# High repetition rate diagnostics with integrated machine learning analysis for a new paradigm of actively controlled Inertial Fusion Energy experiments

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**Executive summary**

On a typical Inertial Confinement Fusion shot at the state-of-the-art National Ignition Facility, over one hundred diagnostics will independently acquire data amassing more than 150 GB on a range of instruments including spectrometers and imaging diagnostics for particles such as neutrons, x-rays, electrons and protons, and electromagnetic radiation across the spectrum from EMP to gamma-rays. Bespoke diagnostics were designed for dedicated purposes and implicitly to perform at repetition rates of one shot per several hours, which is suitable for this system. However, the next generation of Inertial Fusion Energy relevant research, and ultimately any demonstration facility, will operate at repetition rates of Hz, aided by high power laser technology advancing around the world. Conventional diagnostics must therefore now be upgraded and keep pace with laser repetition rates and current detection techniques based on single-use detectors, films, and image plates, are inherently incapable of meeting this challenge. We, therefore, introduce a general framework for developing high repetition rate diagnostics that take advantage of the innovation of their predecessors and will equip them to be ready for this challenge. By harnessing machine learning based techniques, the output of these diagnostics can also be meaningfully analyzed in real time, which provides an enabling technological framework for using real time experimental data to perform automated closed-loop Inertial Fusion Energy relevant research. Such a closed loop system would lead to opportunities for a dramatically increased rate of learning about HED environments, mapping vast experimental phase spaces, and would find applications in IFE experimental optimization and stabilization.

## I. Introduction

High repetition rate (HRR) (> Hz), high energy laser systems with nanosecond pulse lengths and pulse shaping capabilities now routinely operate around the world[1,2] heralding an era where High Energy Density (HED) conditions can be produced at unprecedented rates. These have the capability to revolutionize the way Inertial Fusion Energy (IFE) experiments are done by providing opportunities for precision study of these extreme environments, and as an IFE program matures these laser systems will inevitably take a central role as studies are ramped up to the repetition rates required for advanced testing and demonstration facilities.

However, a significant bottleneck to conducting HRR HED experiments lies in our capability to diagnose these experiments at a repetition rate matching that at which the lasers can operate. Detector media has been slow to progress beyond the hourlong recovery and processing timescales required for single-use film and image plate detectors which represent the prevailing state of the art, and without innovation will effectively become the rate-determining step between creating HED relevant conditions and studying them in real time.

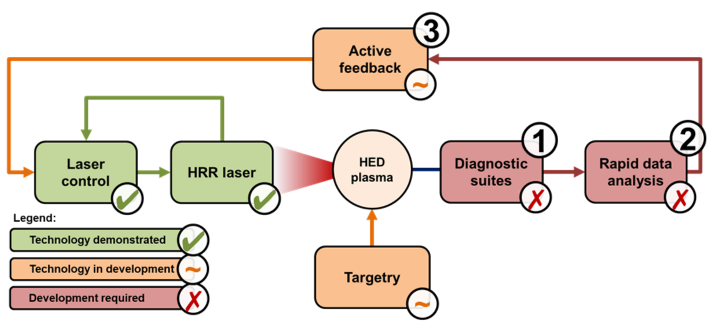


**Figure 1:** A schematic illustrating how development of HRR diagnostic suites with integrated rapid data analysis algorithms will enable closed loop operations of actively controlled experiments.

Even with HRR diagnostics, extracting physically relevant measurements from these diagnostics and using this information in real time would remain a major obstacle to HRR-operation since data analysis is typically heavily human-operator dependent and time intensive.

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To address this, diagnostic analysis algorithms must be developed, and we outline how developing machine learning (ML) techniques for this purpose is a robust way forward. This will enable the real-time distillation of diagnostic data into key experimental metrics with precise uncertainties gathered from diagnostic calibration and characterization, and uncertainty quantification gathered from the statistically significant dataset.

