

Lighter: Configuration-Driven Deep Learning

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DOI: [10.xxxxxx/draft](https://doi.org/10.xxxxxx/draft)

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Submitted: 01 January 1970

Published: unpublished

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Summary

Lighter is a configuration-driven deep learning (DL) framework that separates experimental setup from code implementation. Models, datasets, and other components are defined through structured configuration files (configs). Configs serve as snapshots of the experiments, enhancing reproducibility while eliminating unstructured and repetitive scripts. Lighter uses (i) PyTorch Lightning (Falcon & The PyTorch Lightning team, 2019) to implement a task-agnostic DL logic, and (ii) MONAI Bundle configuration (Cardoso et al., 2022) to manage experiments using YAML configs.

Statement of Need

Lighter addresses several challenges in DL experimentation:

- 1. Repetitive and Error-Prone Setups:** DL typically involves significant boilerplate code for training loops, data loading, and metric calculations. The numerous hyperparameters and components across experiments can easily become complex and error-prone. Lighter abstracts these repetitive tasks and uses centralized configs for a clear, manageable experimental setup, reducing tedium and potential for errors.
- 2. Reproducibility and Collaboration:** Inconsistent or complex codebases hinder collaboration and experiment reproduction. Lighter's self-documenting configs offer clear, structured snapshots of each experiment. This greatly improves reproducibility and simplifies how teams share and reuse setups.
- 3. Pace of Research Iteration:** The cumulative effect of these challenges inherently slows down the research cycle. Lighter streamlines the entire experimental process, allowing researchers to focus on core hypotheses and iterate on ideas efficiently.

State of the Field

Config-driven frameworks like Ludwig (Molino et al., 2019), Quadra (Mammana et al., 2025), and GaNDLF (Pati et al., 2023) offer high level of abstraction by providing predefined structures and pipelines. While this approach simplifies usage, it limits flexibility to modify the pipeline or extend components, often requiring direct source code changes. Lighter takes a different

approach by providing medium-level abstraction. It implements a flexible pipeline that maintains direct compatibility with standard PyTorch components (models, datasets, optimizers). The pipeline itself is modifiable to any task via [adapters](#), while custom code is [importable via config](#) without source code modifications.

Design

Lighter is built upon three fundamental components ([Figure 1](#)):

1. **Config**: serves as the primary interface for interacting with Lighter. It parses and validates YAML configs that define all components, creating a self-documenting record of each experiment.
2. **System**: encapsulates the components (model, optimizer, scheduler, loss function, metrics, and dataloaders) and connects them into a pipeline that can be customized through [adapters](#) ([Figure 2](#)).
3. **Trainer**: PyTorch Lightning's Trainer handles aspects like distributed or mixed-precision training and checkpoint management. Lighter uses it to execute the protocol defined by the System.

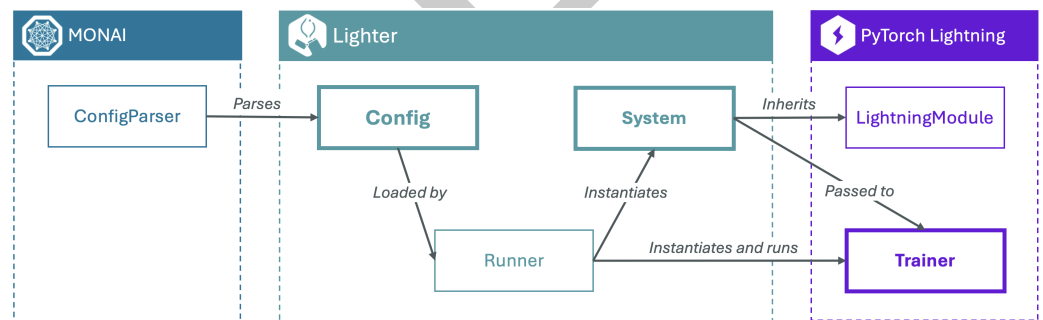


Figure 1: Lighter Overview. Config leverages MONAI's ConfigParser for parsing the user-defined YAML configs, and its features are used by Runner to instantiate the System and Trainer. Trainer is used directly from PyTorch Lightning, whereas System inherits from LightningModule, ensuring its compatibility with Trainer while implementing a logic generalizable to any task or type of data. Finally, Runner runs the paired Trainer and System for a particular stage (e.g., fit or test).

