Droplet Combustion Image Analysis Using CNN

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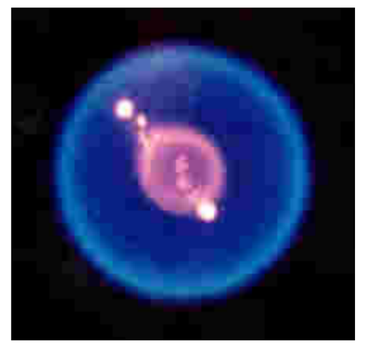
Motivation

With the motivation to improve fuel efficiency, the aerospace industry strives to gain a better understanding of the combustion process. For this purpose, free-floating droplet combustion experiments were conducted within the CIR at the International Space Station[1]. Droplet burning history, recorded by a back-lit black and white camera, can be used to measure the droplet diameter (D). Currently there's two ways to measure the diameter of the droplet: a) a rule-based computer algorithm, and b) manual measurements[2]. The first method is prone to noise and the second is tedious. Neither of these paths is ideal, and a robust algorithm that can extract droplet diameter, even from sooty images, is desired. Therefore this study looked into using ML to measure droplet diameter from the images.

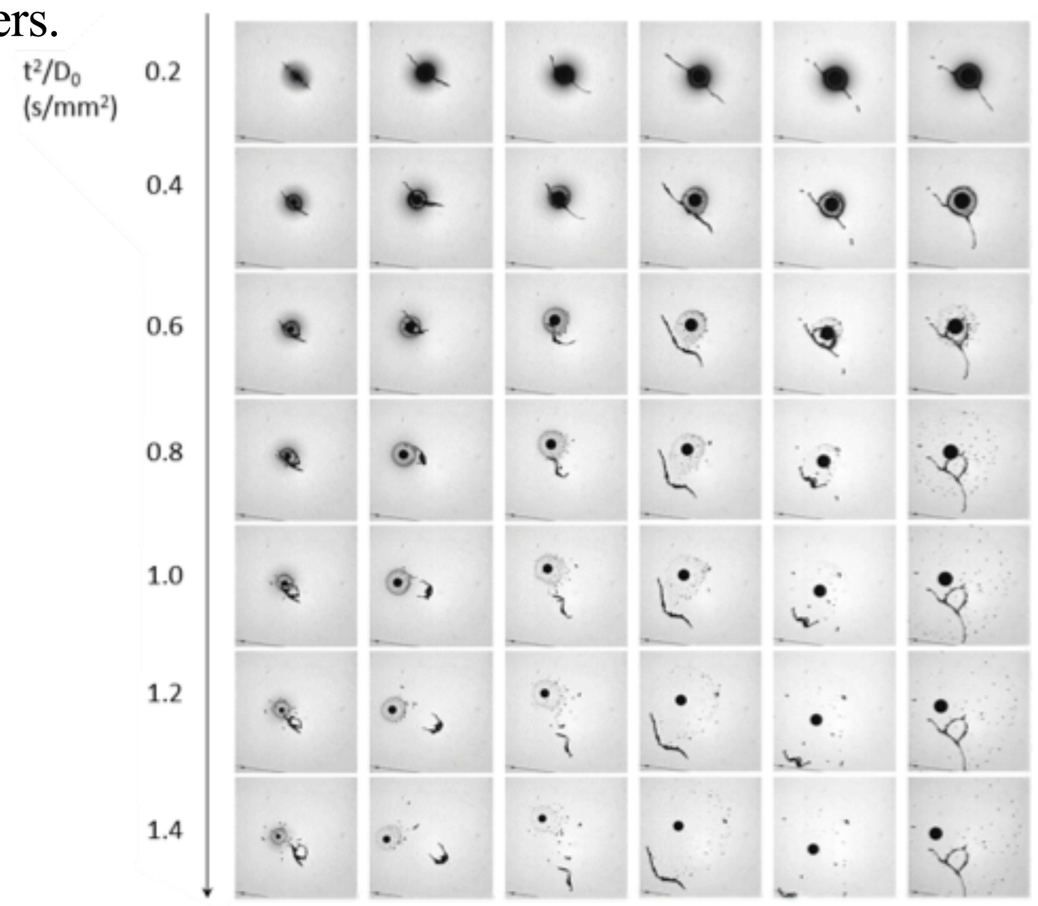


PC: Dryer http://www.princeton.edu/~fldryer/nasa.dir/

PC: NASA http://www.space-stationresearch.com/hardware/combustion-integrated-rack-cir/

Dataset

The dataset of images for this study was downloaded from NASA's Physical Science Information System[3]. A total of **6022** images were imported for Decane-Propylbenzene droplets in combustion. The dataset had droplet combustion sequences with various initial diameters.



