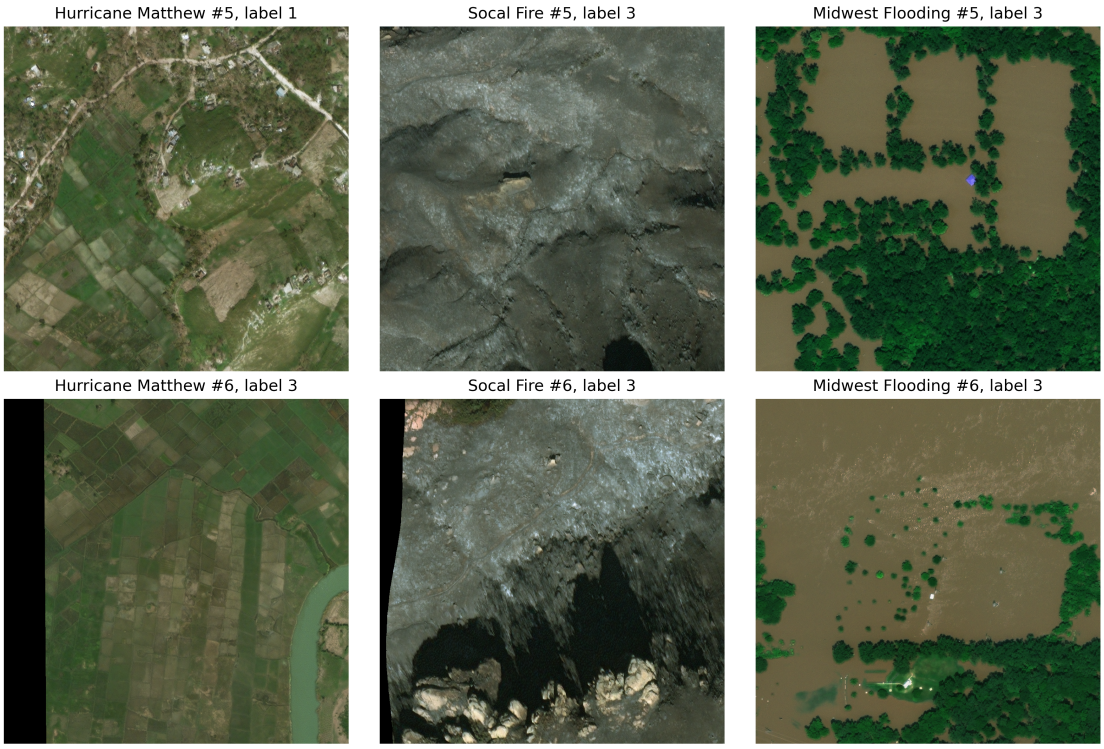

Seeing Through the Chaos: Automated Disaster Assessment from Satellite Imagery

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Abstract

We present a systematic analytical framework for classifying disaster types and assessing damage levels in satellite imagery under severe data scarcity and extreme class imbalance. Our methodology extracts signal from noisy, limited data through three interdependent components: (1) structure-preserving artifact correction (mirroring-based occlusion handling) that outperforms naive imputation and generalizes across model families; (2) exploratory data analysis guiding feature engineering to identify generalizable discriminative features based on color distributions and structural patterns; and (3) task-aware model selection comparing classical and deep learning approaches under realistic constraints. To ensure fair comparison and robust generalization, we develop fully automated training and prediction pipelines that tune hyperparameters via stratified k-fold cross-validation and grid search, evaluate the resulting models on held-out sets, and finally retrain the selected configurations on the full dataset for deployment. For disaster-type classification, color-based features prove nearly linearly separable (logistic regression: 99-100%), with augmented CNNs achieving comparable performance despite severe data sparsity. For damage assessment (200 images, extreme minority imbalance with 6 level-2 samples), classical ensemble methods (LightGBM: 49.43% macro F1) substantially outperform deep learning, suggesting tree-based models more robustly navigate sparse feature regions than neural networks under severe data constraints. We demonstrate that systematic artifact correction, principled feature analysis, and empirically-grounded model selection are essential for reliable classification from noisy, limited satellite data, with direct implications for resource-constrained disaster response.

1 Introduction

Natural disasters inflict severe humanitarian and economic consequences throughout the world, causing economic losses that exceed $300 billion annually [1]. The frequency and intensity of these events are increasing due to climate change [2], with recent devastating hurricanes and wildfires—including Hurricane Matthew [3] and the Southern California wildfires [4]—exemplifying the growing threat to communities and critical infrastructure. An effective disaster response is critically dependent on the availability of timely and reliable information. However, acquiring such information in fast-moving disaster environments remains a significant operational challenge. Satellite imagery presents a viable means of addressing this challenge: it offers detailed visual cues that can be automatically analyzed to produce rapid, objective damage assessments. Yet, manual interpretation of satellite images remains time-consuming, costly, and prone to human error, making large-scale analysis a slow and resource-intensive process. These limitations motivate the development of automated machine learning systems capable of delivering near real-time assessments.

1.1 Motivation

This work addresses two fundamental challenges in automated disaster assessment from satellite imagery: (1) *disaster type classification*—distinguishing between different disaster types (wildfire versus flooding) from post-event imagery, and (2) *damage level assessment* — quantifying the severity of building damage in hurricane-affected areas on a four-level scale. These tasks differ significantly in their complexity: disaster type classification relies primarily on color and spectral signatures (fire-scorched landscapes versus flooded areas), while damage assessment requires fine-grained structural analysis to distinguish subtle differences between damage severity levels.

Our dataset, derived from the xView2 Challenge Dataset [5], presents several challenges typical of real-world satellite image analysis: limited training data (400 and 200 training images respectively), severe class imbalance (the rarest damage category contains only 6 samples), and image quality issues in the form of black bars likely due to sensor failures or preprocessing artifacts. These constraints make this problem an ideal testbed for evaluating the effectiveness of different machine learning approaches under data scarcity conditions.

1.2 Related Work

Automated damage assessment from satellite imagery has progressed from classical computer vision to modern deep learning. The xView2 Challenge established a benchmark with the xBD dataset of 850,736 building annotations across 19 disaster events [5]. Top-performing teams achieved F1-scores near 0.80 using ensemble deep learning methods, though at the cost of requiring the full large-scale dataset and substantial computational resources.

Classical approaches rely on hand-crafted features (color histograms, Haralick descriptors, edge detection) paired with traditional classifiers like SVMs or random forests [6–8]. While interpretable and efficient, these methods struggle to capture the spatial patterns needed for fine-grained damage assessment [9].

CNNs have shown promise for satellite image analysis, though training from scratch requires large datasets to avoid overfitting [10]. Transfer learning—leveraging pre-trained neural networks by reusing their learned feature

representations and training only a new task-specific classifier head—has proven more effective on smaller datasets [11]. However, transfer learning from ImageNet models (trained on natural camera images) to satellite imagery can be limited by the domain gap between these image types [12].
Recent self-supervised vision transformers offer new possibilities. DINOv2, pre-trained on diverse imagery including satellite data, achieves strong performance with minimal fine-tuning [13]. Satellite-specific models like SatMAE (using masked autoencoding on Sentinel-2 time series) and Prithvi (trained on over 1 TB of Landsat–Sentinel-2 data) demonstrate state-of-the-art results but require substantial data and computational resources [14, 15].
For small datasets, data augmentation and class-imbalance mitigation are critical [12]. Yet most prior work relies on thousands of images or more, leaving severely data-constrained regimes underexplored.

