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Virtual Sensor Design Using Convolutional Neural Networks and Image Processing Techniques

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ABSTRACT
To achieve rapid decarbonisation and improve the performance of future internal combustion engines (ICEs), virtual sensors have emerged as a promising alternative to physical sensors. This study proposes a novel methodology for developing virtual sensors using advanced machine learning techniques, including image-based classification and generative adversarial networks (GANs), to predict key engine performance metrics and emissions. Real-time engine parameters such as in-cylinder pressure, engine speed, fuel injection rate, and oxygen concentration were used as input to train multiple machine learning models including ANN, Random Forest, SVM, XGBoost, and Decision Trees. Among these, the XGBoost regressor demonstrated the highest prediction accuracy with minimal computational cost. Furthermore, combustion data were transformed into grayscale images and used to train GANs, enabling the reconstruction of the rate of heat release (R.H.R) profiles. The results confirm that virtual sensors can achieve over 97% accuracy in predicting combustion characteristics and emissions, making them a viable tool for robust feedback control in ICEs operating under transient conditions.

Keywords: Virtual sensors, Internal combustion engine (ICE), Machine learning, XGBoost, Neural networks, Generative adversarial networks (GAN)

1. INTRODUCTION

To achieve rapid decarbonisation by 2030, efficient internal combustion engines (ICEs) should include hybridisation and electrification [1–3]. Despite the rapid advancement of vehicle electrification, the majority of future transportation and propulsion systems will continue to use internal combustion engines using hydrogen, e-fuels, and other fuels. Furthermore, there are challenging categories for electrification, including large vehicles, marine systems, and stationary propulsion systems. Recent research and development efforts aim to enhance the thermal efficiency of internal combustion engine brakes by over 50% by hybridisation, shown by initiatives like as Japan's national SIP program [4, 5]. These engines include sophisticated technology to enhance thermal efficiency, hence augmenting the latitude for control and calibration. Traditionally, lookup or map-based tables have been used in ICE control and calibration under steady-state settings. Nonetheless, these tables exhibit great dimensionality under various engine running circumstances and disturbances. Contemporary internal combustion engines use alternative fuels, hydrogen, e-fuels, or other low-carbon fuels and are often integrated with various technologies to enhance performance and reduce emissions. These technologies (turbocharging, exhaust gas recirculation systems, and sophisticated dual-fuel injection systems) prolong the duration required to generate the lookup or map-based tables. The prior engine calibration was adequate for steady-state operation; however, this traditional method is inadequate for engine feedback management owing to several challenges, particularly in transient-cycle situations. A potential approach for feedback control and calibration is to include additional physical sensors into internal combustion engines. Nonetheless, supplementary sensors elevate vehicle expenses, and the physical sensors are susceptible to malfunctions, potentially transmitting erroneous data to controllers. The primary goals for creating virtual sensors are to decrease the expenses associated with real sensors and to attain rapid reaction times for feedback management throughout a broad operational range of internal combustion engines, which are characterised by high transience and cold starts.

The virtual sensors exhibit no diagnostic concerns regarding durability and may serve as substitutes or operate concurrently with actual sensors to enhance control and calibration robustness [6–9]. The development of virtual sensors for feedback control systems has been increasing due to advancements in machine learning theory. Liu et al. used several machine learning regressors to forecast the exhaust gas temperature of natural gas engines [10] and ammonia engines [11]. The models were capable of predicting exhaust gas temperature under various running situations and other engine performance metrics without noise interference. Menink et al. [12] introduced an online implementation of a virtual NOx sensor for EURO-VI heavy-duty diesel engines. During engine operation, the crank angle signal fluctuates at high frequencies, making it challenging to acquire a stable value. The virtual NOx sensor was calibrated offline and then implemented online. During offline calibration, in-cylinder pressure data was analysed at intervals of 0.1 degrees of crank angle, while in real-time, the step size was increased to 1 degree. This research presumes uniformity among all cylinders and bases its analysis on a singular in-cylinder pressure measurement. This advancement demonstrates the rapid reaction of virtual NOx sensors with great precision, especially under transient engine conditions. This study demonstrated that the virtual NOx sensor might serve as a viable alternative to the traditional physical NOx sensor. Henningsson et al. [13] proposed a methodology for forecasting engine emissions using in-cylinder pressure data. They affirmed that the hyperparameters of the developed neural network must be optimised in every conceivable manner. Furthermore, the selected input parameters have little correlation with the goal values. Studies in [14–17] explore an enhanced technique for estimating NOx emissions to minimise the reliance on engine parameter monitoring sensors. A physical model was created to predict engine combustion characteristics, including cylinder temperature, air flow rate, EGR rate, and combustion phasing, which are significantly correlated with engine-out NOx emissions. The neural network model is unable to monitor NOx emissions during tip-in acceleration.