To reduce the number of features and make the problem computationally tractable, an algorithm was developed to identify the droplet, iteratively update location of ROI, and perform cropping. This technique (illustrated below) proved to be useful and robust.

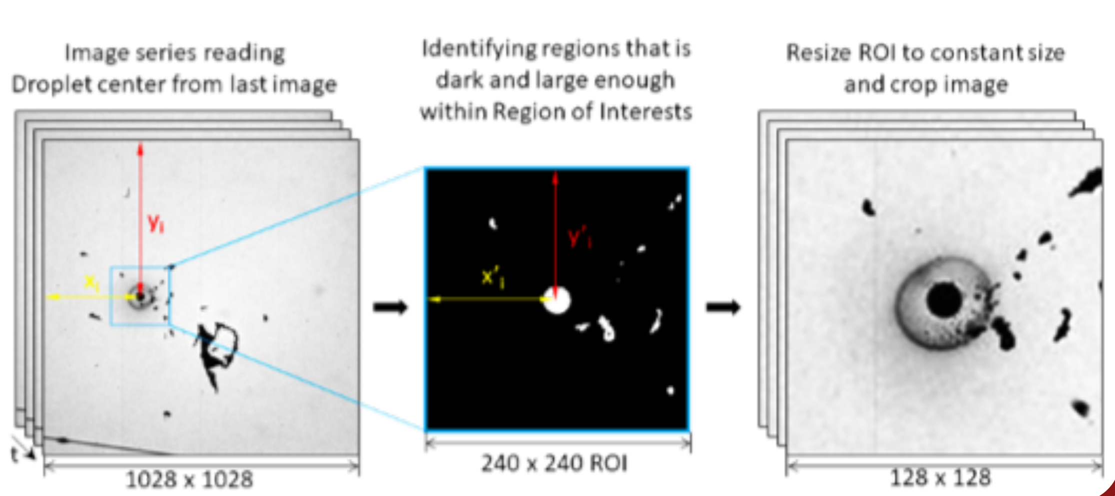
$$ny'_{i+1} = \sum y_{marked}$$

$$nx'_{i+1} = \sum x_{marked}$$

n: number of pixels that are above thresholds

$$y_{i+1} = y_i + \Delta y'_{i+1}$$

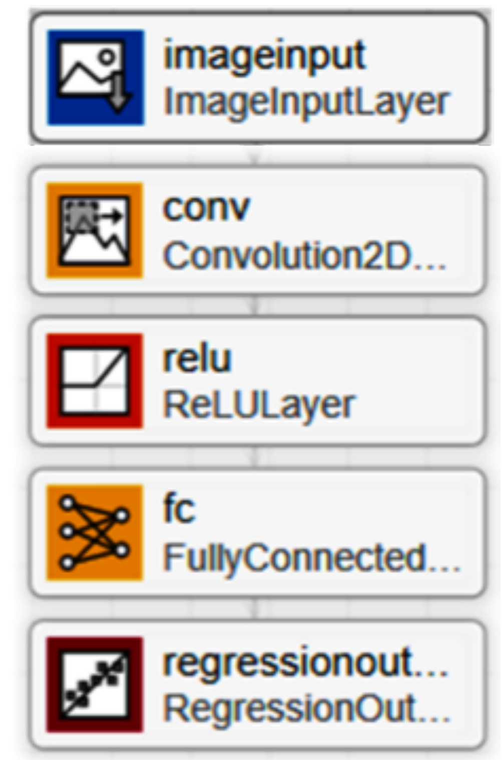
$$x_{i+1} = x_i + \Delta x'_{i+1}$$



Network Training and Architecture

The Convolutional Neural Network (CNN) structure used can be seen on the right. The convolution layer uses 20 100x100 pixel convolutions on cropped images. A ReLU activation function is used after the convolutional layer followed by a fully-connected layer and a regression layer that outputs the measured diameter.

Initially the network was trained on compressed raw images (128x128 px). In this set up, the largest droplet was about 30 pixels in diameter and a best-performance convolutional layer (CL) used 40 40x40 pixel convolutions. It was found that noise in raw image skewed the regression, therefore the images were cropped as discussed in the dataset section. The performance of the CNN improved significantly on cropped set since a large part of the noise was filtered out.