1.3 Our Contributions

This work presents several contributions to the field of automated disaster assessment:

1. We compare classical and deep learning methods on a small, imbalanced satellite image dataset. Our evaluation includes logistic regression, gradient boosted trees (LightGBM [16]), CNNs, and transfer learning with DinoV2, offering insights into which approaches are most effective for different tasks.
2. We experiment with techniques for handling extreme class imbalance and data scarcity, including stratified k-fold cross-validation, upsampling, and augmentation.
3. We achieve near-perfect performance on binary disaster type classification, obtaining close to 100% accuracy using simple logistic regression on hand-crafted color features. This result shows that classical methods remain highly competitive when features are strongly discriminative and training data is sparse.

1.4 Paper Organization

The remainder of this paper is organized as follows. Section 2 describes our dataset, including its structure, challenges, and preprocessing steps. Section 3 details our methodology, including feature engineering, model architectures, and training procedures. Section 4 presents our results, comparing performance across different models and analyzing per-class performance. Section 5 discusses our findings, limitations, and future directions. Section 6 concludes with a summary of contributions and practical implications.

2 Data

2.1 Dataset Overview

Our analysis is based on a subset of the xView2 Challenge Dataset [5], consisting of 200 high-resolution satellite images ($1024 \times 1024 \times 3$ RGB) divided equally into three disaster-specific subsets: 200 wildfire images (`socal-fire`), 200 flooding images (`midwest-flooding`), and 200 hurricane images (`hurricane-matthew`). These collections support two supervised learning tasks. For disaster type classification, we distinguish wildfire from flooding imagery using the `socal-fire` and `midwest-flooding` subsets. For damage level assessment, we use only the `hurricane-matthew` subset, whose images are annotated with building damage severity on a 4-level scale (0–3).

The dataset exhibits substantial damage level imbalance. Within the damage assessment subset, level 2 (major damage) contains only 6 examples (3%), making it the scarcest category. Figure 2, included in the appendix, summarizes the distribution of disaster types and damage levels.

2.2 Image Quality and Black-Bar Artifacts

A notable artifact across the dataset is the presence of large black pixel regions (RGB = (0,0,0)), typically appearing as nearly horizontal or vertical bars along image borders. Approximately 20% of all images contain such bars, and in extreme cases they cover more than 85% of the total image area. While `hurricane-matthew` contains no images with more than 50% black coverage, both wildfire and flooding subsets include heavily occluded samples (Figure 4).

These artifacts distort color and texture distributions and risk introducing spurious predictive cues if not addressed. We evaluated several correction strategies: mean/median imputation (filling black pixels with the mean/median non-black color of the image) and mirror-based filling (reflecting the nearest valid region across the black area). Mean/median imputation produced large uniform regions that skewed spectral features, whereas

mirroring better preserved local structure and avoided artificial color artifacts. We also attempted slicing the images to smaller images to remove the black bars, but we did not find this useful.

Since black bar treatment is generic and can be used for all model types, all images were corrected using the mirroring approach prior to any feature extraction or modeling.

2.3 Exploratory Data Analysis

Our exploratory analysis revealed clear visual differences between disaster types and more subtle distinctions across damage levels. Rendering representative samples across all disaster–damage combinations (Figure 1) showed that wildfire images typically contain warmer tones and higher textural complexity, while flooding scenes exhibit cooler blue–green hues and smoother textures. These qualitative observations guided a more systematic evaluation of color, texture, and structural characteristics.

Color-based statistics proved highly discriminative for the disaster type task. Mean RGB intensities showed that `socal-fire` images have elevated red-channel values, whereas `midwest-flooding` images show stronger blue-channel responses. HSV distributions reinforced these findings: saturation values in particular distinguished fire from flooding (Figure 7). Color-ratio features such as red-to-green and green-to-blue further amplified these separations and later became useful hand-crafted features (Figure 8).

Texture and structural features contributed complementary information. Edge-to-area ratios derived from Sobel and Canny operators showed slightly higher fragmentation in wildfire scenes (Figure 10). Local Binary Pattern metrics (mean, entropy, nonzero counts) captured finer-grained differences in surface texture across disasters (Figure 12). Haralick features, extracted from gray-scaled versions of the images, highlighted subtle variations in texture homogeneity and contrast, though individual features had limited discriminative power (Figures 15–**??**). Additional structural indicators such as corner counts and connected-component statistics showed modest but consistent differences between wildfire and flooding imagery (Figures 9). Although no single structural feature was strongly predictive on its own, their combination informed a broad texture–structure component of the classical feature set.

2.4 Data Preparation for Modeling

Insights from the EDA guided the construction of our modeling pipeline. All images were first corrected for black-bar artifacts using the mirroring procedure. For classical machine learning methods, we extracted a 227-dimensional feature set comprising color histograms, HSV statistics, color ratios, Haralick features, Local Binary Pattern metrics, edge densities, corner counts, and connected-component summaries. These features reflect the color and texture characteristics that showed distributional differences during EDA.

For CNNs trained from scratch, images were downscaled to 64×64 and normalized to the $[0, 1]$ range. For transfer learning with DINOv2, images were only resized by a few pixels for compatibility with the model in order to preserve fine-grained structural cues important for damage classification.

Given the severe imbalance, we used stratified 5-fold cross-validation for all models and applied balanced upsampling for the damage assessment task during training. Disaster type classification was left unupsampled as classes were balanced already.

Overall, the EDA exposed clear spectral differences between disaster types, subtle structural cues for damage assessment, and significant data-quality and balance issues—directly informing our feature engineering and preprocessing choices for the modeling that follows.

3 Methodology

We systematically compare classical and deep learning approaches for two supervised tasks, disaster type classification and damage level assessment, under realistic constraints of limited data, severe class imbalance, and image artifacts. Our methodology encompasses feature engineering, model selection and implementation, training procedures with hyperparameter optimization, and evaluation strategies. All models are wrapped in a unified training interface that standardizes fitting, prediction, and preprocessing, enabling consistent cross-validation and hyperparameter optimization across model families.

3.1 Feature Engineering

We used pixel-based and structure-based features for damage level and disaster type classification. We selected the features we found to be most promising to distinguish the different classes, as identified through our exploratory

data analysis. Our CNN models automatically embed images into feature space, while classical models use hand-crafted features.

3.1.1 Pixel-based Features

As color-based features we use aggregated statistics of single pixel values. These features do not reflect relations between pixels, but rather the distributions over all pixels within one image. The numbers in brackets in the lists below represent the total numbers of corresponding feature values.

- Color entropy values for each channel (3)
- Color ratios for each pair of channels (3)
- Color moments: mean, std, skewness for each channel (9)
- Color histogram bins for each channel (96)
- Hue, saturation and value (HSV) histogram bins for each channel (96)

3.1.2 Structure-based Features

Structured features reflect the relationships between pixels.

- Haralick features [6] (13)
- Number of nonzero elements after Haralick filtering [6] (1)
- Edge to area ratio after Canny filtering [8] (1)
- Corner count (1)
- Local Binary Pattern features: entropy, mean, std, nonzero count (4)

Note: During EDA, we explored Sobel edge detection [7] and connected component statistics (count, mean, and std), but these were excluded from the final feature set because they caused models to predict only a single class on the holdout set, likely due to distributional differences between training and test data. The final combined representation is 227-dimensional (207 color + 20 structural) for classical damage prediction models.

