568	0.523929	0.596371	0.328437	0.00884
Lars	0.835437	0.128433	0.249937	0.835377	0.010961
LarsCV	0.891132	0.08497	0.222619	0.891086	0.114237
Lasso	0	0.780317	0.733576	-0.0002	0.008824
LAssoLarsCV	0.927315	0.056735	0.175612	0.927278	0.132557
Bayesian	0.927313	0.056737	0.175619	0.927276	0.013464
ARd	0.927314	0.056736	0.175622	0.927277	0.025343
DecisionTree	0.999537	0.000361	0.003925	0.999537	0.481415
ExtraTree	0.999872	0.0001	0.004148	0.999872	0.108875
AdaBoost	0.960786	0.031864	0.149446	0.959157	7.702117
GradientBoost	0.995162	0.003779	0.044563	0.995156	10.12313
RandomForest	0.796481	0.158832	0.282938	0.796411	4.293062

Table 2. Regressor performance of the raw dataset after scaling

Regressor	EVS	MSE	MAE	RScore	Running Time (ms)
Linear	0.927315	0.002991	0.040319	0.927278	0.014054
Ridge	0.923947	0.003129	0.041637	0.923918	0.007322
ElasticNet	2.22E-16	0.041131	0.168421	-0.0002	0.008195
Lars	0.835437	0.00677	0.057383	0.835377	0.009842
LarsCV	0.888621	0.004582	0.051742	0.888568	0.120207
Lasso	2.22E-16	0.041131	0.168421	-0.0002	0.007112
LAssoLarsCV	0.927315	0.002991	0.040319	0.927278	0.128553
Bayesian	0.927313	0.002991	0.04032	0.927276	0.013427
ARd	0.927314	0.002991	0.040321	0.927277	0.022931
DecisionTree	0.999488	2.11E-05	0.000913	0.999488	0.454782
ExtraTree	0.999076	3.80E-05	0.001028	0.999076	0.094728
AdaBoost	0.96048	0.00171	0.035508	0.958426	9.517552
GradientBoost	0.995243	0.000196	0.010097	0.995237	12.69882
RandomForest	0.796481	0.008372	0.064959	0.796411	5.407051

6. CNN Activation Layer Results and Performance Analysis

The raw data set is subjected to subjected to Convolutional neural network Conv1D with various activation layers like Relu, Sigmoid, softmax,Softplus, Softsign, Tanh, Selu, Elu and exponential layers and the performance of the target features with the testing data is shown in Fig. 6 – Fig. The performance of the CNN activation layers is shown in Table 3 and Table 4, the accuracy and the running time comparison is shown in Fig. 6 - 7.

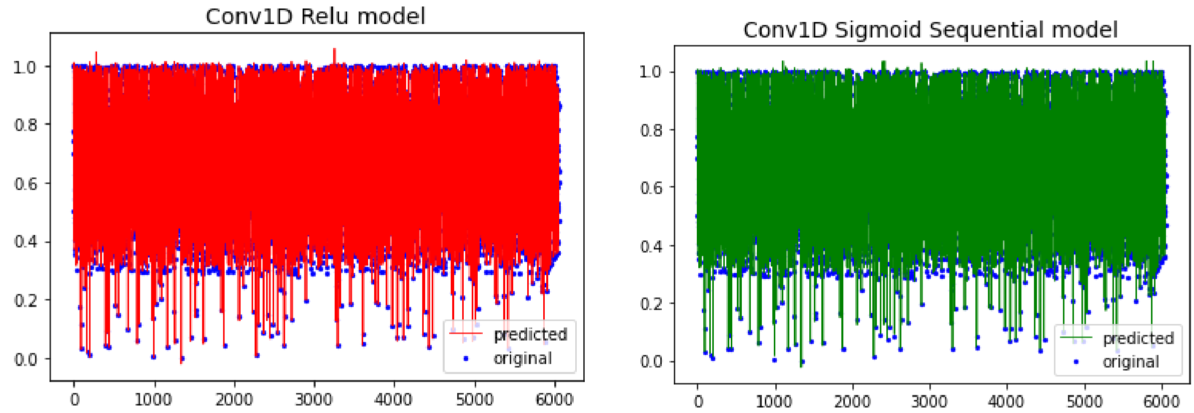

Fig.6. Performance of testing VS predicted target for RELU and Sigmoid CNN Activation