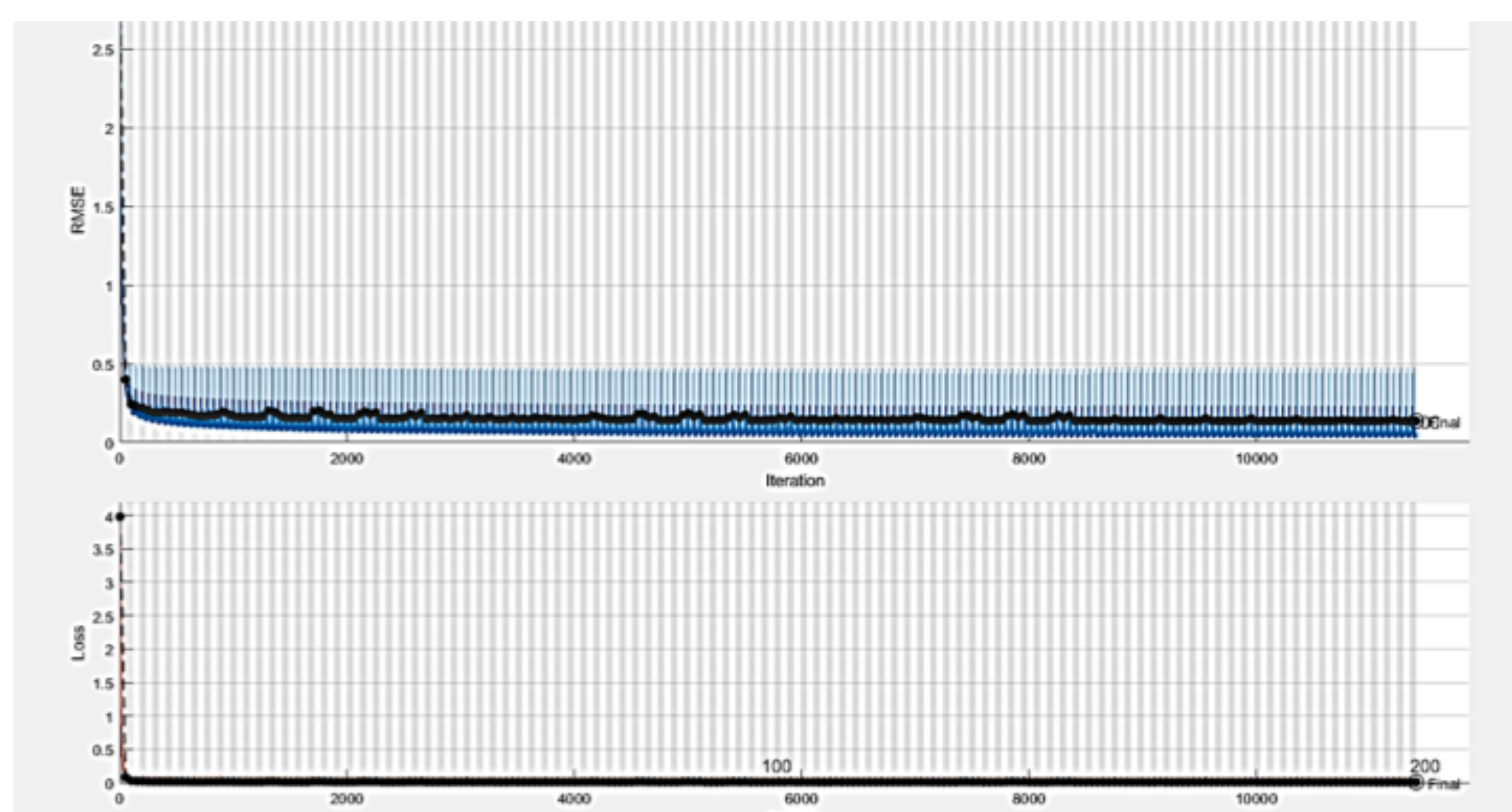


Results

Through extensive experiments, reasonable levels of accuracy were achieved. Regression deviation bins of ±5% and ±2.5% were set to categorize CNN performance on acceptable and good performance. During training, we found our model had high error on CV set and low error on training set, therefore regularization was added to mitigate high variance error. This modification helped improve accuracy. The neural net. performance for different runs can be seen in the table below.

