Using machine learning over Fast Camera images to classify the plasma confinement mode within the MAST experiment

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Plasma Confinement Modes

Inside a Fusion Tokamak, plasma is primarily designed to be in one of several confinement modes: Low confinement (L-Mode), High Confinement (H-Mode), Dithering Confinement (D-Mode) and I-Mode.

The plasma starts initially in L-Mode and after sufficient heating has been applied spontaneously transitions into H-Mode [1].

If this H-Mode is stable then it is a true H-mode, however in some cases the plasma alternates between the two modes resulting in a third apparent state D-Mode. [2]

For a fusion reactor having the plasma in a stable H-Mode is preferred as as we observe better confinement often with twice the confinement time and greater transport barrier due to steeper pedestal. [3]

Fast Cameras on MAST

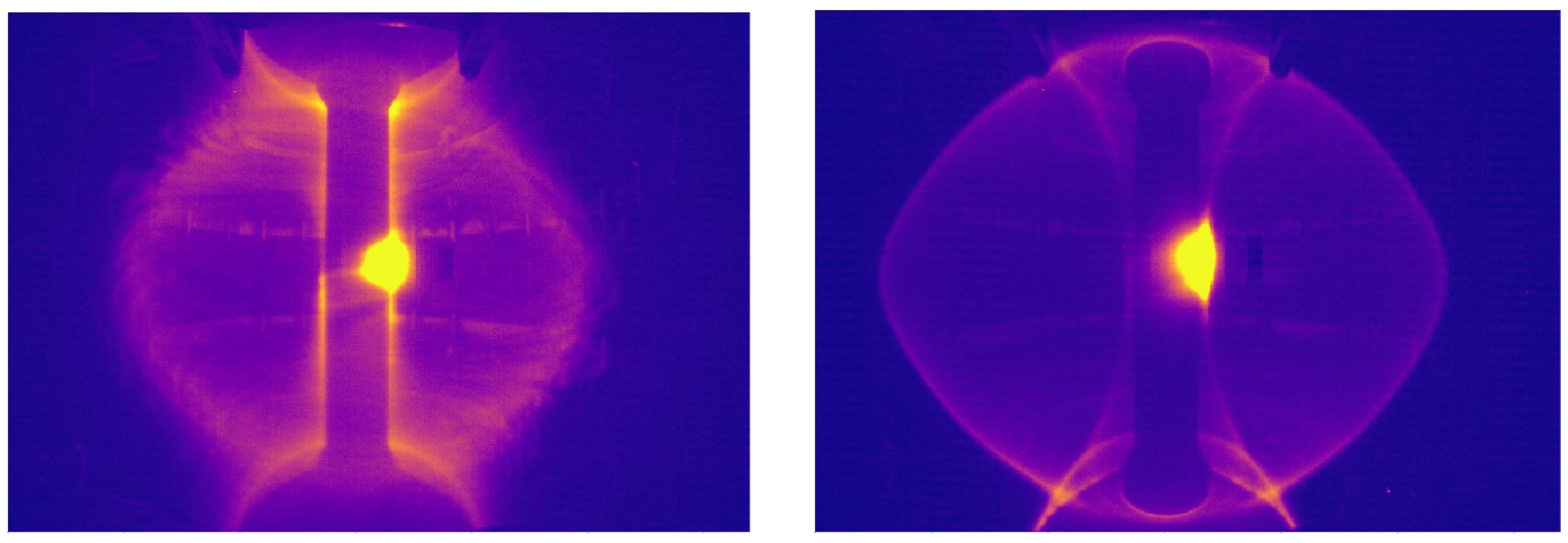
The MAST experiment was previously equipped with several sets of diagnostic cameras imaging the experiments (Shots) in several wavelengths and viewing different regions of the Tokamak. [4]

Of interest for this project was the RBB camera, the fast camera at the midplane viewing across the central solenoid in the visible spectrum.

Typically this camera operates at 500Hz producing around 400 images (Frames) per shot and its resolution is variable depending on the experiment.

Below in figure 1 are example images taken by this camera illustrating the difference between plasma in L-Mode (Left) and H-Mode (Right) from the perspective of the RBB camera.

Note the roughness at the edge of the L-mode plasma, this is due to the effects of edge turbulence, which is damped in H-mode because of its greater transport barrier leading to the smoother edge that is seen. [3][4]



L-Mode H-Mode

Figure 1: Example images taken from the RBB camera in MAST illustrating plasma in L-Mode (Left) and H-Mode (Right). (Shot 30298, frames 58 and 248)

Data Processing

For this project 100 shots from the RBB fast camera were selected such that they all had the same resolution (448 by 640). They were selected from this camera as it provides a good overview of the plasma as a whole allowing for easy identification of confinement mode.

