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Deep Learning Approaches for the Classification of Diesel Injector Spray Patterns

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Abstract: Accurate classification of diesel injector spray patterns is critical for evaluating fuel atomization quality and optimizing combustion efficiency in internal combustion engines. Traditional image analysis methods often struggle to capture the complex and dynamic nature of spray structures. In this study, we explore deep learning-based approaches particularly Convolutional Neural Networks (CNNs) for the automated classification of diesel spray images. A comprehensive dataset of high-speed diesel spray images was used, capturing a range of injector conditions and operating parameters. Several CNN architectures, including VGG16, ResNet50, and custom shallow networks, were trained and evaluated for their performance in classifying spray patterns into predefined categories based on shape, dispersion, and uniformity. Data augmentation techniques were employed to improve generalization and robustness. The results demonstrate that deep learning models significantly outperform traditional machine learning approaches in terms of classification accuracy and resilience to noise and image distortion. The best-performing model achieved over 95% accuracy in distinguishing between normal and defective spray patterns. These findings highlight the potential of deep learning techniques to assist in real-time diagnostics and quality control of fuel injection systems, ultimately contributing to cleaner and more efficient diesel engine performance.

Keywords: CNN architectures, VGG16, Diesel Injector Spray Patterns.

1. Introduction

In recent years, research has shown that the combustion and emission characteristicsof modern diesel engines are dependent on a multitude of parameters, including: fuelatomization, nozzle geometry, injection pressure, shape of inlet port, and otherfactors. In order to improve air-fuel mixing and the resulting combustion, it isimportant to understand the underlying fuel atomization and spray formationprocesses. Experimental and theoretical approaches have been adopted by researchersin order to investigate the characteristics of spray behavior, formation and structurefor the high-pressure injector, in order to improve engine efficiency; in practice thegoals are: improved combustion, performance and reduced exhaust emissions.However, further detailed studies of the atomization characteristics and spraydevelopment processes of high-pressure diesel sprays are still needed.Intelligent systems, i.e. software systems incorporating artificial intelligence (AI),have demonstrable benefits for control and modeling of engineering systems. Forexample, they feature the highly useful ability to rapidly model and learncharacteristics of multi-variety complex systems, offering performance advantagesover more conventional mathematical techniques. This has resulted in theirapplication in diverse applications within power systems, manufacturing,optimization, medicine, signal processing, control, robotics, and social/psychological sciences.

The AI approach is well-suited to the analysis of many combustion-related problems;AI has considerable potential for making faster, more accurate predictions than sometraditional

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methods. Increasingly, the availability of complex sensory and computingsystems is resulting in the production of vast quantities of information-rich data.Historically, the analysis of such complex data has required very substantial humaneffort, often with every image of every video needing to be evaluated by human eye.The aim of this investigation, and the partner investigation featured in, has beento apply intelligent systems tools and techniques to the problem of effectively, andsemi-automatically, processing and analyzing large complex data sets.

2. Literature Review

Pawletko [1] attempted to determine the usefulness of NNs for diagnosing selected states of a marine engine. The author verified an experimental diagnostic algorithm on a su-percharged engine simulator. The diagnostics of the marine engine used the quantification of the parameters of the structure and the identification of the states that can be simulated in the computer program. Some marine engine inadequacies remained challenging to diagnose accurately and quantitatively due to occurrence and other failures. This author used advisory systems and experimental database research to extract diagnostic rules automatically. Acquiring knowledge from specialists was inefficient and ime-consuming. The research presented in Klimkiewicz's [2] study involved compression-ignition engine (CIE) vehicles equipped with distributor pumps. As input variables were selected, which were symptoms, measurements, and checkups, based on which experts determined the damage to the injector apparatus were the input variables and the engine one output variable. The best classification quality was obtained using probabilistic networks. An indicator of the suitability of individual variables for the classification performed by the network was the quotient of the network error obtained without using a given variable to the baseline error. The author did not make a quantitative assessment of the accuracy of correct classifications since only cases where the experience of the workers did not allow for the damage to be detected quickly were studied. The observed damage included the incorrect order of installation of injection lines, gasoline content in diesel fuel, low compression pressure, obstructed exhaust system, and fuel system airing. However, the impact of all significant and graded damage was not demonstrated. Klimkiewicz [3] attempted to optimize the process of detecting defective components in injection pumps using artificial intelligence. A neural model based on probabilistic NNs was used. With the built model's help, the depth indicator's value for locating damaged components could be reduced. However, there was more than pump damage and unmeasurable factors. Brzozowski and Nowakowski [4] presented the application of ANNs in a computational model of the working cycle of a CIE. To evaluate the usefulness of the method, the task of selecting the values of control parameters to achieve a reduction in the content of nitrogen oxides in the exhaust gas was solved as an optimization task. The model's equations were solved for parameter values obtained as the response of NNs to variable control parameters, including changes in emissions of harmful compounds and exhaust smoke.

