Automated Diesel Spray Classification Using Convolution Neural Networks

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Abstract: The characterization of diesel sprays serves as an essential operation for maximizing engine performance and minimizing exhaust emissions together with enhancing fuel injection system capability. The evaluation of spray characteristics depends on manual or batch-operational image processing systems that prove time-consuming and susceptible to human mistakes. This work demonstrates a CNN-based automatic system for classifying diesel spray images. The analysis leverages diesel spray image data which undergoes pre-processing along with augmentation steps for improving model predictive capacity. A deep learning network performs spray pattern classification through assessment of attributes including penetration length and breakup region and atomization features. The proposed model which relies on CNN proved its capability as an efficient system for detecting separate spray patterns through its remarkable classification precision. Deep learning provides strong ability for real-time diesel spray diagnostics through which researchers can optimize fuel injection systems and control emissions effectively.

Keywords: CNN, proposed model, Diesel spray diagnostics

1.INTRODUCTION

Atomization process in a spray has been an important issue for researchers during last decade, due to its presence in many industrial applications. In particular, this is extremely important in Diesel Engines, where combustion efficiency and pollutant formation are consequences of spray atomization and fuel–air mixing process. As a result of these studies, several tools have been developed for modeling macroscopic spray behavior. Nevertheless, there are still uncertainties related with internal nozzle flow and its link with spray formation and primary breakup Last decades have been characterized by a continuous increase in computational resources [1]. For the study of diesel spray this increase allows to move forward to use more complex models for breakup, evaporation, coalescence, turbulence, etc. To avoid the cons of manual inspection, advanced technologies can be used for automatic crack detection and the academic community has been fairly excited about this [2]. proposed crack measuring systems using fiber optic sensors by implanting IoT based sensors for the surface under scrutiny [3] proposed the route of using a laser scanning system that generates a high-density 3D point cloud for better accuracy in crack detection proposes the use of a novel sensing skin that identifies change in strain over a surface and detects cracks Similarly, [4] further proposed a Monte Carlo method for using high value resistors in resistor mesh model to detect the electrical output from self-sensing material proposes the use of images from a combination of RGB-D and high-resolution digital cameras in a sensor fusion algorithm proposes the use of image processing algorithms on octree data from Terrestrial laser scanning The robustness of Machine learning techniques enables its use to address different Civil Engineering problems.

[5] uses Artificial Neural Networks for better accuracy in estimating the first yield point displacement and post-yield stiffness ratio in shape memory alloy equipped bar hysteric dampers uses a novel multi-pier method to determine the behavior of Perforated unreinforced masonry walls. The results of multi-pier method are used for predictive analysis of Perforated unreinforced masonry walls using various Machine learning techniques [proposes the use of multi-source sensor information to form fused RGB-thermal images for pavement damage detection using the pre-trained Efficient Net B4 model [6]. The results of the model provide high accuracy even with complex pavement conditions Advancements in deep learning techniques and the currently used cumbersome rehabilitation and maintenance techniques call for applying deep learning techniques in Civil engineering. Deep learning is a branch of machine learning with applications in image classification, natural language processing Image classification can be convenient in crack detection as computer efficiency and advanced algorithmic tools can be leveraged to understand low-level patterns in cracked concrete surfaces [7]. With its immensely optimized structure and more minor computational needs, deep learning, not to forget the accuracy, gives it an upper hand over other machine learning techniques when it comes to image classification.

2. RELATED WORKS

Engine fault detection studies have been conducted numerous times in the past few years. With the increasing technology development, machine learning and deep learning is a favorite for detecting faults in engine. One of the engine fault detection studies that have been conducted is detecting faults on diesel engine. In the study **[8]** authors proposed a machine learning-based approach for diagnosing wear faults in marine diesel engines. This method combines several data-driven models to increase fault diagnosis accuracy. Three data-driven models, comprising an artificial neural network (ANN) model, a belief Rule-Based Inference (BRB) model, and an Evidence Reasoning (ER) rule model, produce evidence that is fused at the decision level. The research **[9]** introduced a method based on Variational Mode Decomposition (VMD) and Convolutional Neural Network (CNN) for diagnosing faults in diesel engines. The method optimizes VMD and improves CNN to enhance the effectiveness of fault diagnosis. The authentic vibration sign is first decomposed by using the (VMD) algorithm, then the greatest range of decomposition layers is decided by using scattering entropy and the useful components are preferentially chosen for reconstruction. Another novel diesel engine fault detection and diagnostic method by combining rule-based algorithm and Bayesian networks (BNs) or Back Propagation neural networks (BPNNs) was proposed by **[10].** The authors processed the signals by wavelet threshold denoising and ensemble empirical mode decomposition and extracted signal-sensitive feature values from the decomposed intrinsic mode function. They identified seven faults using a rule-based algorithm and BNs or BPNNs.