The prior research focused only on emission forecasts. The combustion forecasts relied on several physical sensors and short time intervals. Furthermore, the sensors were not used to forecast engine performance and emissions throughout driving cycle activities. The neural network architectures and parameterizations were neither optimised nor documented. The GAN image classification and translation models have not been used in the development of virtual sensor ICE feedback control systems. This paper introduces a unique approach for constructing virtual sensors using several machine learning techniques, including GAN-based picture categorisation and translation. Diverse machine learning regression methodologies are used to identify the ideal regressor for superior predictive accuracy and computational efficiency. To the authors' knowledge, this novel technique for the development of virtual sensors for future ICE feedback control using image processing and translation is being offered for the first time.

2. METHODOLOGY

2.1. Data collection and virtual sensor development

The virtual sensors are designed to forecast engine performance metrics and emissions attributes for onboard engine management and diagnostics. A standardised method has been established for constructing virtual sensors, which are built offline and may be deployed online. The neural network has provided exceptional generalisation via off-board learning, enabling an optimised and adaptive engine management system to enhance the engine's thermal efficiency and other combustion and emissions parameters. This study employs real-time engine data inputs, including in-cylinder pressure sensor readings, engine speed, working gas quantity, and oxygen concentration, to forecast instantaneous engine performance metrics such as indicated torque (Tind), fuel consumption (Qfuel), maximum pressure rise rate ($dP/d\theta$), brake thermal efficiency (BTE ηbr), and exhaust emissions, specifically NOx and CO_2. This prediction enables the engine to function within a predetermined area, such as minimal emissions, optimal performance, and improved engine economy.

2.2. Neural network selection

The AI engine model must accurately forecast combustion characteristics while minimising processing time for onboard sensors. The generated virtual sensors must meet the processing time requirements of the electronic control unit. In the first section, the authors evaluated the predictive capabilities of the Artificial Neural Network (ANN) against the XG-Boost regressor focussing on model performance. Consequently, this study only presents the final parameter optimisation and machine learning frameworks. Numerous machine learning algorithms were evaluated, since the optimal choice cannot be predetermined; the training and validation performance of machine learning models is significantly influenced by each method and the optimisation of hyperparameters. The hyperparameter tuning for the artificial neural network (ANN) was conducted using Bayesian optimisation and search methodologies, whereby the goal function for selecting suitable hyperparameters relies on a probabilistic model. This study examines the artificial neural network (ANN) hyperparameters, including the number of hidden layers (ranging from 1 to 3), the quantity of hidden neurones (spanning from 10 to 200 in increments of 20), activation functions (ReLU and Tanh), the Tree-Structured Parzen Estimator (TPE) algorithm, epochs (100, 500, 1000), iterations (5 to 30), and the R^2 evaluation metric. The GridSearchCV function was used for hyperparameter adjustment of the Random Forest to improve model training and validation. The random forest hyperparameters include min_sample_split, min_sample_leaf, max_depth, and n_estimators. The hyperparameters of XGBoost include learning rate (0.05–0.3), max_depth (1–15), n_estimators (40–200), alpha (L1 regularisation), gamma, and lambda (L2 regularisation).

2.3. Data to image transformation

The Python multiplatform data visualisation toolkit, Matplotlib, is used for data-to-image conversion. This research used greyscale pictures to diminish the pixel value for each image (image size). Consequently, the potential colours derived from the greyscale picture are black and white.