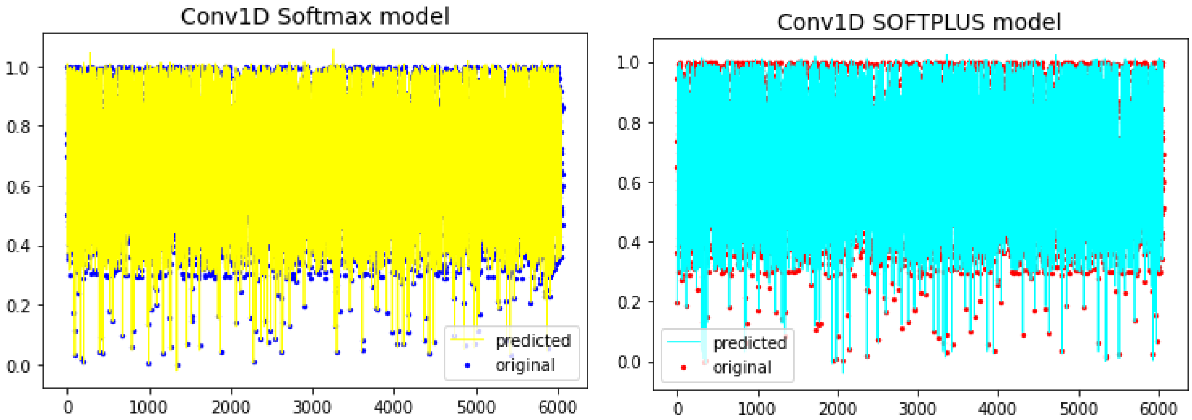

Fig.7. Performance of testing VS predicted target for Softmax and Softplus CNN Activation

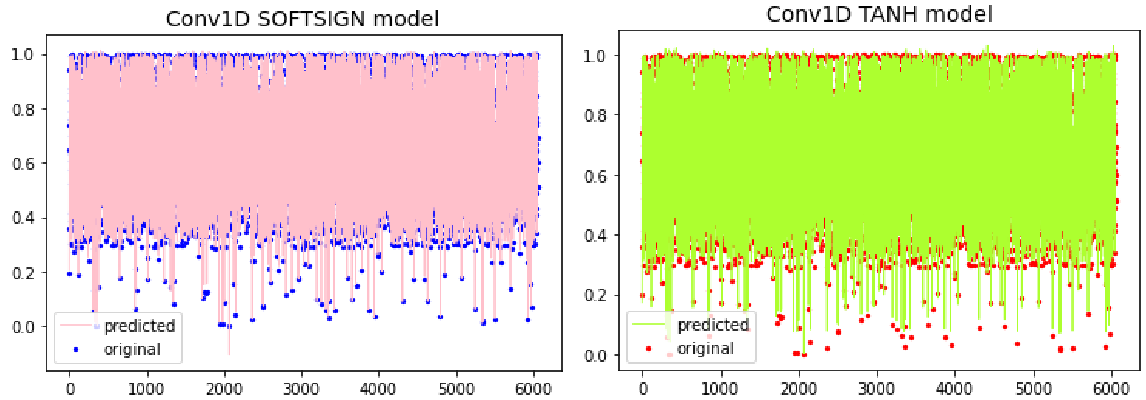

Fig.8. Performance of testing VS predicted target for Softsign and TANH CNN Activation