Data generated during engine operation, using a diagnostic model based on ML, can help users of marine ICEs correctly identify types of damage and take prompt action to avoid serious accidents according to Xu et al. [5]. A multi-model fusion system was proposed based on the principle of evidence inference based on an ANN model. A method for determining the dependability of evidence by using the precision and stability of tested models was presented. A genetic algorithm optimized the validity to improve the efficiency of the merger arrangement. The suggested system was verified against a set of actual specimens taken from the operating ship's CIEs. In their paper, Logan et al. [6] presented new developments in damage diagnosis on intelligent software representatives. The studies aimed to design a real-time agent capable

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of actual continuous ML using an ANN. A combustion engine simulator that modeled regular and abnormal operations was used to develop the controller's learning system and test results. An intelligent sensor validation and online fault diagnosis technique were proposed and studied for a 6-cylinder turbocharged self-ignition engine (SIE) [7].

3. Data processing

The data processing technique was as follows. Each of the 80 .AVI video clipscomprised 300 images, each of 320x128 pixels. Key images were automaticallyselected from each video – in this case those images in which peak spray penetrationwas attained; Fig. 1 shows examples of the peak penetration images for each of thefour classes of data.

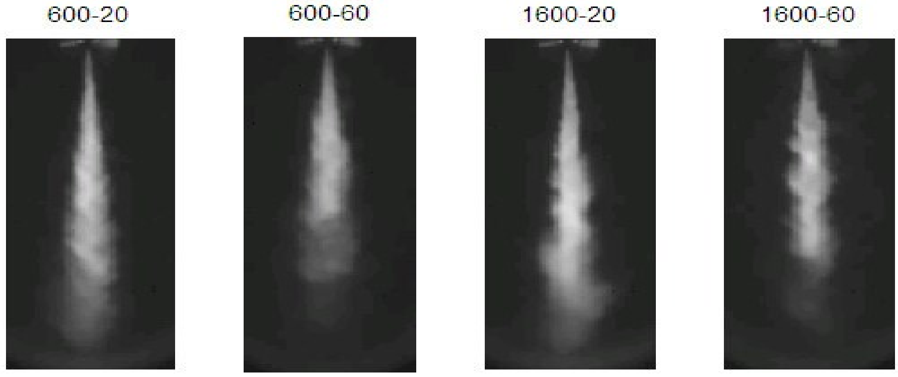

Fig. 1 Peak Penetration Spray Image Examples for each Set of Conditions

The grey-scale images were thresholded [10], yielding binary (black and white)images, as shown in Fig.2