3.1.3 Learned Representations: DinoV2 Embeddings

For the damage task, we also evaluate learned representations using DinoV2 [13]. First, we scale all image pixel values to the range [0,1] and then normalize per channel using ImageNet's mean and standard deviation (mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]). We resize the images to 1022x1022 for compatibility with the model and feed them through a frozen DinoV2 ViT-S/14 encoder to produce 384-dimensional embeddings per image. In an attempt to increase model performance, we apply nine augmentations on every image in the training data, including rotations, flipping, and color jittering (brightness, contrast, and saturation). We included each augmentation as part of the training data (for both cross validation and the final training) whenever the model was being trained on the original image, i.e. the unaugmented image, using a `TrainableDataset` object. However, the results did not significantly improve performance, which is also suggested by [17]. This is not surprising, as DinoV2 is trained to be insensitive to such transformations.

3.2 Model Selection and Rationale

We tested different models for both tasks, including simple **logistic regression** models, **boosted trees** (i.e., **LightGBM** [16]), and **neural architectures** like **multi-layer-perceptrons** (MLPs) as well as **convolutional neural networks** (inspired by AlexNet [18]).

Logistic regression by nature requires minimal hyperparameter tuning. For the disaster type task, where color features strongly discriminate classes, logistic regression is appropriate as it provides interpretable coefficients and handles linearly separable problems efficiently. For damage assessment, logistic regression serves as a baseline to evaluate whether hand-crafted features capture sufficient information for the more nuanced damage classification task.

Convolutional neural networks (CNNs) enable automatic feature learning through sequences of convolutional filters and pooling layers. However, we note that deep networks typically require more examples to reach their full potential. CNNs are appropriate for tasks requiring spatial pattern recognition, but our small dataset limits their effectiveness.

LightGBM seems well-suited for damage prediction because it can capture nonlinear feature interactions between color and texture features, which may be necessary to distinguish subtle differences between damage levels. Its tree-based structure also handles class imbalance naturally through class weighting.

For the damage task, we also evaluate **transfer learning with DinoV2**, which is appropriate given our small dataset size. Pre-trained vision transformers can leverage knowledge learned from large-scale image datasets, making them good candidates for few-shot learning scenarios like our damage level 2 class with only 6 samples.

3.3 Model Implementation

We built an abstract `ModelTrainer` class providing a unified `sklearn`-inspired API for both Scikit-Learn [19] and PyTorch [20] models, with utilities for state management (resetting parameters, saving/loading checkpoints). This abstraction enables consistent cross-validation and hyperparameter tuning across all model types, including our logistic regression and CNN implementations.

3.3.1 Disaster Prediction Model

For disaster type classification, we trained a logistic regression on all 207 color-based features after scaling with `StandardScaler`. We built a `StandardScalerTransformer` wrapper implementing a `Transformer` interface for state management consistency with model classes.

We classify images from `midwest-flooding` (class `0`) and `socal-fire` (class `1`). The logistic regression uses tabular features extracted via preprocessing, while a CNN learns directly from raw pixels downscaled to 64×64. This downscaling risks losing structural information like edges and textures, but larger networks would require more data to avoid overfitting from many trainable parameters across deep layers.

With limited samples, the CNN achieved only 90-95% accuracy. To address data sparsity, we applied augmentations (rotations at different angles, horizontal and vertical flips; see 19), increasing dataset size 9-fold. CNNs do not require explicit standardization.

3.3.2 Damage Prediction Model

Based on our disaster type classification results, where logistic models excelled, we began with logistic regression for the damage prediction task. We briefly experimented with linear regression but quickly returned to logistic models due to their substantially better performance.

Our multiclass logistic regression model classifies `hurricane-matthew` images into four damage levels (0-3). Unlike the disaster prediction model, we trained on both pixel-based (207) and structure-based (20) features for a total of 227 features. All features were scaled using our StandardScaler transformer.

We also evaluated LightGBM on the same 227-dimensional feature set. LightGBM's ability to capture nonlinear feature interactions makes it a strong baseline for the more subtle damage prediction problem.

For transfer learning, we train a shallow MLP on standardized 384-dimensional DinoV2 embeddings. The MLP architecture consists of one or two hidden layers (e.g., $[128]$ or $[128, 64]$) followed by a linear output layer. Balanced upsampling further improves performance on the underrepresented damage level 2 class. We experimented with segmenting the full 1024×1024 into smaller regions that can be used for CNN inference independently, but didn't pursue this further as aggregation of multiple patches turned out challenging given the low <30% accuracy of patch level predictions.

3.4 Training Scheme

To effectively train, regularize, and validate our models, we designed a pipeline based on cross-validation, which we applied for both prediction tasks. We trained our final model on the full dataset that was provided to us, excluding the evaluation set. A graphical representation of the scheme can be found in 20.

3.4.1 Regularization

To find optimal regularization in logistic regression, we train models with different complexity regularization values ($C = 0.01, 0.05, 0.1, 0.5, 1.0, 2.0, 5.0, 10.0, 20.0, 50.0, 100.0, 200.0, 500.0, 1000.0, 10^4, 10^5, 10^6$) for both classification tasks. For each C value, we perform 5-fold cross validation and compute accuracy, precision, recall, and F1-score from confusion matrices on validation sets, with precision, recall, and F1-score macro-averaged across classes. This allows us to assess generalization of the model and gives us control over the bias variance tradeoff (more regularization $\rightarrow$ less overfitting). Performance metrics are averaged across folds to assess each C value.

For the binary disaster type task, we additionally sweep probability thresholds between 0.05 and 0.95 in increments of 0.01 to optimize the decision boundary. This confirmed that the standard 0.5 threshold performs near-optimally.

3.4.2 Grid Search and Hyperparameter Tuning

Hyperparameter tuning is performed through systematic grid search across all model families. For each hyperparameter configuration in the grid, we split the training data into 5 stratified folds using `sklearn`'s `StratifiedKFold`, ensuring each fold has equal distributions for all classes. We then train the model on 4 folds and evaluate on the held-out fold, computing performance metrics (accuracy for disaster type, macro F1-score for damage assessment) on each validation fold. The metrics are averaged across all 5 folds to obtain a robust estimate of generalization performance for that configuration. This process is repeated for all configurations in the grid, and we select the configuration achieving the best mean performance across folds.

For logistic regression, we search over regularization strengths C ranging from 0.01 to 10^6. For LightGBM, we explore combinations of tree depth (6, 8, 10), number of leaves (31, 50, 63), minimum samples per leaf (1, 5, 10), and class-weighting strategies (balanced vs. none). For CNNs, we search over learning rates (10^{-4}, $5 \cdot 10^{-5}$), batch sizes (16, 32, 64), numbers of epochs (8, 12, 16, 32), and channel configurations (e.g., $[64, 32]$ or $[64, 64, 32]$). For DinoV2+MLP, we evaluate learning rates ($5 \cdot 10^{-5}$, 10^{-4}, $5 \cdot 10^{-4}$), hidden-layer widths ($[128]$, $[256]$, $[128, 64]$, $[64, 32]$), batch sizes (32, 64, 128), numbers of epochs (32, 48, 64). We also experimented with the following loss function types: `nn.CrossEntropyLoss`, `nn.SoftF1Loss`, and `nn.CrossEntropyLoss` weighted by the original class distribution in order to compensate for the disadvantage of minority classes in the sampling process.

3.4.3 Sampling

Due to class imbalance, we built a `Sampler` class for upsampling or downsampling. It can either match all classes to the smallest class size or sample (with replacement) to reach predefined class sizes. For disaster type classification with logistic regression, we avoid upsampling because logistic regression is sensitive to duplicate samples and the given dataset is already balanced. However, for damage assessment, balanced upsampling consistently improves minority-class performance despite this sensitivity and is therefore applied. For CNNs on the disaster type task, we use balanced upsampling as CNNs are less sensitive to duplicate samples than linear models.