Regularization (λ)	CL size	Dataset Type	Accuracy (±5%)	Accuracy (±2.5%)
0.0	20 20x20	Raw	36%	19%
0.0	40 40x40	Raw	56%	31%
0.0	20 100x100	Cropped	92%	62%
3.00E-03	20 100x100	Cropped	92%	63%
1.00E-02	20 100x100	Cropped	88%	58%
3.00E-02	**20 100x100**	**Cropped**	**96%**	**71%**
1.00E-01	20 100x100	Cropped	78%	47%

For training, a piecewise learning rate drop scheme using minibatch gradient descend was used. Best performance was achieved using a minibatch size of 64, 200 epochs and an initial learning rate of 0.0001, dropping every 150 epochs by a drop factor of 0.3. These parameters were tuned in a manner similar to tuning λ.



Discussion

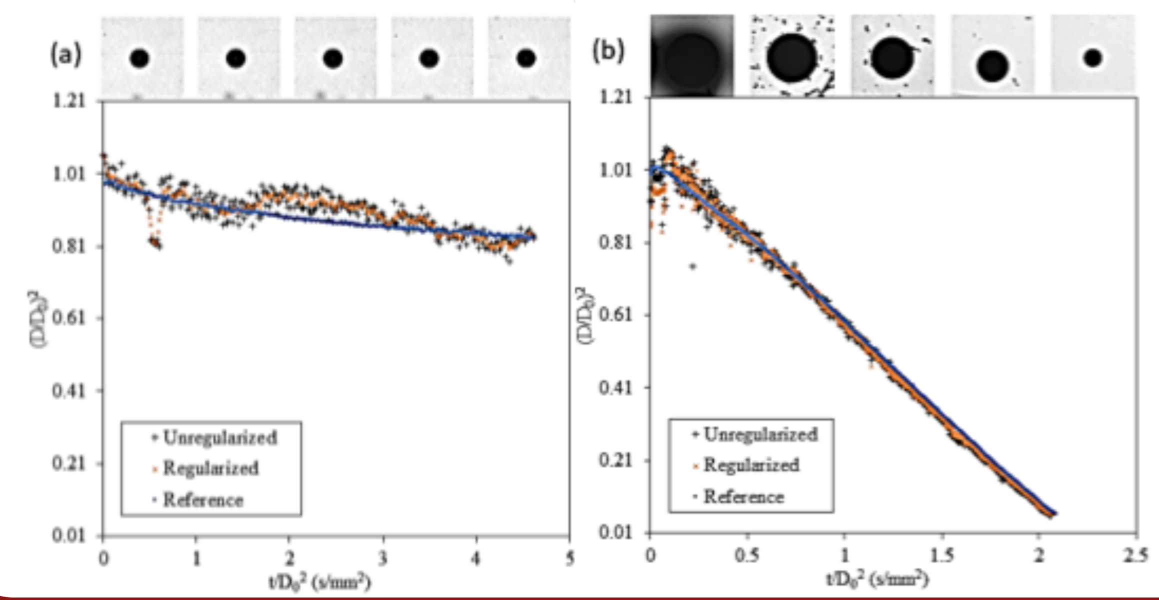
- Feature Reduction

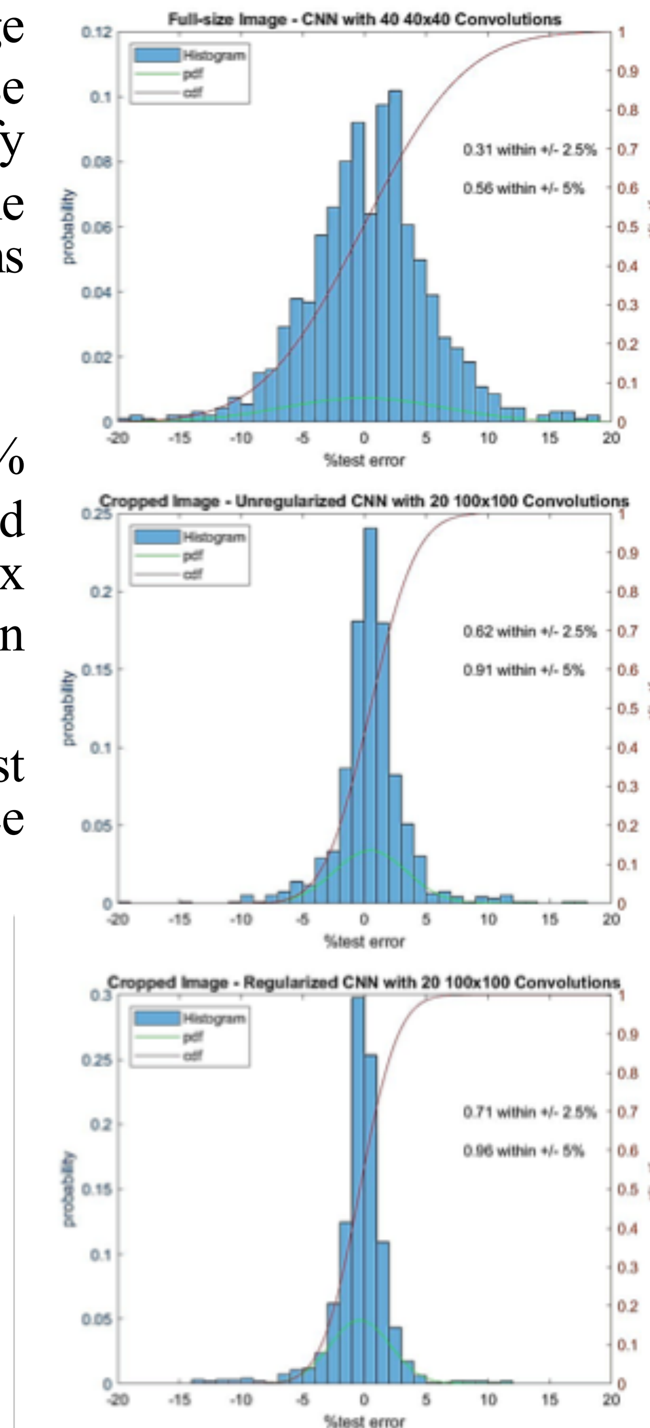
Excessive features such as soot aggregates on raw image created difficulties for the regression model as the noise looks similar to the droplet and the model failed to identify the correct object to measure. Cropping images removes the disturbances; the improvements can be seen in histograms on the right.

- Regularization

The accuracy on reduced dataset, especially within ±2.5% bin, was low. This is due to high variance error and regularization was applied to the regression model to fix this. The right bottom histogram shows how regularization helps to increase accuracy in ±2.5% bin.

The plots below show the predicted diameters using the best case regularized and unregularized CNNs with reference data from manual measurements.