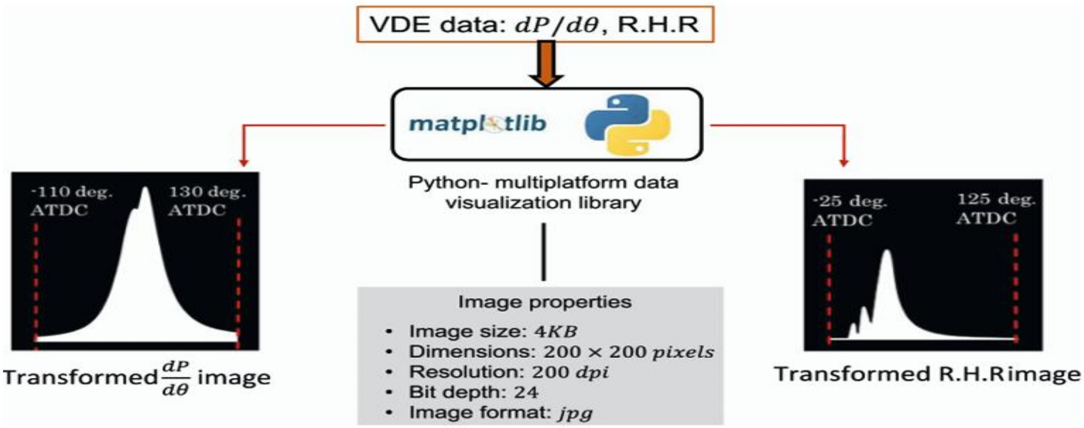

Figure 1. Image transformation process

The cylinder pressure dP/dθ and RHR are forecasted using the VDE model and converted into black and white pictures with Matplotlib. This study utilises cylinder pressure data ranging from -110 degrees (intake valve closure or IVC timing) to 130 degrees (exhaust valve open or EVO timing), while RHR data spans from -25 degrees (pre-injection time) to 125 degrees near EVO. The selected crank angle ranges (cylinder pressure range = -110 to 130 degrees, RHR range = -25 to 125 degrees) are deemed realistic intervals that influence the combustion and emission characteristics of internal combustion engines, rather than including the whole 720 degrees of the four-stroke cycle. Furthermore, the chosen crank angle ranges will diminish the picture characteristics for a rapid GAN model by minimising image augmentation and feature extraction. This study examines actual JPG-format picture attributes to optimise the calculation speed of the GAN model.

2.4. Construction of generative adversarial network (GAN)

The primary objective of developing the GAN is to evaluate the R.H.R. profile using an in-cylinder pressure picture and outputs from the virtual sensor, including indicated torque, brake thermal efficiency, maximum pressure increase rate, and engine exhaust emissions of NOx and CO2. The R.H.R. profile estimated by GAN is juxtaposed with the target R.H.R. profile value. The error serves as feedback for regulating injection parameters, including amount and duration, known as injection patterns. The thermal efficiency of the engine brake and exhaust emissions may be enhanced by regulating the R.H.R. configuration. An overview of GAN is presented as follows. It is an unsupervised machine learning technique that requires the identification of regularities and patterns within the input data. The GAN model is designed to evaluate the optimiser.

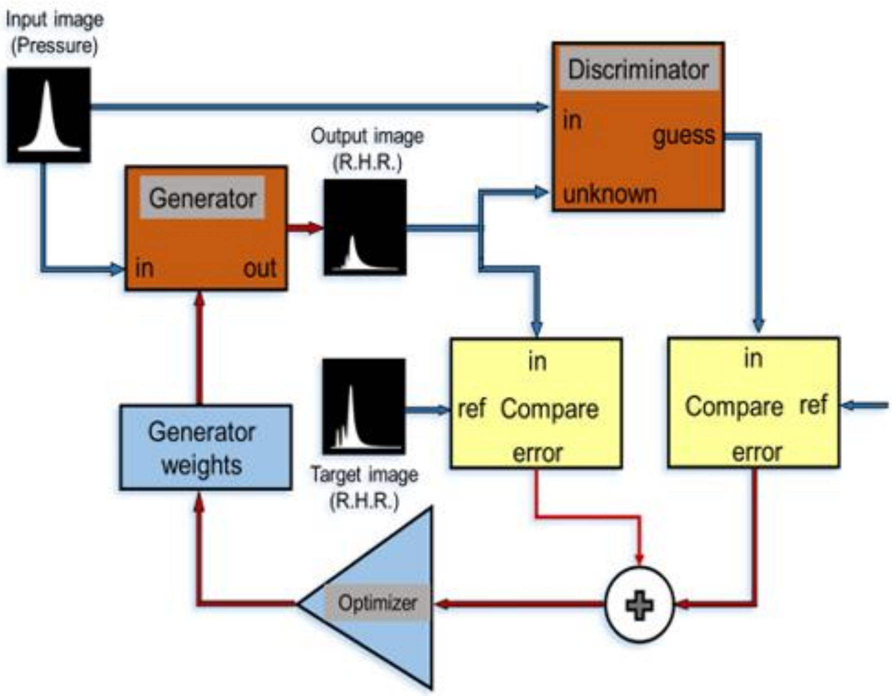

Figure 2. Construction of generative adversarial network

The discriminator model is trained directly using actual and produced pictures, whereas the generator model is trained utilising the discriminator model. The weights are adjusted to reduce the prediction loss by the discriminator for the produced picture.