3.4.4 Ensemble Models

In an effort to leverage the inherent stochasticity of model training, we incorporated an ensemble strategy into our pipeline. By averaging predictions from multiple models trained with different random seeds but similar parameters and on the same data, we achieved more robust performance.

3.5 Training and Inference Pipelines

3.5.1 Disaster prediction

Both pipelines (Figure 17) share a similar structure: data loading and preprocessing, then model-specific stages. The logistic regression pipeline standardizes tabular features, optional hyper-parameter tuning, and trains via regularized logistic loss. The CNN pipeline converts inputs to 64×64 images, applies augmentations, and trains using PyTorch. During inference, both load saved transformers and models to generate predictions on holdout data, exporting results as CSV files.

3.5.2 Damage level prediction

The damage-level prediction pipeline mirrors Figure 17, following the same stages (`load_disaster_data`, `preprocess_data`, optional hyper-parameter tuning, training, and artifact persistence) but with different features and labels and an additional upsampling step. Instead of `feature_pipeline_flood_fire_logistic_regression` and disaster-type labels, it uses `feature_pipeline_hurricane_logistic_regression` to extract task-specific features and predicts damage severity class. For DinoV2 models, it uses `feature_pipeline_hurricane_dinov2` to extract embeddings for the images after manipulating them for compatibility and consistency with DinoV2's training data and optionally augmenting them. Inference reuses the same artifact-handling and prediction logic, again exporting results as CSV files.

4 Results

4.1 Evaluation Setup

We evaluate all models using stratified 5-fold cross-validation on the labeled training data. We also use an additional test holdout split to not let the hyperparameter search in disaster prediction leak into the accuracy estimate. Our

`k_fold_cross_validation(...)` helper accepts feature–label pairs, a model wrapped in our `Trainer` interface, and optional `Sampler`, `Transformer`, and `Augmenter` modules for preprocessing and augmentation. For the disaster type task, we use overall accuracy as the primary metric, since the task is binary and classes are relatively balanced. For the damage level task, we use macro-averaged F1-score (unweighted mean across classes) to account for the severe class imbalance, along with macro precision and recall for completeness.

4.2 Disaster Type Classification

Table 1 and Figure 32 summarize wildfire vs. flooding performance. Both logistic regression and the CNN achieve near-perfect accuracy, with logistic regression performing slightly better.

Model	Accuracy	Macro Precision	Macro Recall	Macro F1	Evaluation Accuracy
Logistic Regression	99.50	99.51	99.50	99.50	100
CNN	98.75	98.79	98.75	98.75	100

Table 1: 5-fold cross-validation results for disaster type classification. The evaluation score was computed on the test set provided to us on Pensieve. All values are in %.

These results confirm the patterns identified in our EDA: the 207 color-based features, especially color ratios and HSV distributions, nearly linearly separate wildfire and flooding imagery. Logistic regression exploits this structure effectively, slightly outperforming the CNN (trained with C equal to 0.05), whose additional capacity provides little benefit in this small-data regime.

4.3 Damage Level Assessment

Damage prediction is substantially more challenging, and results vary across model families (Table 2 and Figure 32).

Model	Accuracy	Macro Precision	Macro Recall	Macro F1	Evaluation F1
Logistic Regression (tabular)	60.00	45.16	43.66	43.66	53.61
LightGBM (tabular)	72.50	51.09	49.23	49.43	+-71
CNN (pixels, 64×64)	53.00	44.91	40.63	40.00	65.62
DINOv2 + MLP (embeddings)	66.95	46.74	47.59	46.82	76.61

Table 2: 5-fold cross-validation results for damage level identification. Precision, recall, and F1 are macro-averaged across the four classes. The evaluation score was computed on the test set on Pensieve. All values are in %. DinoV2 + MLP achieved the strongest performance on the evaluation set.

The logistic regression baseline (macro F1 $\approx$ 42.71%) shows that hand-crafted features contain useful but incomplete signal. LightGBM improves to about 49% (71% on the evaluation set) by modeling nonlinear interactions among features. The CNN trained on downscaled pixels reaches only 40.00% macro F1 (65% on the evaluation set), reflecting the difficulty of learning spatial representations from just 200 images. The DINOv2+MLP model achieves performance comparable to LightGBM (around 47% macro F1, but around 77% on the evaluation set), suggesting that while pre-trained embeddings provide rich representations, they do not automatically solve the extreme class-imbalance problem in this small dataset. The different loss functions we implemented (weighted cross entropy loss and soft F1 loss) did not yield better results.

4.4 Difference in Performance Between Methods

The performance differences across models reflect the interaction between dataset size and task complexity and the different inductive biases of the models.

In disaster type classification, color statistics already provide a nearly linearly separable representation. Logistic regression achieves the highest accuracy because a linear decision boundary is sufficient, and complex models add unnecessary variance. CNNs do not provide additional benefit and can overfit in small-data regimes. We thus find classical models to be sufficient for disaster type classification.

In damage level assessment, prediction requires understanding spatial structure (collapsed roofs, debris patterns, texture changes) that global handcrafted statistics cannot fully capture. Logistic regression (43.66% macro F1) is limited by its linear nature. LightGBM (49.43%) captures nonlinear feature interactions and improves meaningfully. CNNs (40.00%) have the right inductive bias but insufficient data to learn strong filters from scratch. Finally, DINOv2+MLP (46.82%) provides a rich pre-trained representation but does not outperform LightGBM, likely due to extreme class imbalance (level 2 has only 6 samples) and insufficient training data to effectively fine-tune the classifier head. The results suggest that in severely data-constrained settings with extreme imbalance, traditional gradient-boosted trees can match or exceed transfer-learning approaches, possibly because they handle sparse regions of feature space more robustly.

5 Discussion

5.1 Evaluation of Approach

Our systematic comparison of classical and deep learning methods reveals clear trade-offs between model complexity and performance. For disaster type classification, logistic regression achieved near-perfect performance (99-100%) with minimal hyperparameter tuning, demonstrating that classical methods remain highly competitive when features strongly separate classes. This validates our EDA-guided feature engineering process.

For damage assessment, the progressive increase in model sophistication, from logistic regression and LightGBM to CNNs and DinoV2+ML, revealed that LightGBM and DinoV2 embeddings achieve the best performance. The comparable results between classical and transfer-learning approaches suggest that in severely data-constrained settings with extreme class imbalance, traditional ensemble methods can match deep learning methods. The unified `ModelTrainer` abstraction was crucial for enabling fair comparison across model families by standardizing preprocessing, cross-validation, and evaluation procedures.

5.2 Limitations

5.2.1 Dataset Size and Class Imbalance

Our dataset is small by deep learning standards: only 200 images for damage assessment and severe class imbalance. The CNN achieved only 40.00% F1 over cross-validation despite heavy augmentation (9×), suggesting that even aggressive augmentation cannot fully compensate for insufficient training data. The extreme imbalance in level 2 limits all models' ability to learn reliable decision boundaries for that class.

5.2.2 Feature Engineering Limitations

The exclusion of Sobel edge detection and connected component statistics from the final feature set highlights the difficulty of feature engineering for distribution-shifted test data. These features showed promise during EDA but caused models to fail on the holdout set (predicting only a single class), likely due to distributional differences between training and test images.

5.2.3 Evaluation Constraints

Our holdout set evaluation is limited by the lack of ground truth labels. Additionally, visual inspection suggests the holdout set may be sorted by disaster type, which could inflate apparent performance. Without true random sampling, our performance estimates may not generalize to new disaster events.

5.3 Discoveries

5.3.1 Transfer Learning Did Not Outperform Classical Methods

We expected DinoV2 embeddings to substantially improve damage assessment performance, but the model achieved only 46.82% F1 in cross-validation, comparable to LightGBM. This counterintuitive result suggests that in extremely small, imbalanced datasets, traditional gradient-boosted trees may be more robust than deep learning approaches, possibly because they handle sparse regions of feature space more effectively.