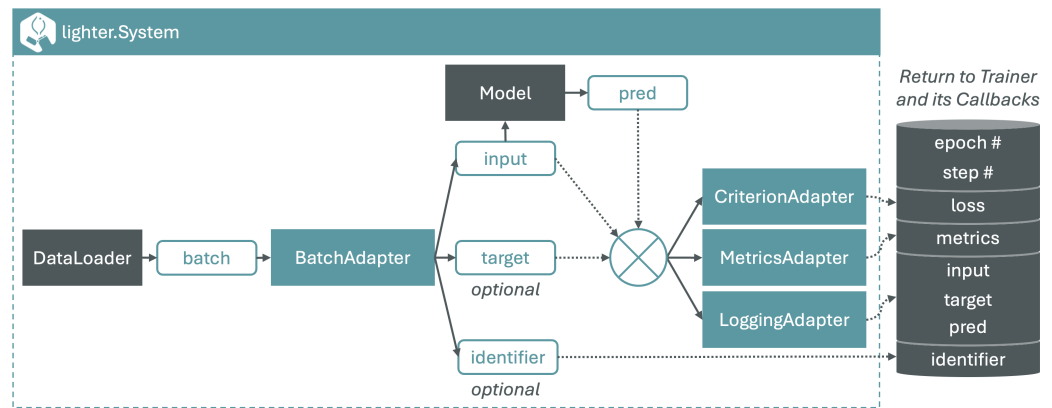


Figure 2: Flowchart of the `Lighter.System`. A batch from the `DataLoader` is processed by `BatchAdapter` to extract input, target (optional), and identifier (optional). The `Model` generates `pred` (predictions) from the input. `CriterionAdapter` and `MetricsAdapter` compute loss and metrics, respectively, by applying optional transformations and routing arguments for the loss and metric functions. Results, including loss, metrics, and other data prepared for logging by the `LoggingAdapter` are returned to the `Trainer`.

Adaptability Through Modular Design

Adapters

If we consider all possible DL tasks, we will find it challenging to implement a single pipeline that supports all. Instead, frameworks often implement per-task pipelines (e.g., segmentation, classification, etc.). By contrast, `Lighter` implements a unified pipeline modifiable via *adapter classes*. In software design, *adapter design pattern* enables components with incompatible interfaces to work together by *bridging* them using an adapter class. In `Lighter`, these bridges (Figure 2) specify how components should interact across data types and tasks. For example, a model's output will differ based on the task (e.g., segmentation, regression), and the adapter will specify how to pass them on to the next component (e.g., criterion or metrics). This design allows `Lighter` to handle any task without requiring changes to the source code.

```

# Example of an adapter transforming and routing data to the loss function
adapters:
  train:
    criterion:
      _target_: lighter.adapters.CriterionAdapter
      pred_transforms: # Apply sigmoid activation to predictions
        _target_: torch.sigmoid
      pred_argument: 0 # Pass 'pred' to criterion's first arg
      target_argument: 1 # Pass 'target' to criterion's second arg

```

Project-specific modules

Using custom components does not require modifying the framework. Instead, they can be defined within a *project folder* like:

```

joss_project
├── __init__.py
├── models/
│   ├── __init__.py
│   └── mlp.py

```

By specifying the project path in the config, it is imported as a module whose components can be referenced in the config:

```
project: /path/to/joss_project # Path to the directory above
system:
  model:
    _target_: project.models.mlp.MLP # Reference to the custom model
    input_size: 784
    num_classes: 10
```

Research Contributions That Use Lighter

- Foundation model for cancer imaging biomarkers (Pai et al., 2024)
- Vision Foundation Models for Computed Tomography (Pai et al., 2025)

Acknowledgments

We thank John Zielke for the adapter design pattern idea. We thank Wenqi Li, Nic Ma, Yun Liu, and Eric Kerfoot for their continuous support with MONAI Bundle.

References

- Cardoso, M. J., Li, W., Brown, R., Ma, N., Kerfoot, E., Wang, Y., Murray, B., Myronenko, A., Zhao, C., Yang, D., Nath, V., He, Y., Xu, Z., Hatamizadeh, A., Zhu, W., Liu, Y., Zheng, M., Tang, Y., Yang, I., ... Feng, A. (2022). *MONAI: An open-source framework for deep learning in healthcare*. <https://doi.org/10.48550/arXiv.2211.02701>
- Falcon, W., & The PyTorch Lightning team. (2019). *PyTorch Lightning* (Version 1.4). <https://doi.org/10.5281/zenodo.3828935>
- Mammana, L., Malli, R. C., Polidori, A., & ebernatene. (2025). *Orobix/quadra*. <https://github.com/orobix/quadra>
- Molino, P., Dudin, Y., & Miryala, S. S. (2019). Ludwig: A type-based declarative deep learning toolbox. *CoRR, abs/1909.07930*. <http://arxiv.org/abs/1909.07930>
- Pai, S., Bontempi, D., Hadzic, I., Prudente, V., Sokač, M., Chaunzwa, T. L., Bernatz, S., Hosny, A., Mak, R. H., Birkbak, N. J., & Aerts, H. J. W. L. (2024). Foundation model for cancer imaging biomarkers. *Nat. Mach. Intell.*, 6(3), 354–367. <https://doi.org/10.1038/s42256-024-00807-9>
- Pai, S., Hadzic, I., Bontempi, D., Bressen, K., Kann, B. H., Fedorov, A., Mak, R. H., & Aerts, H. J. W. L. (2025). *Vision foundation models for computed tomography*. <https://doi.org/10.48550/arXiv.2501.09001>
- Pati, S., Thakur, S. P., Hamamcı, İ. E., Baid, U., Baheti, B., Bhalerao, M., Güley, O., Mouchtaris, S., Lang, D., Thermos, S., Gotkowski, K., González, C., Grenko, C., Getka, A., Edwards, B., Sheller, M., Wu, J., Karkada, D., Panchumarthy, R., ... Bakas, S. (2023). GaNDLF: The generally nuanced deep learning framework for scalable end-to-end clinical workflows. *Communications Engineering*, 2(1), 23. <https://doi.org/10.1038/s44172-023-00066-3>