Final Showcase: Multi-label Image Classification

Supervise Me!

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Supervise Me

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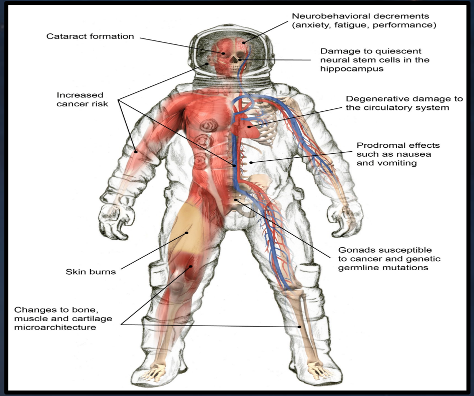
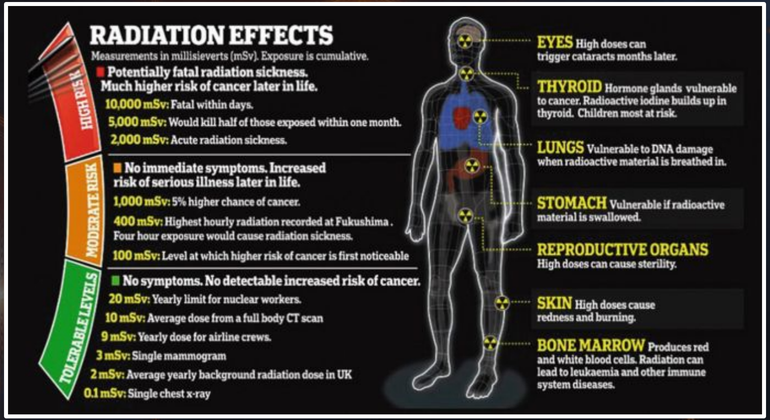
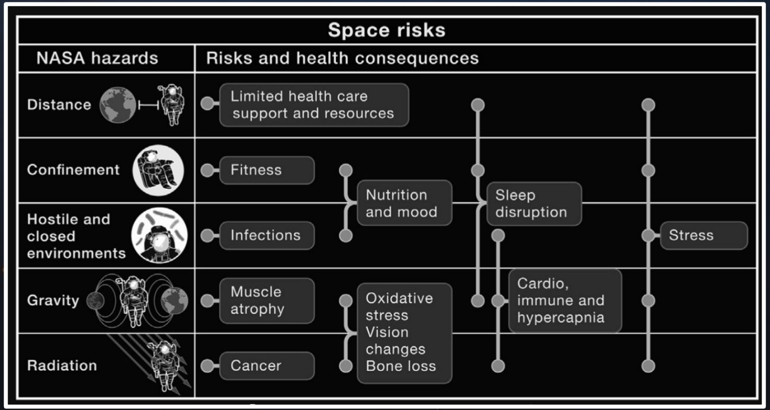
Introduction to the Problem

- Astronauts’ exposure to ionizing radiation can cause …
  - DNA damage
  - central nervous system effects
  - immune system effects







Why is This Problem Significant?

- Leveraging artificial intelligence to help us understand spaceflight-induced biological changes
- To conduct direct experiments on humans during space travel raises ethical concerns and risks to human subjects
- Exploring biologically similar organisms
- Enables valuable insights while ensuring ethical treatment of human subjects

The Dataset

The mice cell image data used is sourced from the Biological and Physical Sciences (BPS) Microscopy Benchmark Training Dataset, which is provided by NASA through Dr. Lauren Sanders and is hosted on an AWS S3 bucket.

The Dataset

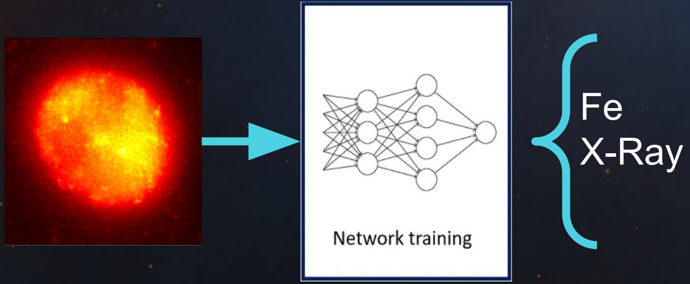
Number of **Observations** in The **Training Dataset**	**7,092** mice cell images, 4 hr post exposure
Number of **Observations** in The **Validation Dataset**	**1,774** mice cell images, 4 hr post exposure

	filename	dose_Gy	particle_type	hr_post_exposure
0	P242_73665006707-A6_003_013_proj.tif	0.82	Fe	4
1	P242_73665006707-A6_008_034_proj.tif	0.82	Fe	4
2	P242_73665006707-A6_009_007_proj.tif	0.82	Fe	4
3	P242_73665006707-A6_009_031_proj.tif	0.82	Fe	4
4	P242_73665006707-A6_009_038_proj.tif	0.82	Fe	4