5.3.2 Classical Methods Competitive for Simple Tasks

The near-perfect performance of logistic regression on disaster type classification (99-100%) exceeded expectations. The strong discriminative power of color features, particularly RGB ratios and HSV distributions, made the problem

nearly linearly separable. This reinforces the value of thorough EDA and feature engineering before moving to complex models.

5.3.3 CNN Underperformance Despite Augmentation

Despite applying 9× data augmentation using geometric transformation, the CNN (40.00% F1) for damage assessment achieved lower performance than LightGBM. This suggests that geometric augmentations (rotations, flips) may not create the diversity needed for effective CNN training on small datasets, and 200 images provide insufficient examples of damage patterns.

5.4 Extensions

5.4.1 Multi-Scale Patch Analysis

Split images into smaller subregions (e.g., 32×32 grids), classify each independently, and aggregate predictions via majority voting or logical OR—this mirrors AlexNet's augmentation strategy [18], increasing training data while capturing finer-grained local patterns lost in full-image classification.

5.4.2 Building Detection Preprocessing

Currently, we analyze entire images, but damage indicators appear primarily in residential areas. Forests, water, and empty terrain add noise with no visible damage patterns in examined examples. Using object detection (e.g., YOLO) to identify housing regions, then computing features only on those areas, should significantly improve performance by filtering irrelevant pixels. This work could proceed in parallel by researching open-source pretrained residential detection models suited to our data.

5.4.3 Temporal Change Detection

When pre-disaster imagery is available, comparing before and after images could provide more direct damage signals than single-image classification. Computing difference features (e.g., structural changes, color shifts) between temporal pairs might capture damage more reliably.

5.4.4 Further Exploration into Transfer Learning

Leverage additional models pretrained on ImageNet (ResNet, EfficientNet) or satellite datasets (Sentinel-2, Landsat). Models like SatMAE [14] or Prithvi [15, 21] already understand infrastructure and land-use patterns relevant to poverty. We would fine-tune classification heads for our tasks.

5.4.5 Model-based Augmentations

Xu et al. [22] present augmentation strategies based on Generative Adversarial Networks (GANs) to mitigate class imbalance and limited data availability in deep learning. These include ImbCGAN, which applies Conditional GAN to imbalanced classes, and GAN-MBD (Multi-Branch Discriminator), which translates images to match other labels). Specifically for satellite imagery classification, Adedeji et al. [23] suggest that Deep Convolutional GANs (DCGANs) and Wasserstein GANs with Gradient Penalty (WGAN-GP) improve results compared to non-augmentation, especially when combined with geometric augmentations.

5.4.6 Ensemble Methods

Combining predictions from DinoV2+MLP and LightGBM through weighted voting or stacking could potentially leverage complementary strengths: DinoV2's high-level visual understanding and LightGBM's nonlinear feature interactions.

5.5 Implications for Practice

For disaster type classification, logistic regression's over 99% accuracy, computational efficiency, and interpretability make it suitable for real-time deployment.

For damage assessment, LightGBM's 49.43% macro F1 suggests it is among the best performing methods we tested and offers a practical balance between accuracy and computational efficiency. While 49% F1 is modest, it could still provide value for initial triage and priority mapping when combined with human review. The model could flag potential high-damage areas for immediate inspection while allowing faster coverage of large affected regions.

5.6 Societal Benefits to Automated Disaster Assessment

The ability to identify natural disasters and the level of damage they cause in (near-)real-time is critical for effective and fast natural disaster response. It allows emergency responders to prioritize rescue actions and to understand where help is needed most. Our work extracting critical information from satellite imagery is a step toward carefully and cost-effectively monitoring disaster-prone locations at scale, including the regions which are harder to reach. Especially when resources are scarce, automatic natural disaster assessments can provide governments and stakeholders with a deeper understanding of disaster damage and leads as to how to provide help efficiently.

5.7 Ethical Concerns

Despite the numerous societal benefits associated with disaster monitoring using satellite imagery, there are some ethical concerns too.

First, space monitoring using high-resolution imagery may invade individuals' privacy. Image data may contain sensitive information about individuals and should therefore be handled with care. This highlights the importance of regulatory frameworks that protect against malicious surveillance or any other misuse using satellite images.

Second, the models may be biased, potentially leading to consistently incorrect predictions for specific locations. For example, if the model structurally underestimates the damage level for a particular region, that region might receive structurally less support. Over-reliance on this technology, especially in a safety-critical context like disaster response, can lead to serious harm.

Lastly, we recognize the environmental impact of large-scale monitoring due to the high computational cost associated with training models, extracting features, and classifying satellite images.

6 Conclusion

Our work demonstrates that automated satellite image analysis is feasible for disaster type classification but remains challenging for fine-grained damage assessment in small-data regimes. Traditional methods (LightGBM) provide similar results to classification models based on DINOv2 embeddings for damage level prediction, while simple logistic models based on hand-crafted features suffice for disaster type classification.

A Appendix

A.1 Exploratory Data Analysis

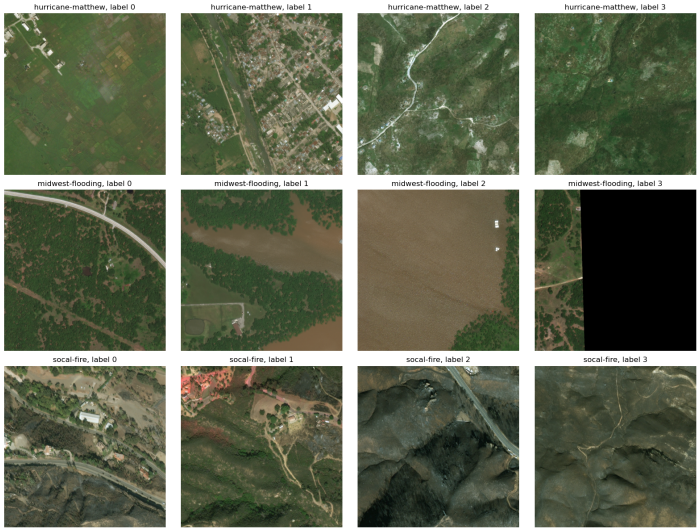

Figure 1: Twelve 1024×1024 satellite image, one for each combination of disaster type and level of damage, illustrating distinct color and texture patterns that differentiate flooding from wildfire and hurricane damage.

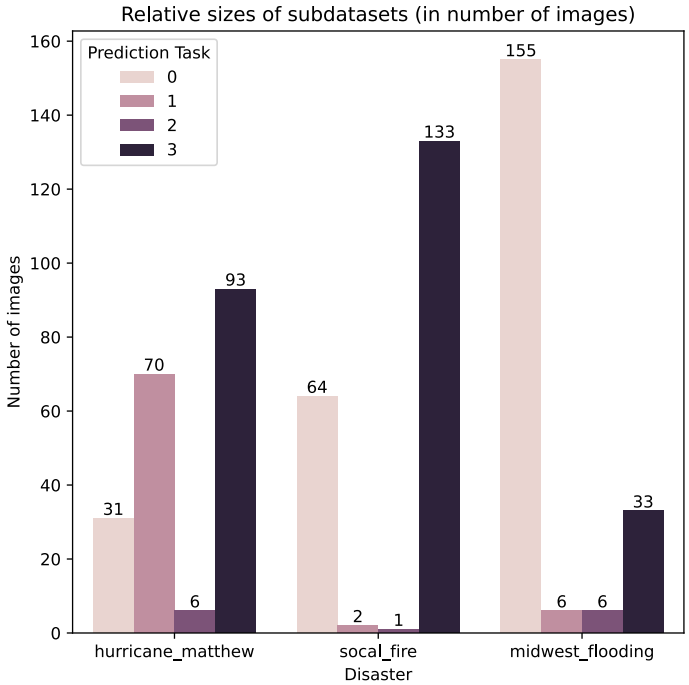

Figure 2: Distribution of image counts across four damage levels (0-3) for three distinct disaster types: hurricane-matthew, socal-fire, and midwest-flooding. The chart reveals significant class imbalance, with Damage Level 3 being most prevalent for hurricane-matthew and socal-fire, while Damage Level 0 dominates midwest-flooding. Damage Levels 1 and 2 are generally underrepresented across all disaster types (except for hurricane-matthew, where a fair amount of Damage 1 is observed).