Such a HRR diagnostic suite, coupled to automated ML data analysis algorithms, represents an enabling framework to realize a fully integrated experimental system with active feedback to the laser at HRR. This framework would enable rapid scans of experimental parameter space to form data-driven models or provide a means of quickly optimizing and/or stabilizing an experiment and opening up pathways to investigating new physics where an optimizer may find an optimal condition in a previously neglected point in the parameter space.

## II. A general scheme for high repetition rate diagnostic development

In general, diagnostics are composed of a front and back end, as illustrated in Figure 2. The front end includes combinations of species selection mechanisms, dispersion mechanisms and/or imaging systems, and is often intrinsically suited for HRR operation. A myriad of sophisticated instruments exist in the literature, and HRR diagnostics can re-use designs for front ends of these instruments. The crux of the matter is therefore usually to develop a suitable HRR back end that replaces existing image plate or film back ends. This back end upgrade to electronic readout enables instrument operation at HRR[3].

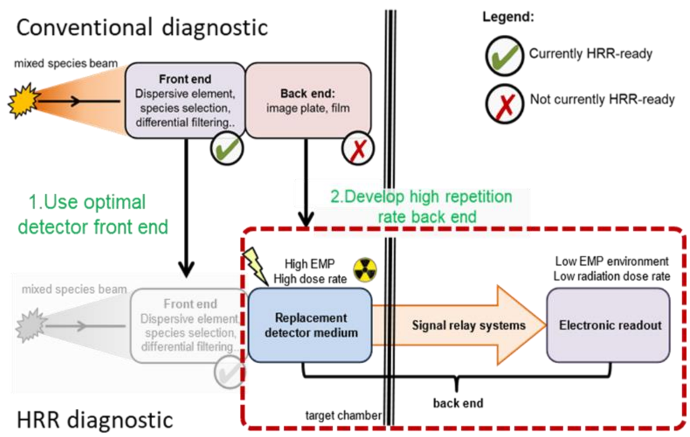


**Figure 2:** A schematic detailing the concept of adapting a conventional diagnostic to for HRR operation

Developing a back end that is robust to the unique environments that exist in a high-power laser interaction chamber is challenging, as sensitive electronic equipment that would otherwise be a suitable choice as a detector medium, fail in the harsh high radiation, high EMP[4] environment where vacuum itself also poses a challenge. For this reason, the back end of existing HRR diagnostics is usually composed of a HRR-capable detector medium to be fielded near the interaction, a signal transport system, and an electronic readout system at a safe distance from the interaction. The detector medium for these diagnostics is almost routinely based on scintillator technologies, however, these have not yet been demonstrated to be robust to HRR operation and a detailed study of their suitability should be conducted, and alternatives sought as a contingency. CMOS/CCD or oscilloscopes are often used for the electronic readout of the detector, however more advanced systems which offer temporally resolved measurements exist and should be considered for use to maximize information obtained on experiments.

*Some key development needs include*:

- Assessment of the appropriateness of scintillator materials
  - Radiation hardening development and hardness assessments
  - Performance with high average and single shot radiation dose over time
  - Susceptibility to background radiation sources (x-rays, Cerenkov etc.)
- Development of dedicated scintillator materials
  - Fast (ps-ns), high light yield scintillators for temporally resolving detectors
  - Low light afterglow (on µs-ms timescales) scintillators for prolonged exposure to high average dose rates
  - High spatial resolution pixelated or granular scintillators for imaging applications[5,6]
- Absolute calibration of diagnostics and components
- Design of novel optical signal transport systems
  - Shaped fiber optic plates for shaping of back end detector planes
  - Fiber optic multiplexers to preserve temporal information
  - Similar assessments are required for radiation hardening of these components
- Development of fast temporally resolving electronic detectors (ps-ns)
  - High dynamic range, streaked detectors or ultrafast diodes
  - hybrid-CMOS detectors for ultrafast gated imaging

## III. Rapid machine learning based analysis

Conventional data analysis often relies on time-intensive processes that are heavily human-operator-dependent and are thus subject to individual biases and systematic errors. Even auto-analyzed data, from NIF for example, takes minutes to process, which is a paradigm that cannot realistically scale to HRR experiments operating at several Hz. ML algorithms however are widely used to identify and extract measurable quantities from large datasets of diverse types, including images and time-series data, and these techniques can be developed for use with specific diagnostics to vastly increase the data processing rate.