Label Attribute	Values	Total Data Instances
Radiation Type	Iron(“Fe”) or X-ray(“X-ray”)	77,177 Images
Radiation Dose	Iron Doses: [0, 0.3, 0.82] or X-ray Doses: [0. 0.1, 1.0]	
Imaging Time Post-Exposure	4, 24, 48 hours	

Can we use Machine Learning models to predict the radiation particle type based on the DNA damaged mice cells?

We want to understand the health effects of radiation exposure on astronauts in order to potentially discover optimal recovery paths for individuals exposed to radiation particles during space travel.



SUPERVISE-ME!

Building a Multi-Label ML Pipeline

Setting Goals

Our primary objective is to implement a CNN architecture to achieve exceptional performance in single-label and multi-label image classification that surpasses the limitations of a fully-connected NN. By carefully analyzing our evaluation metrics, we aim to gain valuable insights into the performance of our models and make meaningful comparisons with our baseline.

80% 80%

MAIN TARGET

Our target was to achieve an 80% validation performance threshold on our deep-learning architectures. Through rigorous experimentation, tuning hyperparameters, and the assistance of Weights and Biases, we aim to optimize our models to reach our desired accuracy.

DATA PREPARATION

Acquire and preprocess our image data for ML-readiness.

BASELINE MODEL

Establish and train baseline using MLPClassifier from sklearn package.

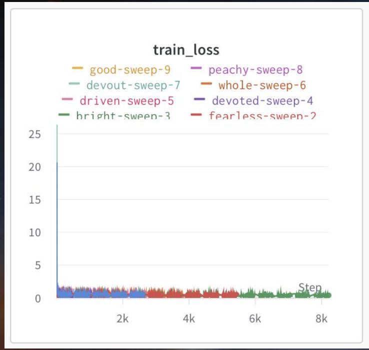
DEEP-LEARNING MODEL

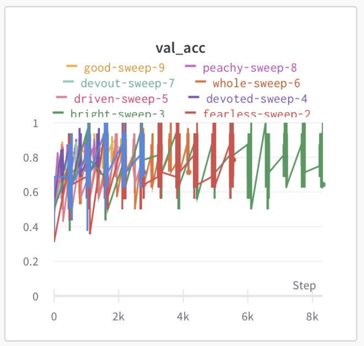
Implement LeNet-5 CNN architecture using PyTorch for both single and multi-label classification tasks.

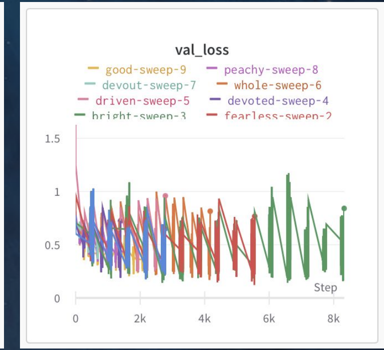
RESULTS AND ANALYSIS

Analyze our evaluation metrics from the LeNet architecture and compare them to our baseline