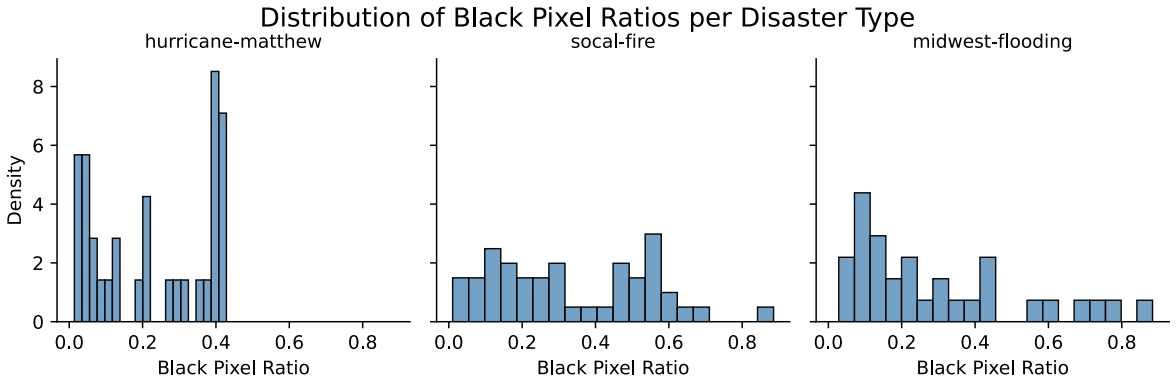

Figure 3: Density distributions illustrating the distribution of black pixel ratios for the three distinct disaster types. The hurricane-matthew distribution is notably bimodal, with prominent peaks around 0.05 and 0.40. The socal-fire distribution is more spread out across the range of black pixel ratios, showing multiple smaller peaks. In contrast, midwest-flooding exhibits a right-skewed distribution, with the majority of black pixel ratios concentrated at lower values, primarily below 0.20.

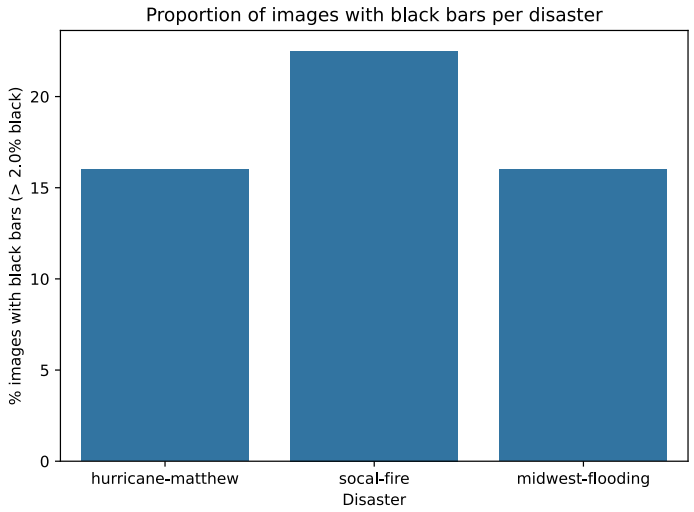

Figure 4: There is a relatively similar proportion (20%) of images for each class having black bars.

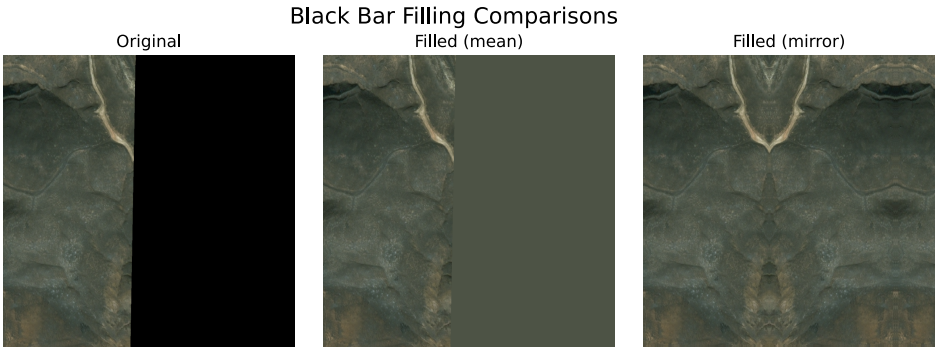

Figure 5: An image with a black bar, covering about 50% of the image. In the second image, the black pixels are replaced by the mean color. In the third, half of the image is mirrored onto the other half to fill the black bar.

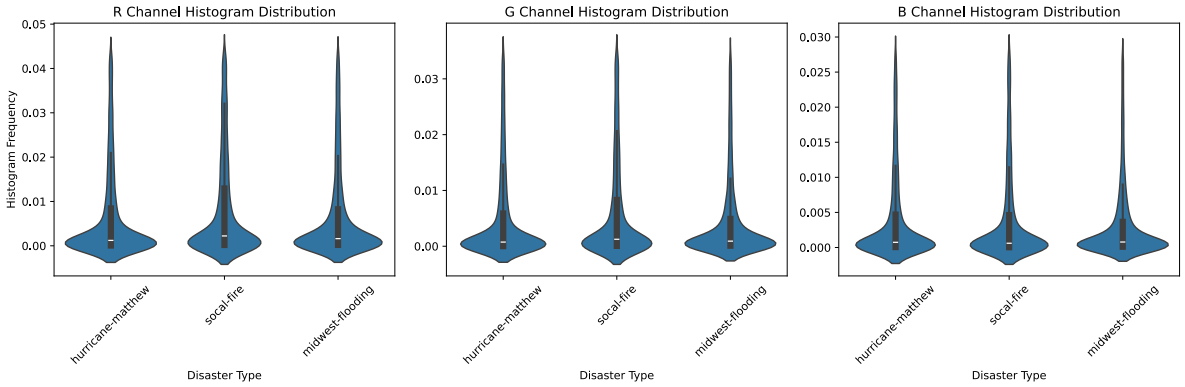

Figure 6: RGB histogram distributions condensed to violin plots (IQR filtered) to better compare color patterns across disaster types. We drop outliers beyond deviating more than 10% from the IQR.