3. RESULTS AND DISCUSSION

After optimizing the hyperparameters, the prediction accuracy is verified by cross-validation. The prediction accuracy is evaluated by the coefficient of determination R^2. R^2 value measures the proportion of variability in the output with respect to the input parameters explained by the regression model. The model accuracy and prediction time are shown in Table 1.

Table 1 Accuracy comparison using cross validation of machine learning model (XG-Boost)

Parameter	R^2 value (Model validation)	R^2 value (Cross validation)
Indicated torque (Nm)	0.995	0.988
Brake thermal efficiency (%)	0.987	0.982
NOx emissions	0.969	0.968
CO_2 emissions	0.978	0.968

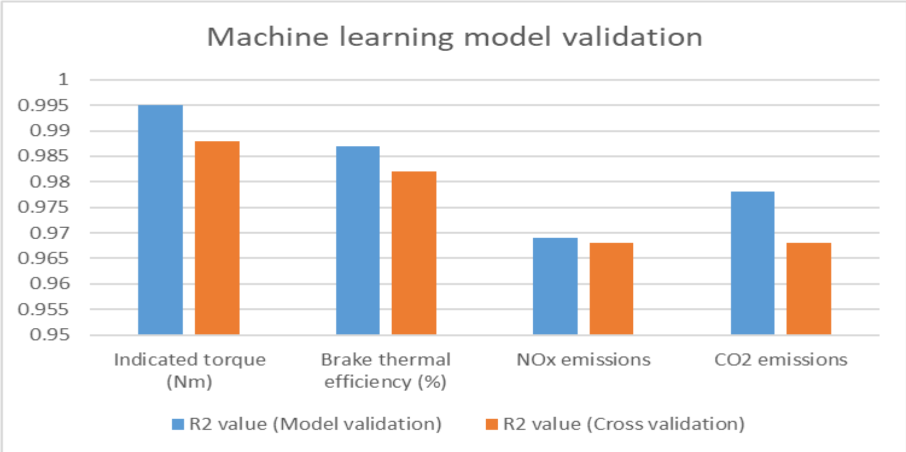

Figure 3. Graphical representation of model cross valdation

Accuracy can be used as an effective metric only if the model is trained with an equal number of sample images (balanced training dataset). In this work, the authors train the model using a balanced dataset; therefore, accurate results are relied on. From the above model classification results, the model training and validation accuracy value are over 97%, showing that the AI image classification model could accurately classify the desired and undesired combustion of the engine. The results also confirm that the engine performance parameters and exhaust emissions strongly correlate with cylinder pressure and R.H.R. profile shape. The cross-validation accuracy of R.H.R. image classifica- tion model is higher than that of the pressure image classification model. Therefore, the engine parameters are highly dependent on the shape of the R.H.R. profile. Fig. 4(a and b) shows the model accuracy and loss curve of the in-cylinder pressure image classification model. The accuracy curve helps to understand the model training progress of neural networks more efficiently. The gap between the training and validation accuracy indicates the amount of overfitting in the model. In the pressure image classification model, the value of training loss continuously decreases with an increase in epoch. In contrast, the vali- dation loss decreases to a certain point and begins to increase again. This may be subject to model fitting. In R.H.R. image classification model, the validation accuracy tracks the training accuracy reasonably well, the value of training loss decreases to a point of stability, and the validation loss decreases to a point and has a small gap with the training loss.

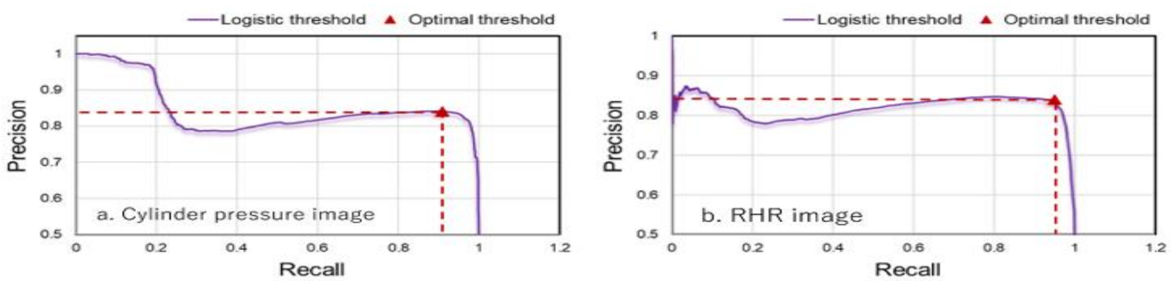

Figure 4. Precision and recall tradeoffs result of the image classification model for a) cylinder pressure image, b) R.H.R image as a function of recall