Each shot had on average just over 400 frames for a total of around 60444 images.

For each shot the L-H transition point was manually located and every frame before this point labeled as L-mode and every point after labeled as H-mode.

This labeled data was split into training, testing and validation sets, with shots being kept together to provide each set with a variety of time instances to evaluate. The distribution of the data into these sets was 70/15/15 across the training, testing and validation sets respectively.

References

[1] Xu G.S. et al. 2014 Nucl. Fusion 54 103002

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[3] M. Keilhacker, H-mode confinement in tokamaks, Plasma Phys. Control. Fusion 29 (1987) 1401-1413

[4] A Kirk et al 2006 Plasma Phys. Control. Fusion 48 B433

[5] Alex Krizhevsky, et al. 2017. ImageNet classification with deep convolutional neural networks. Commun. ACM 60, 6 (June 2017), 84–90. https://doi.org/10.1145/3065386

[6] Vignesh Gopakumar, et al. Fourier neural operator for plasma modeling, NeurIPS AI for science 2023

Machine Learning Classifier

For this project a simple classification neural net was constructed. The architecture was based on the AlexNet architecture as it is an established and proven architecture suitable for what should be a simple classification task. [5]

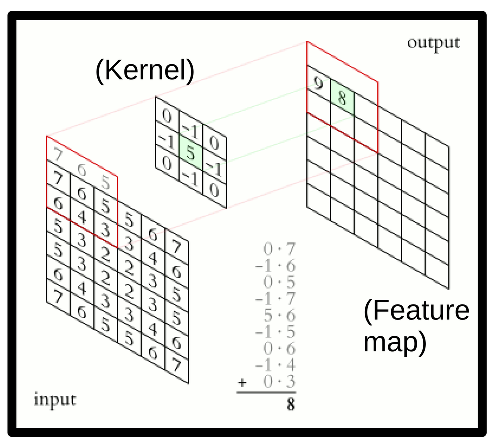
AlexNet is a convolutional Neural Network (CNN) that utilizes strided convolutions along the spacial domain in order to produce feature maps of images given as inputs to the network. In this process a kernel is passed over the image and its interaction with said image produces the feature map. An example of how a convolution works is given on the left of figure 2.

For this project there are 5 convolution layers with kernels of 11x11, 5x5 then three 3x3 kernels, these are the default in AlexNet.

The AlexNet architecture was modified to account for the spatial resolution of the RBB camera images (448 x 640) at the input, while the output layer was engineered for performing binary classification with a single output.

The trained classification model outputs a probability between 0 and 1 as to whether the camera frame represents plasma in H-Mode. We set a confidence bound on the probability output such that those with 80 percent probability or more are classified as H-mode and all others as L-mode.

We deployed a Binary Cross Entropy Loss to train the model for the classification task, and train over 100 epochs.



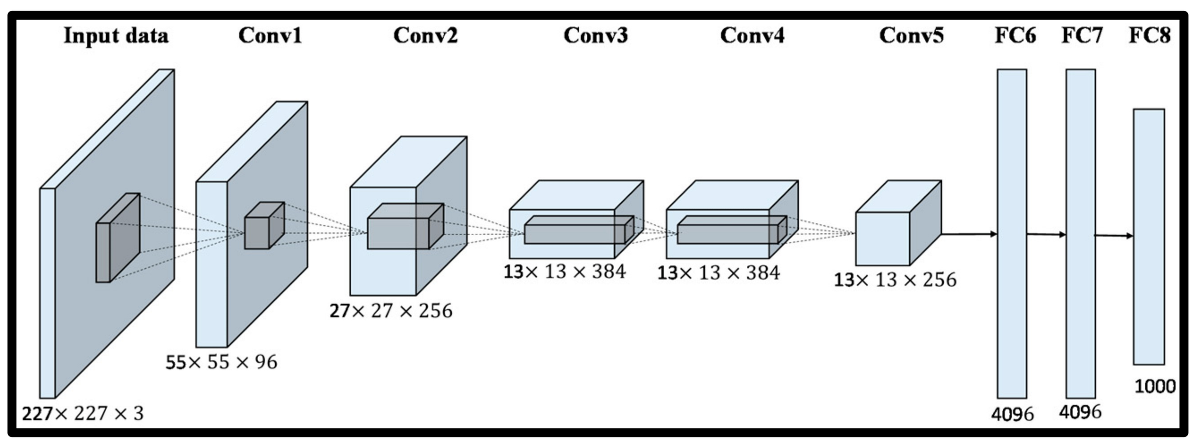


Figure 2: (Left) An example of how a convolution works with a kernel passing over an input.