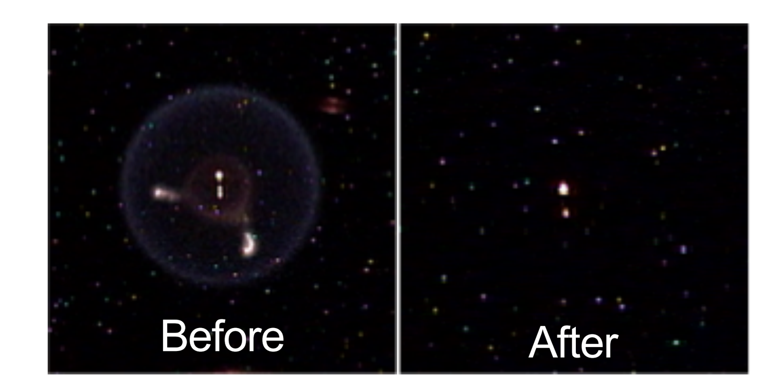




Future Work

Stewart and Ermon [4] demonstrated the use of CNNs to solve regression problems with un-labeled data using knowledge of the dynamics of the system. One of the issues with the prediction of droplet diameter in this project was that the output was noisy and the burning rate, which is proportional to the derivative of the diameter-squared, would have a high error. Using the knowledge of the dynamics of the system, this problem can possibly be fixed. The reason this was not attempted was that the dynamics differ for when the droplet is burning and after flame extinguishment for some test runs. The capturing of this transition requires analyzing color images simultaneously with our dataset. In the future a model of the dynamics of the system may be applied to improve the performance of our regression model.

Color image for flame extinguishment



References and Acknowledgement

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[1] Dietrich et al.,"Droplet combustion experiments aboard the int. space station,"Micro-gravity Sci. & Tech., 2014

[2] Dembia et al., "Automated data anal. for consecutive images from droplet combustion experiments", 2012.

[3] NASA Physical Science Information System. https://psi.nasa.gov/

[4] R. Stewart et. al., "Label-free supervision of neural networks with physics and domain knowledge.," 2017.