Deep learning ML techniques are particularly suited to these tasks[7], and have been demonstrated to instead train algorithms to learn to identify these metrics directly from raw experimental images, and analysis that would normally take on the order of minutes to hours through traditional means is performed on few fractions of a millisecond through ML-based data analysis techniques.

Training of such neural networks does not rely on having real-world data but instead, a repository of modeled synthetic data from the diagnostics can be used as a surrogate before real experimental data is used to refine these models with practical corrections such as detector-specific noise, misalignments, source non-uniformities, or other idiosyncrasies. Amassing larger data sets from calibration or experimental data can subsequently be used to update the analysis model through active learning and transfer learning methods, to continually improve our algorithms. Further, this methodology enables rigorous assessment of the uncertainties in the distilled quantities.

*Some key development needs include*:

- Repository for ML analysis routines, training, and test data for standardized diagnostics
  - Should be based on opensource tools such as TensorFlow, Pytorch etc.

- Incorporate cutting edge hardware that interfaces with diagnostics
  - Develop purpose built ASICS chips or FPGAs for each diagnostic type
  - Edge computing incorporated into diagnostics for massive parallel data analysis
- Standardized data acquisition, transport, storage, indexing and handling methods
  - Use common and efficient data formats for each diagnostic
  - Centralized data system that can efficiently sort and identify key metrics from massive datasets without information loss
  - Methods for transporting data to and from High Performance Computing resources
  - Robust methods for massive data set distillation into appropriate metadata

## IV. The need for robust diagnostic modeling

Synthetic diagnostic modeling is performed when designing state of the art diagnostics, and in the age of machine learning based diagnostic analysis, synthetic diagnostic modeling will have an essential role. An abundance of synthetic diagnostic output can be generated from well-defined input conditions and provide thousands of datasets for machine learning algorithms to train on.

Codes such as GEANT4 and MCNP can be used to model detector response, including spectral sensitivity, energy resolution, and signal-to-noise ratio for a range of detector media of interest. Through these efforts, we will generate realistic synthetic diagnostic response data for a range of simulated experimental conditions. The data can be tailored with well-defined signal to noise, or unexpected spectral shapes for example, to test the robustness of the algorithms, and can also be used to train the algorithms for error recognition.

Collecting this experimental diagnostic data will enable testing the adaptability of our ML-based analysis. This further allows for updating the algorithms by training them on real data that has features not present in the synthetic through transfer learning.

*Some key development needs include*:

- Use of open-source accessible diagnostic design (CAD) and physics software (e.g. Geant4)
  - Design of tools for interfacing and migrating diagnostics between these
- Open-source repository for back end detector libraries in physics modeling software
- Design of tools for importing numerical modeling output (PIC, hydro, etc.) into physics modeling software

## V. Closing the loop for automated IFE experiments

Research groups in the field of laser driven wakefield acceleration have recently pioneered the use of active feedback loops to optimize electron energy beam charge, and spatial distribution. Optimization via active feedback in this context can and has been performed via an array of methods including gradient descent, genetic algorithms, or Bayesian optimization techniques[8,9], and similar real time analysis of an IFE relevant experiment can optimize aspects of these interactions. This might include optimization of neutron production, or to achieve stability of energy output, such as is being explored in the MFE community. For laser solid interactions, in general, there is a complex and non-linear relationship between experimental laser inputs and particle outputs, necessitating that multi-modal data from heterogeneous data sources be rapidly incorporated for an active feedback demonstration.

*Some key development needs include*:

- Establish the suitability of open source control system codes such as EPICS for much larger quantities of experimental data than have been used to date
- Integrate existing and yet-to-be-developed HRR instruments into control system codes
- Develop software for online (in-the-loop) data analysis and data reduction of HRR instruments
- Incorporate state of the art HED modeling codes into this feedback
- Create open repositories of a range of optimization algorithms

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