Image source: Wikipedia

(Right) The basic AlexNet architecture, the main modification that was made to this was to adapt the input layers to accommodate images of size 448 by 640 and a reduction in the final fully connected layer to only output 2 classes. Image from: https://doi.org/10.3390/rs9080848

Results and future projects

Overall the model achieved a 99% accuracy rating on its predictions with the majority of the errors coming in three main places:

-At the start when the plasma hasn't fully formed yet

-At the end after a disruption has stopped the experiment and the plasma is dissipating

-Uncertainty around the transition point provides insights into the statistical difference around the LH transition

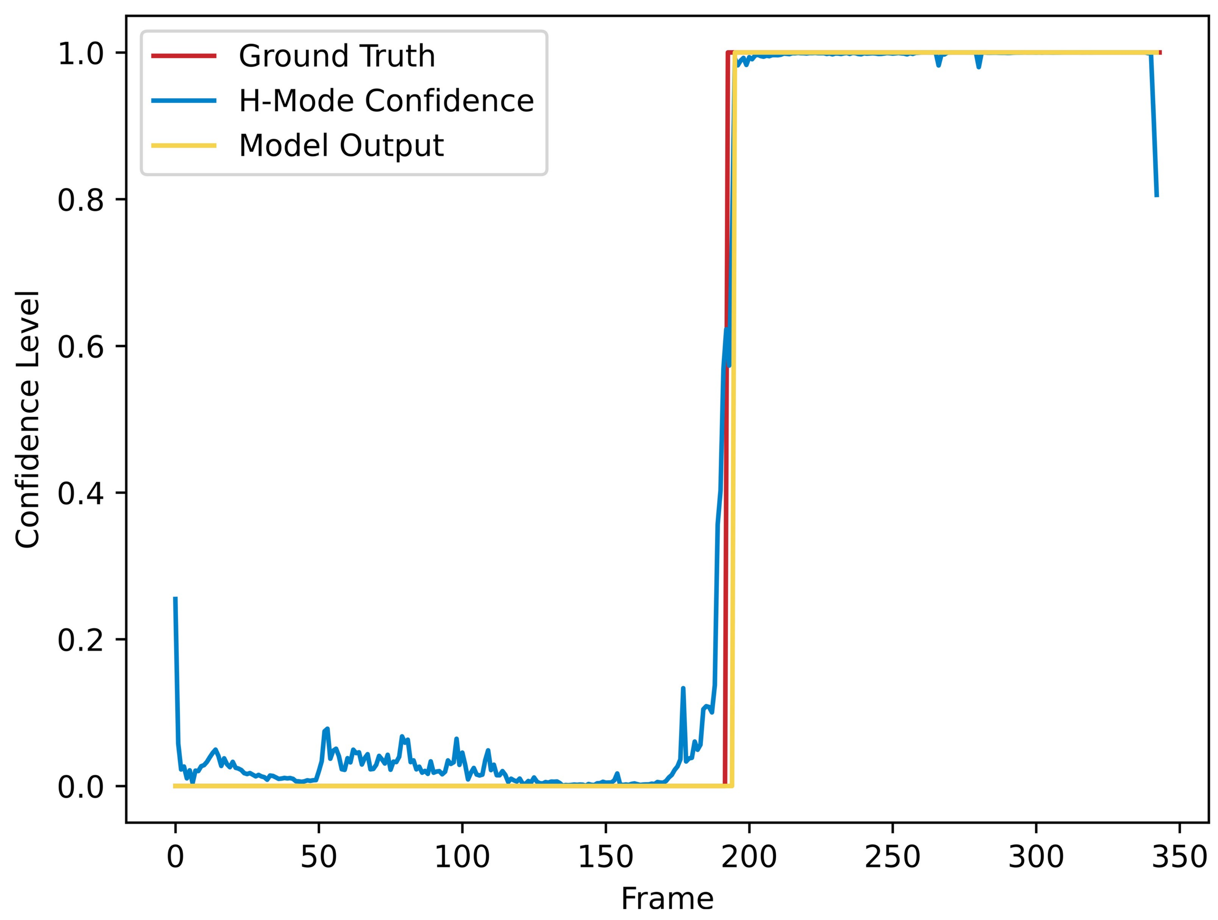


Figure 3: An example shot after the models training. It had on overall 99% accuracy on average, with the majority of the error coming at the start, end and around the transition point. As illustrated in this example.

For the future, the model can be further refined by pre-processing the training data to remove the start and end points as there is no interesting/relevant information there.

In addition to this a better tagging of the data to account for any instances of the shots going into dithering mode could improve performance.

Additionally the model could also be trained on cropped images in an attempt to use it with differnet camera settings.

Going forward the trained model can be used in conjunction with another ongoing project at UKAEA (The use of a Fourier Neural Operator to predict plasma shape evolution) to predict the L-H transition point, potentially in real time. See [6] for more information.