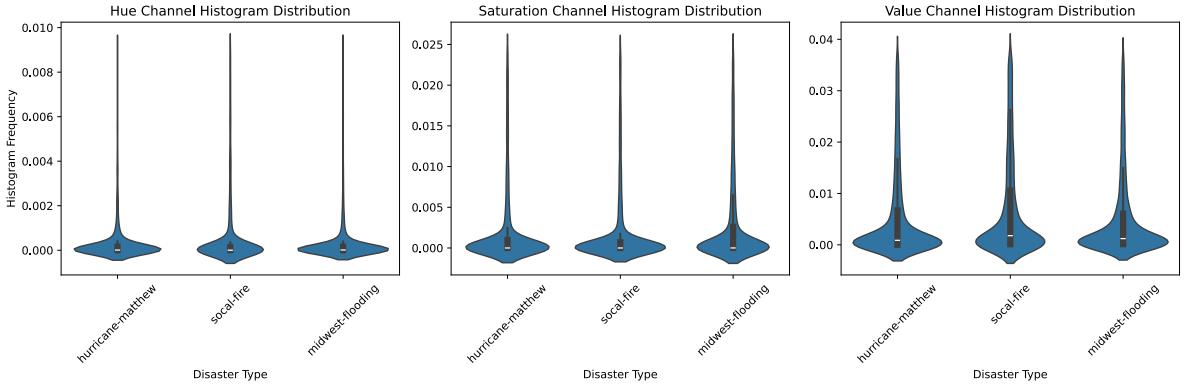

Figure 7: HSV histogram distributions condensed to violin plots (IQR filtered) to better compare color patterns across disaster types. We drop outliers beyond deviating more than 10% from the IQR.

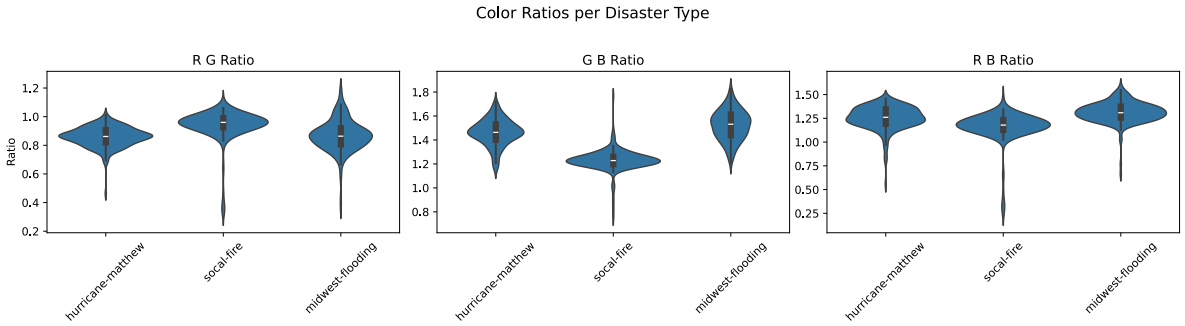

Figure 8: The distributions of the color channel ratios as violin plots, one for each disaster type. Outliers (150% deviation from IQR) were removed.

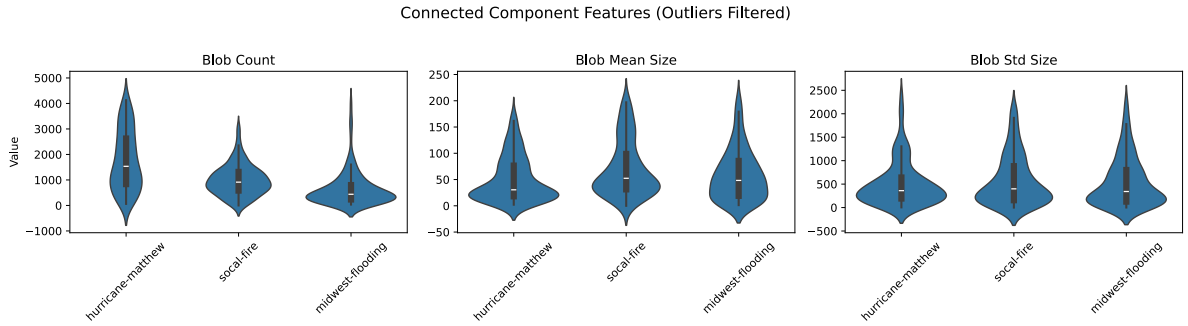

Figure 9: Distribution of connected component statistics (blob count, mean size, and size standard deviation) across disaster types, shown as violin plots with outliers removed to better visualize differences between disaster categories. Outliers (150% deviation from IQR) were removed.

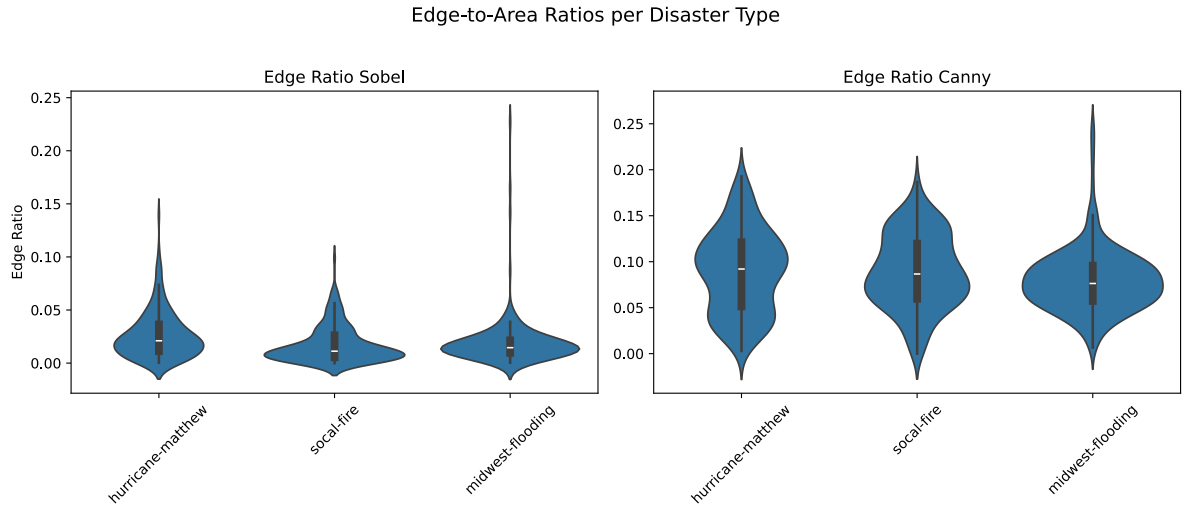

Figure 10: The ratios between the number of edges and the number of non-edges (after edge detection using the Sobel and Canny filters) as violin plots, one for each disaster type. Outliers (150% deviation from IQR) were removed.

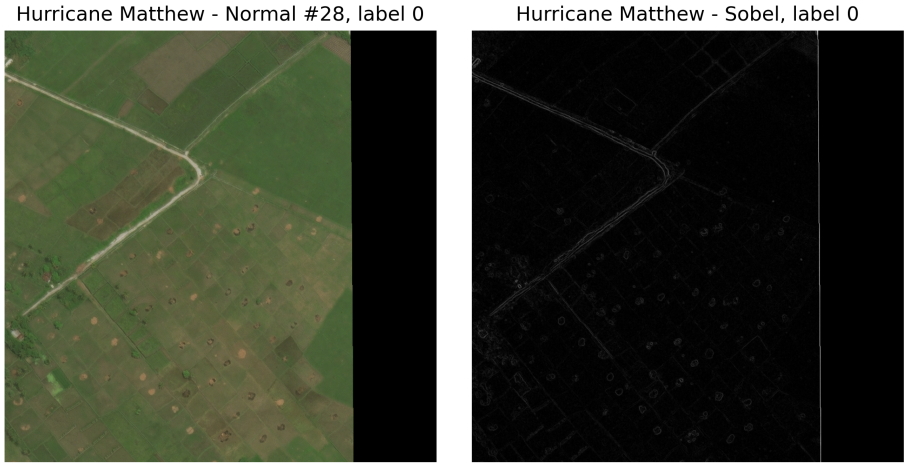

Figure 11: The right image is the left image after transformation using the Sobel filter.