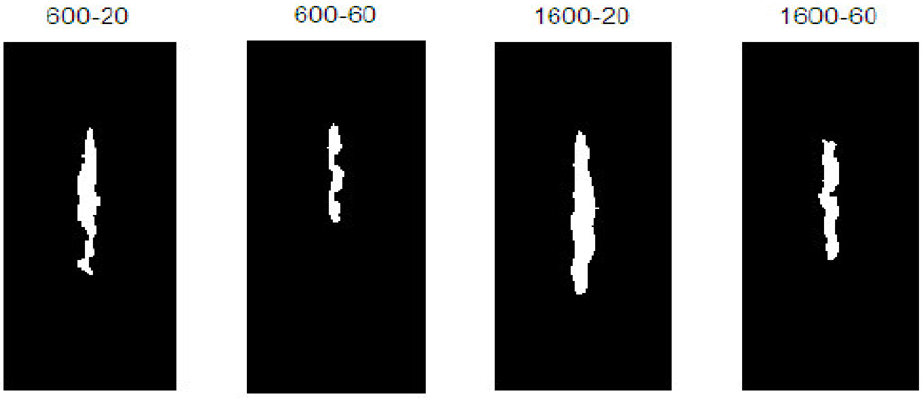

Fig. 2 Thresholded Spray Data for each Set of Conditions

A first pass through all of the videos facilitated the automatic selection of theoptimum scanning window size to reduce redundant unchanging areas of black pixels,and identified the location and data of the 'peak penetration image' in each video. Onthe second pass through the data, the desired 80 peak images were selected out and resampledaccordingly, reducing the window size to 32x7 pixels, hence significantlyreducing the number of data-points referred to the neural network. Figs. 6.3 and 6.4indicate the level of detail discernable after re-sampling. The reduced images werescanned line-by-line, producing a total of 80 vectors, each of which featured 224 datapoints.

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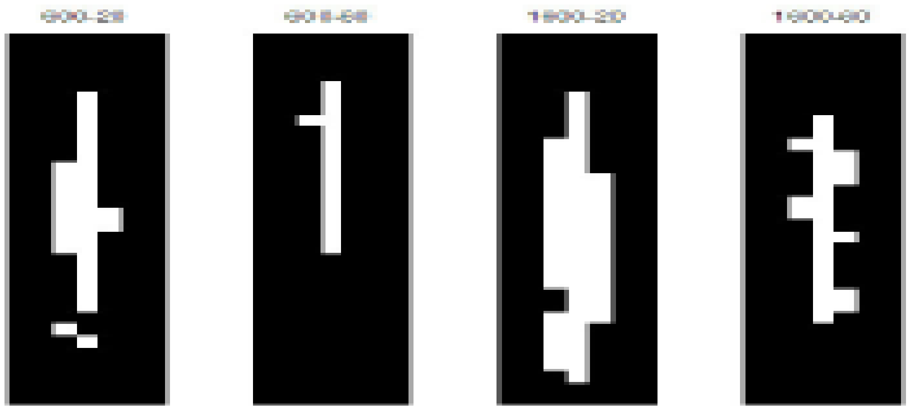