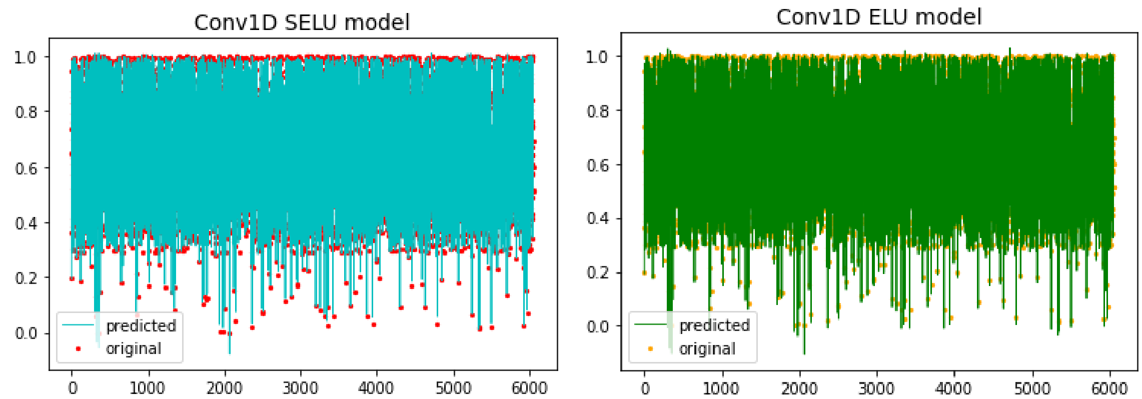

Fig.9. Performance of testing VS predicted target for SELU and ELU CNN Activation

Table 3. CNN Activation Model performance of the dataset

CNN Activation Model	**EVS**	**MSE**	**MAE**	**RScore**
Conv1D- Relu	0.999054	3.87735e-05	0.00441429	0.999054
Conv1D- Sigmoid	0.997218	0.000122209	0.00698987	0.997019
Conv1D-softmax	0.997806	9.00603e-05	0.00615674	0.997804
Conv1D-SOFTPLUS	0.997085	0.000119021	0.00789632	0.997061
Conv1D SOFTSIGN	0.99869	6.37126e-05	0.00543891	0.998427
Conv1D TANH	0.995882	0.000276831	0.0124229	0.993165

Conv1D-SELU	0.997318	0.000108974	0.0073036	0.997309
Conv1D elu	0.995045	0.000226629	0.0111182	0.994404
Conv1D exponential	0.99783	8.80639e-05	0.00663165	0.997826

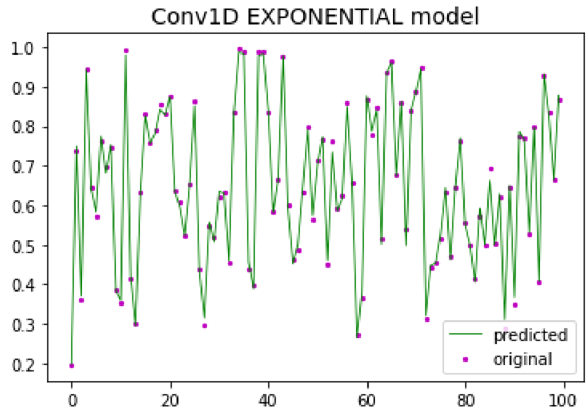

Fig.10. Performance of testing VS predicted target for Exponential CNN Activation

Table 4. Model Evaluation and Loss for CNN Activation Model

CNN Activation Model	**Step Loss**
Conv1D- Relu	3.394002851564437e-05
Conv1D- Sigmoid	9.791656339075416e-05
Conv1D-softmax	6.905803456902504e-05
Conv1D-SOFTPLUS	0.0001155058344011195
Conv1D SOFTSIGN	0.0001346758933367892
Conv1D TANH	0.00025627834838815033
Conv1D-SELU	0.00011110681225545704
Conv1D elu	0.00022326399630401284
Conv1D exponential	8.453158807242289e-05

7. Conclusion

An attempt is made to find the performance analysis of the electric motor temperature dataset in forecasting the ambient temperature of the electric motor by applying various activation layers with convolutional neural network sequential model. The empirical feature examination is done and the relation of motor speed and ambient temperature of the motor is visualized. The correlation of each features in the dataset is extricated and the distribution of target variable with respect to other features are analyzed. Experimental results shows that the Conv1D-Softsign activation layer tends to reach the RScore of 99.842 with the step loss of 0.0001155

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