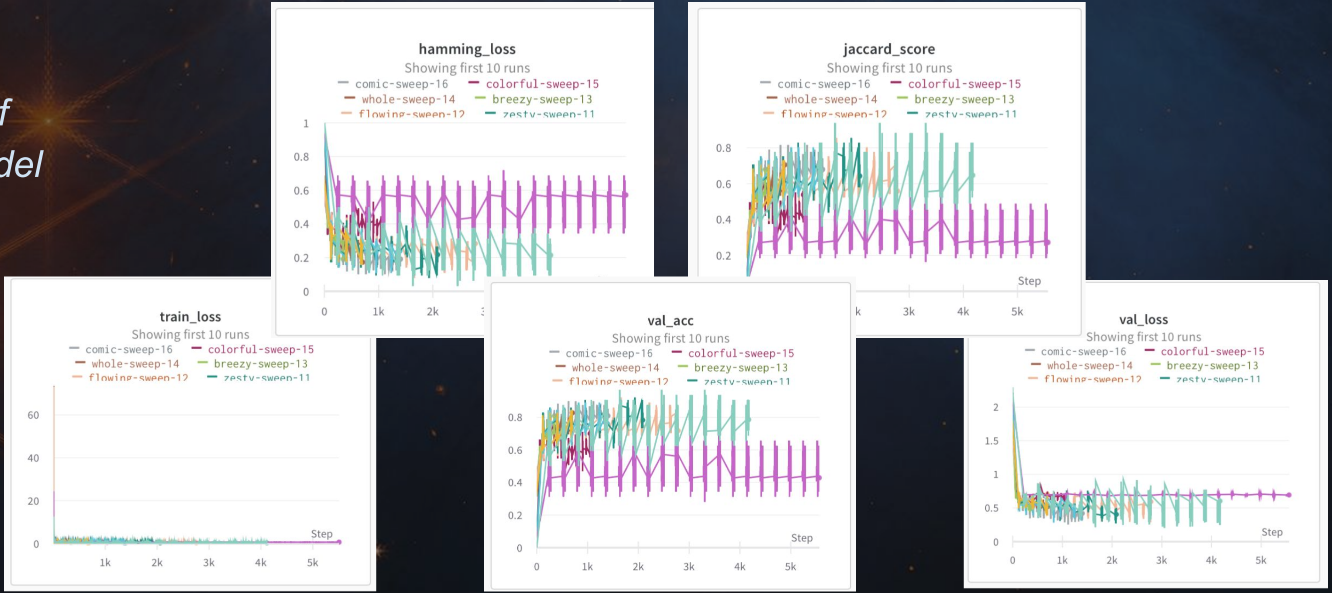
Scores for Sweep of Single-Label LeNet Model