Fig. 3 Re-sampled Spray Data for each Set of Conditions

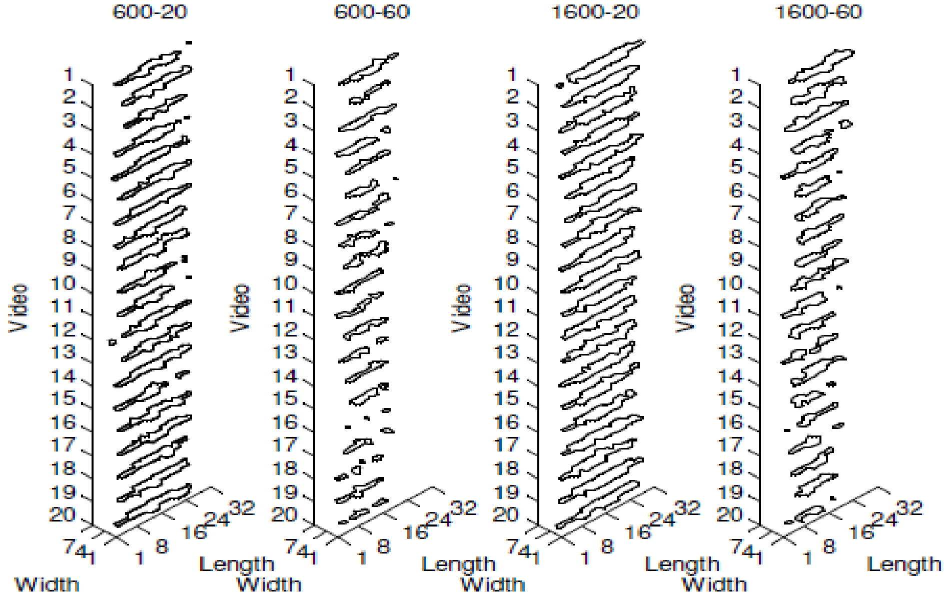

Fig.4 Visualisation of all the Training (1 – 10) and Recall (11 – 20) Data

Fig. 4 depicts as vectors the same image examples as shown in previous figures Figs.1-3. Finally, these vectors were combined with suitable ‘Desired Output’ information,yielding two data files for evaluation of the neural network in ‘Training’ and ‘Autorecall’modes. ‘Auto-recall’ is an automated routine, in which a set of previously-unseen data exemplars are subjected to a ‘Recall’ process; the results yield network-performance statistics.

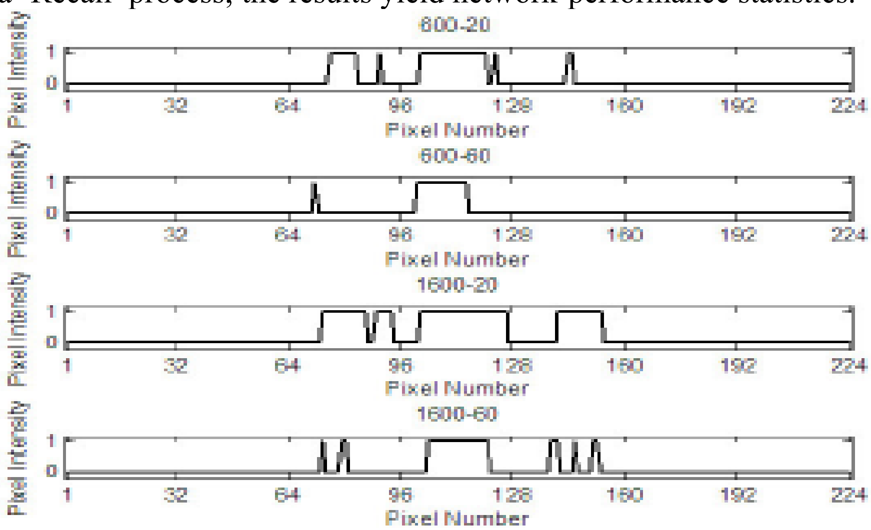

Fig. 5 Examples of Neural Network Input Data for each Set of Conditions

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Two specially-written MATLAB m-files were run in sequence. The first programcalculated the minimum image area suitable for processing any choice of imagesfrom the videos by neural network; the second used this information to process theimages and prepare the training and recall data.The resulting training and recall files were passed to NDA (Neural Data Analyzer,V.7.0), running on the same PC. The NDA software package is an MLP neuralnetwork, implemented in the C-language, in-house at the University of Brighton.After starting NDA, network architecture and training parameters were entered, onthe Network Set-up and Training screens, respectively; these parameters are shown inTable 1. The neural network was trained using the training file and a range ofdifferent numbers of Hidden Nodes, as indicated in Table 1. In order to retain adegree of detail in the images, thus indicating spray break-up and overall shape, 224input data points, hence input nodes, were chosen, as described in Section 2.2.According to the results shown later, this necessitated a fairly large number of hiddennodes, given training data of just 80 exemplars, despite the prediction of a trainingheuristic [8]: 'For good generalisation, the condition: nw<=~nt<=~10nw should besatisfied, where nw = Number of network weight values and nt = Number of trainingexamples'.

Table 6.1.Neural Network Configuration and Operating Parameters

Parameter	Value	Parameter	Value
Input Nodes	224	H Layer Learn. Rate	0.080
Hidden Nodes	10/25/38/50/63/75	O Layer Learn. Rate	0.020
Output Nodes	4	Momentum	0.800
Training Sets	40	Limit	0.200
O Layer Act. Func.	Sigmoid	Initial Value	0.500
O Layer Threshold	0.1	Error Interval	10

4. Results and Discussion

Training was accomplished quickly, in the worst case taking just over 6 seconds.Three training sessions were undertaken for each set of operating conditions, and thenthe mean was taken of each trio of results. Peak 'Training Algorithm Iterations' and'Solution Time', and reduced 'Training Error' were to be found at 50 – 63 hiddennodes, although it should be noted that generalisation performance may notnecessarily have been optimal at the lowest error point.