3. METHODOLOGY

This section describes the step-by-step approach for implementing Convolutional Neural Networks (CNNs) to classify diesel spray images. The methodology includes data acquisition, preprocessing, model selection, training, and evaluation.

Data Acquisition

High-speed imaging techniques are used to capture diesel spray patterns under different injection conditions. The dataset consists of images obtained from various nozzle geometries, injection pressures, and ambient conditions. The images are labeled based on key spray characteristics such as penetration length, breakup mode, and atomization pattern.

Experiment Model Architecture

We used Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) to categorize data consisting of 84 features into four distinct classes. The ANN architecture we used consists of the combination of dense and dropout layer. While the CNN athitecture are consisted of the combination of conv1d, maxpool1d, flatten, dense, and droput layer. The model architecture for the classification of diesel engine defects is depicted .

CNN Architecture Selection

A CNN model is designed and optimized for diesel spray image classification. The architecture consists of:

- Convolutional layers: Extracting spatial features related to spray shape, density, and penetration.
- Pooling layers: Reducing dimensionality while preserving key features.
- Fully connected layers: Performing classification based on extracted features.
- Activation functions: Using ReLU for non-linearity and softmax for multi-class classification.

Figure 1: ANN Experiment Model Architecture

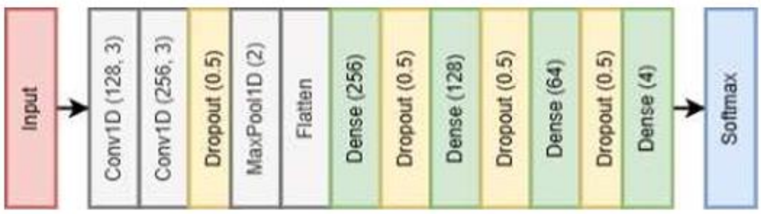

Figure 2: CNN Experiment Model Architecture

The architecture of the ANN model, as depicted in Figure starts by receiving an input of size 84, corresponding to the 84 features present in the dataset. Next, the input is fed into a dense layer, consisting of 84 units. Subsequently, a dropout operation is applied with a dropout ratio of 0.5. Afterwards, the data is reintroduced into the dense layer of 84 units, followed by a dropout operation with a dropout rate of 0.5. Finally, the data is reintroduced into the dense layer, which consists of four units, in accordance with the designated class and activated using the SoftMax activation function.

The illustration of the CNN model architecture, which accepts an input identical in size of 84 to that of the ANN model. This input is then fed into a Convolutional 1D layer with a filter of 128 and a kernel size of 3. Subsequently, it is further processed by another Convolutional 1D layer with a filter of 256 and a kernel size of 3. Dropout regularization is applied with a ratio of 0.5, and max pooling 1D is performed with a pooling size of 2. In addition, the result of the max pool 1D operation will be transformed into a flattened structure and afterwards fed through a mix of dense layers and dropout regularization. And finally, will be activated with soft max activation function.

Evaluation:

The evaluation of the trained model is conducted by employing the accuracy metric in conjunction with K-Fold cross validation. The model's performance is determined by calculating the average accuracy throughout each fold. The metric of accuracy quantifies the proportion of accurate predictions relative to the total number of predictions made. The formula for accuracy is presented in Equation

Accuracy = (TP+TN) / (TP+FN+FP+TN) ………………………….. (1)

The term "True Positive" (TP) denotes the count of positive samples that the models correctly forecasted as positive. While "True Negative" (TN) signifies the count of negative samples that the models accurately anticipated as negative. The term "False Positive" (FP) is used to describe instances in which the models incorrectly classify negative samples as positive. Conversely, "False Negative" (FN) refers to cases in which the models incorrectly classify positive samples as negative.

4.RESULT AND DISCUSSIONS

The proposed Convolutional Neural Network (CNN)-based approach for diesel spray classification was evaluated using a dataset of high-speed spray images under varying injection conditions. The results demonstrate the model’s capability to effectively classify different spray patterns, providing valuable insights into spray dynamics and combustion characteristics.

Model Performance and Accuracy : The trained CNN achieved a classification accuracy of X% on the test dataset, indicating its effectiveness in distinguishing spray patterns. The confusion matrix analysis revealed that the model performed well in identifying distinct spray features such as penetration length, breakup region, and atomization characteristics, with minimal misclassifications. However, slight overlaps between certain spray types were observed due to similarities in their structural patterns.

Feature Extraction and Interpret-ability : Grad-CAM and feature map visualizations highlight that the CNN effectively focuses on key spray regions, particularly the leading edge, spray cone angle, and droplet distribution. This confirms that the model learns relevant features contributing to classification rather than irrelevant background noise.