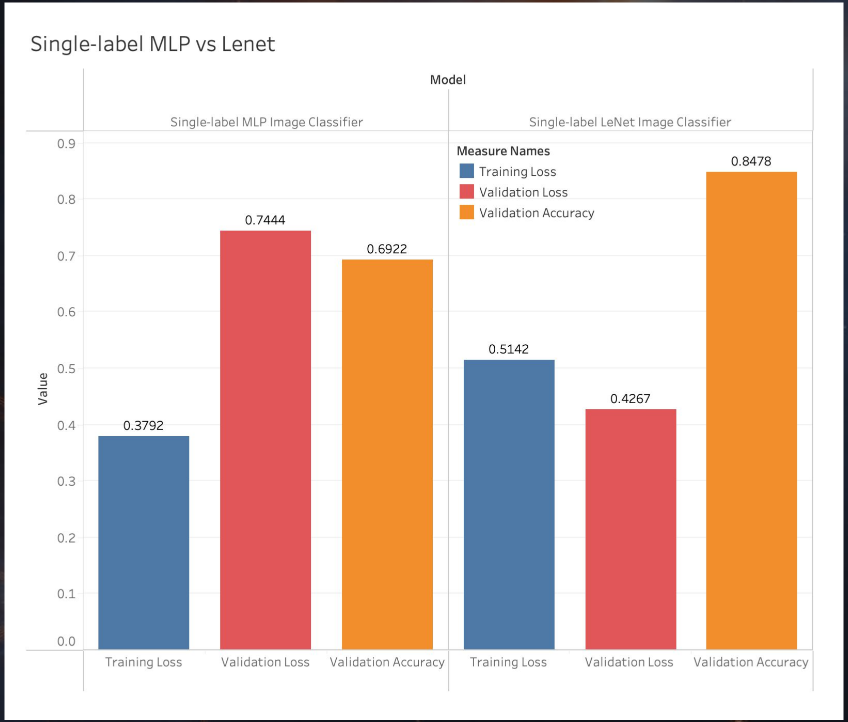




Scores for Sweep of Multi-Label LeNet Model



Analyzing the Results



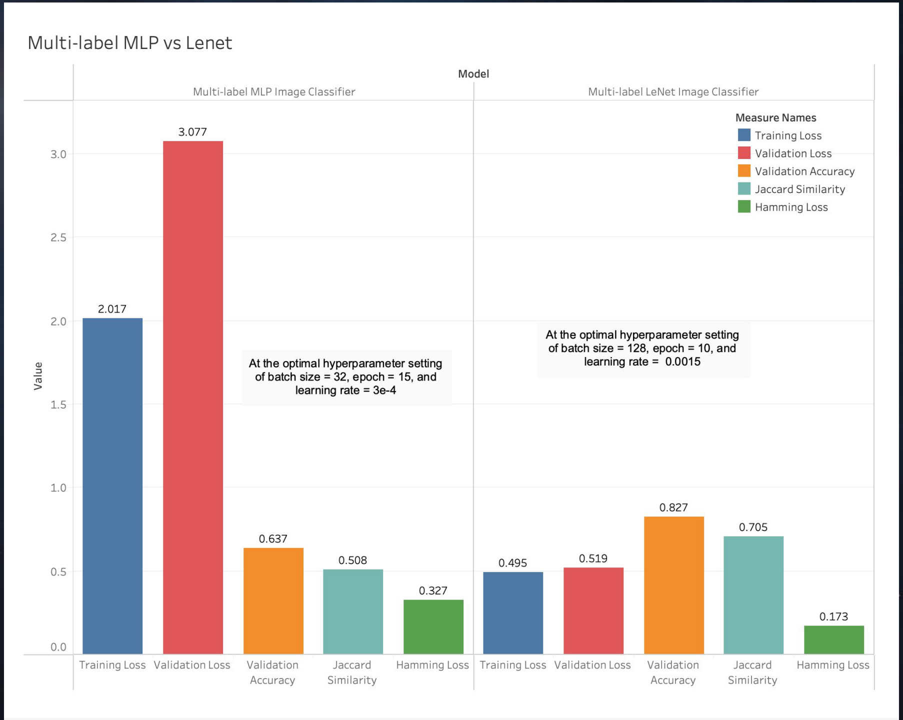
- Single-label evaluation metrics
  - Training loss
  - Validation loss
  - Validation accuracy

	MLP	LeNet-5
Batch size	64	64
Epochs	10	10
Learning rate	3×10^{-4}	3×10^{-4}

Analyzing the Results cont.

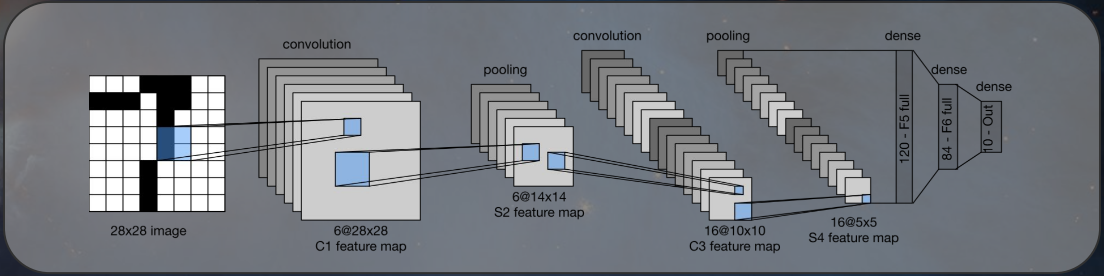
- Multi-label evaluation metrics
  - Single-label's metrics
  - Jaccard similarity
  - Hamming Loss

	MLP	LeNet-5
Batch size	32	128
Epochs	15	10
Learning rate	3×10^{-4}	1.5×10^{-4}



What does this mean?

- Better **validation** performance in both multi and single-label using LeNet-5
- Better Jaccard similarity and Hamming loss
- Batch size contributed most to performance



Takeaways?

- CNN’s are better suited to handle image classification tasks
- There are patterns between images and particle types and dosages

Highlights of Our Models

- Evaluates the performance of the MLP and LeNet models on the mice cell image data
- Analyze patterns of DNA damage and classify them by particle type, as well as by particle type and dosage

Why does this matter?

- Mice share a significant portion of their genetic makeup with humans, which makes them valuable models for studying various biological processes, diseases, and potential treatments.
- Therefore, the use of mice in radiation research and mice cell data predictions may provide valuable information that contributes to addressing radiation-related challenges encountered by astronauts

Acknowledgements

Thank you to all domain experts, guest speakers, and CS 175 staff for helping us throughout this project!!

Sylvain Costes - NASA Domain Expert

Geunwoo Kim - Teaching Assistant

Mitra Behzadi - Teaching Assistant

Kevin Li - Guest Lecturer on ML