Mean Recall results ('Correct Outputs', 'Correct Output Sets' and 'Matching GreatestOutput') are shown in Fig.6. 'Correct Outputs' refers to the total percentage of neuralnetwork output values that registered the desired output, +/- an 'Output LayerThreshold' value; in this first experiment the Threshold was set at 0.1 (i.e. +/- 10%variation allowed). 'Correct Output Sets' refers to the percentage of output sets inwhich the outputs were all within the 'Output Layer Threshold' tolerance of thedesired outputs. 'Matching Greatest Output' refers to the percentage of output sets inwhich the neural network correctly identified the 'winning' output class by setting itsoutput node to the greatest value within the set.

International Journal of
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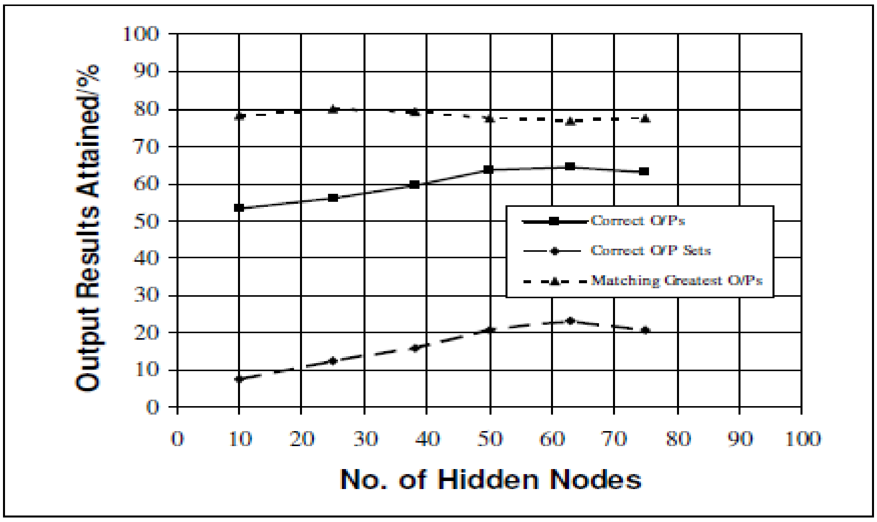

Fig. 6. Variation of Neural Network Performance with Number of Hidden Nodes

The network was best able to maintain +/-10% accuracy of ALL its outputs over 65%of the unseen recall file data, when the number of hidden nodes was between 50 and75; this is shown by the 'Correct Outputs' plot.

Relatively poor performance was achieved on producing exactly 'Correct OutputSets' that were all within +-10%; the best performance was found to be 23% for 63hidden nodes. Since the neural network was only being expected to choose thewinning output node in this test, this poor performance was not considered veryimportant. In an industrial environment, there would probably have been a differentoutput configuration, for example, two output nodes with linear activation functions,each representing an engine parameter. In addition, the chosen 'Output LayerThreshold' value of 0.1 (or +-10%) was considered to be demanding for this initialexperiment.

The 'Matching Greatest Outputs' graph plot was considered important for thisexperiment, as the network was expected just to choose the greatest output as thecorrect one. Best performance was 80%, attained between 25 and 38 hidden nodes.

5. Conclusions

The MLP neural network was trained quickly and effectively for all values of 10 – 75hidden nodes.An output threshold value of 0.1 (or +-10%) was considered strict for this experiment.The choice of output configuration i.e. four outputs for four classes was not ideal forthis application – two linear nodes would be more appropriate and may give betterresults.

Based on the aforementioned results, the best overall performance was considered tobe achieved between 50 and 63 hidden nodes, so the minimum number to give bestperformance was chosen for future work, i.e. 50.

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