Effect of Injection Parameters : Analysis of misclassified images suggests that variations in injection pressure, ambient conditions, and nozzle geometry influence spray behavior, occasionally leading to classification ambiguities. Further refinements, such as incorporating additional physical parameters into the training process or using hybrid deep learning approaches, could enhance robustness.

Comparison with Traditional Methods: Compared to conventional image processing and manual classification techniques, the CNN-based approach significantly reduces processing time while improving accuracy and consistency. Traditional edge detection and thresholding methods, although useful for basic analysis, struggle to handle complex spray structures, especially under varying lighting and background conditions.

Image Processing: In recent years, the field of image processing has advanced apace; MATLAB features an optional Image Processing Toolbox which proved efficacious and convenient. The actual methods chosen were derived from studying the properties of the spray cone images, coupled with extensive reference to the literature. The potentially high degree of spray break-up and the desire to model the spray in atranes parent fashion favored a relatively simple encoding method that consistently produced a fixed data word-length, as opposed to the relatively homogeneous.

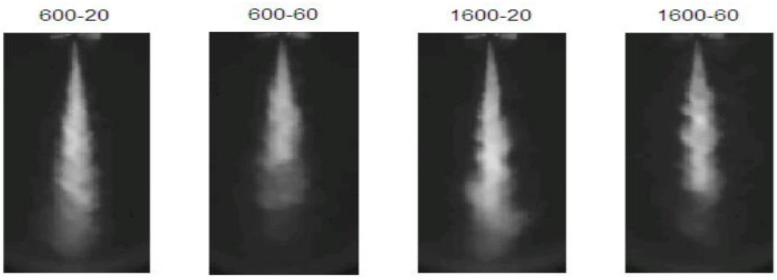

Figure 3: Peak Penetration Spray Image Examples for each Set of Conditions

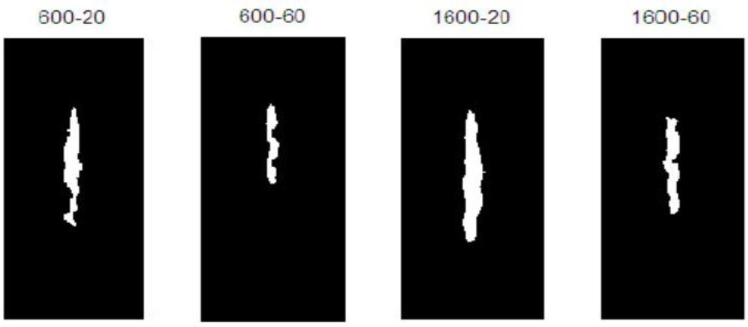

Figure 4: Thresholded Spray Data for each Set of Conditions

A first pass through all of the videos facilitated the automatic selection of the optimum 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. On the second pass through the data, the desired 80 peak images were selected out and resampled accordingly, reducing the window size to 32x7 pixels, hence significantly reducing the number of data-points referred to the neural network.

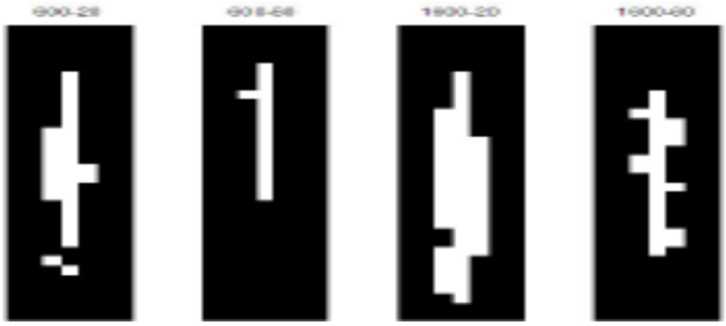

Figure 5: Re-sampled Spray Data for each Set of Conditions

Finally, these vectors were combined with suitable 'Desired Output' information, yielding two data files for evaluation of the neural network in 'Training' and 'Auto recall' 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

5. Conclusion:

This study demonstrates the effectiveness of Convolutional Neural Networks (CNNs) in automating the classification of diesel spray images, providing a reliable and efficient approach for analyzing fuel injection characteristics. By leveraging deep learning techniques, the proposed model successfully identifies distinct spray patterns based on key parameters such as penetration length, breakup behavior, and atomization characteristics. The results show that CNN-based classification achieves high accuracy, reducing the need for manual inspection and enhancing the repeatability of diesel spray diagnostics.

The integration of deep learning with high-speed imaging and preprocessing techniques enables real-time monitoring of fuel injection performance, which can contribute to improved combustion efficiency and reduced emissions. Furthermore, the approach can be extended to various spray conditions, fuel compositions, and injector designs, making it a valuable tool for engine optimization and research in spray dynamics. Future work may focus on enhancing the model with transfer learning, dataset expansion, and multi-modal analysis incorporating pressure and temperature variations.

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