4. CONCLUSION

This study presents an innovative approach to virtual sensor development for internal combustion engines using a combination of regression models and image-based machine learning techniques. By integrating high-fidelity engine data and advanced algorithms like XGBoost and GANs, the proposed method achieves high predictive accuracy and computational efficiency, crucial for real-time engine control and diagnostics. The results demonstrate that the R.H.R. profile plays a significant role in determining engine emissions and performance. The image classification models, especially those based on R.H.R. data, provide strong correlation with target parameters and outperform pressure-based models in classification accuracy. The developed virtual sensors offer a scalable and cost-effective alternative to physical sensors, significantly enhancing the robustness and adaptability of ICE feedback control systems. Future research will aim to integrate this framework into onboard engine control units for real-time applications across various engine architectures and fuel types.

REFERENCES

1. Japan Science and Technology Agency. “Achieving thermal efficiency of over 50% in passenger car engines” FY2019 Results.
2. Senecal P, Leach F. Diversity in transportation: why a mix of propulsion technologies is the way forward for the future fleet. Res Eng 2019; 4:100060.
3. Sok R, Kusaka J, Nakashima H, Minagata H, Dimitriou P, Liu J. Thermoelectric generation from exhaust heat in electrified natural gas trucks: modeling and analysis of an integrated engine system performance improvement. ASME J Energy Resour Technol February 14.
4. Horizon. LONGRUN Project “LONG distance poweRtrain for heavy dUty trucks aNd coaches”. 2020. https://h2020-longrun.eu/, accessed on December 19, 2023.
5. Tahtouh T, Millo F, Rolando L, Castellano G, et al. A synergic use of innovative technologies for the next generation of high efficiency internal combustion engines for PHEVs: The PHOENICE project.
6. US DoE NEXTCAR. “Next-generation energy technologies for connected and automated on-road vehicles (NEXTCAR) program”, https://arpa-e.energy.gov/ne ws-and-media/press-releases/us-department-energy-awards-18-million-cutting-edge-technologies, accessed on December 19, 2023.
7. Zhou L, Song Y, Ji W, Wei H. Machine learning for combustion. Energy AI 2021;7: 100128.
8. Gangopadhyay T, Ramanan V, Akintayo AK, Boor P, Sarkar S, Chakravarthy SR, et al. 3D convolutional selective autoencoder for instability detection in combustion systems. Energy AI 2021; 4:100067.
9. Asakawa R, Yokota K, Tanabe I, et al. Machine learning application to predict combustion phase of a direct injection spark ignition engine. IntJ Automot Technol 2022; 23:265–72.
10. Liu J, Huang Q, Ulishney C, Dumitrescu CE. Machine learning assisted prediction of exhaust gas temperature of a heavy-duty natural gas spark ignition engine. Appl Energy 2021.
11. Liu Z, Liu J. Machine learning assisted analysis of an ammonia engine performance. ASME J Energy Resour Technol November 2022;144(11):112307.
12. Mentink P, Seykens X, Valdiviesco D. Development and application of a virtual NOx sensor for robust heavy-duty diesel engine emission control. SAE Int J Eng 2017.
13. Henningsson M, Tunestal P, Johansson R. A virtual sensor for predicting diesel engine emissions from cylinder pressure data. In: International federation of automatic control (IFAC) volumes, engine and powertrain control, simulation and modelling conference; 2012.
14. Kim J, Park J, Shin Y, et al. Prediction of engine NOx for virtual sensor using deep neural network and genetic algorithm. Oil Gas Sci Technol Novel 2021.
15. Wang, Y., He, Y., and Rajagopalan, S., “Design of engine out virtual NOx sensor using neural networks and dynamics system identification”, SAE Int J Eng: 2011.
16. Arsie I, Pianese C, Sorrentino M. Development of recurrent neural networks for virtual sensing of NOx emissions in internal combustion engines. SAE Int J Fuels Lubr 2010;2(2):354–61.
17. Bellone M, Faghani E, Karayiannidis Y. Comparison of CNN and LSTM for modeling virtual sensors in an engine. SAE Int J Adv & Curr Prac Mobility 2020;2(5):2632–9.