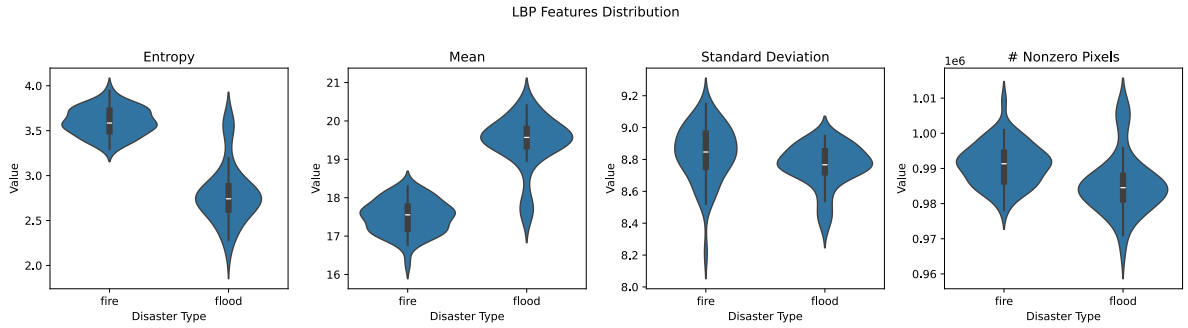

Figure 12: The mean, entropy, and number of nonzero pixels after application of Local Binary Pattern filtering in both classes seem to be indicators for the disaster class.

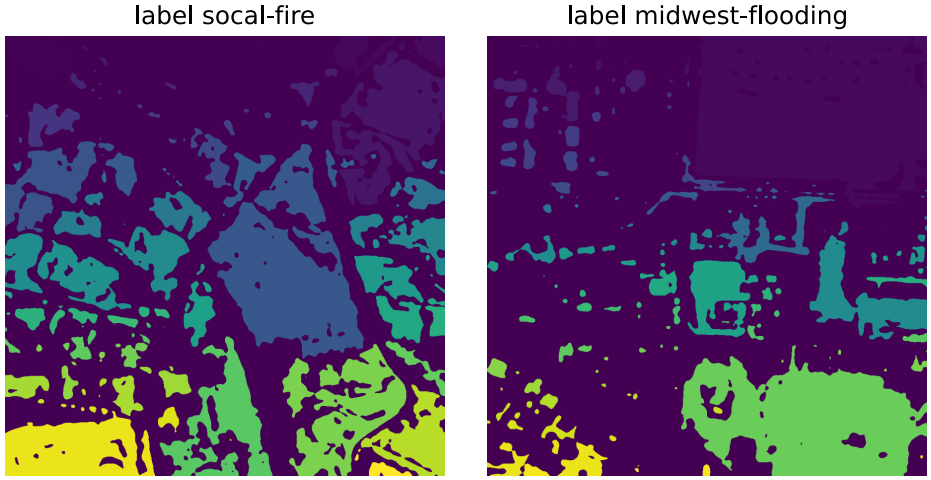

Figure 13: These are two images processed using the Haralick filter. Midwest-floodings seem to have larger, brain-like patterns, motivating us to include the number of non-zero values as an additional structure-based feature to the design matrix.

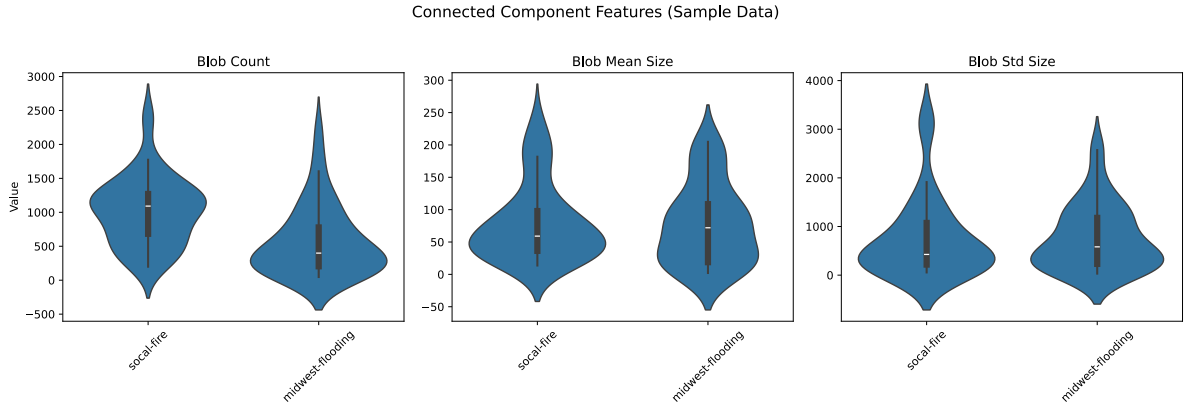

Figure 14: Violin plots showing the distribution of the connected component features (blob count, blob mean size, and blob size standard deviation) over 50 images of each class. Remarkably, there are outliers for each statistic, but specifically for the blob count, all outliers are from the flooding class. Outliers (150% deviation from IQR) were removed.

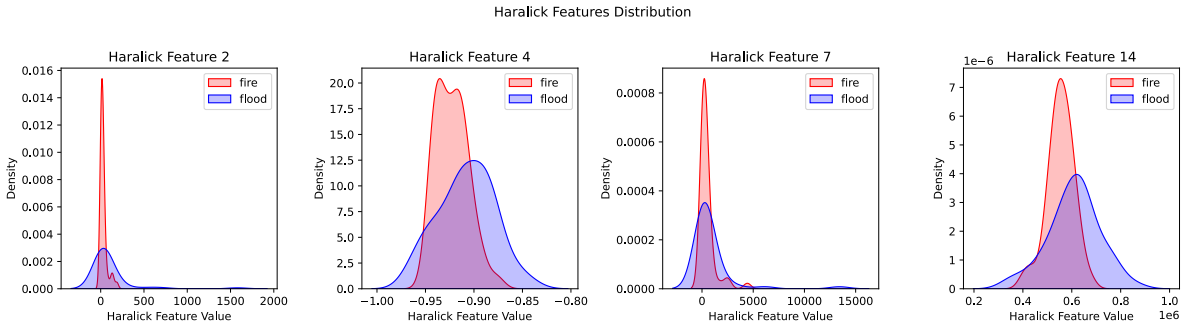

Figure 15: Some of the thirteen Haralick features show potential to help differentiate between fire and flooding images. The distributions show differing local densities in the right tails. The fourteenth feature is derived from the number of non-zero values after application of Haralick filtering.

A.2 Data Preprocessing

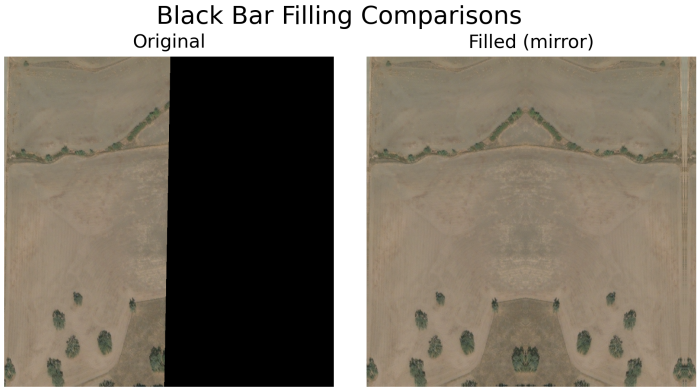

Figure 16: Preprocessing result of image with black bar using mirroring to fill black missing regions.

A.3 Training and inference pipeline

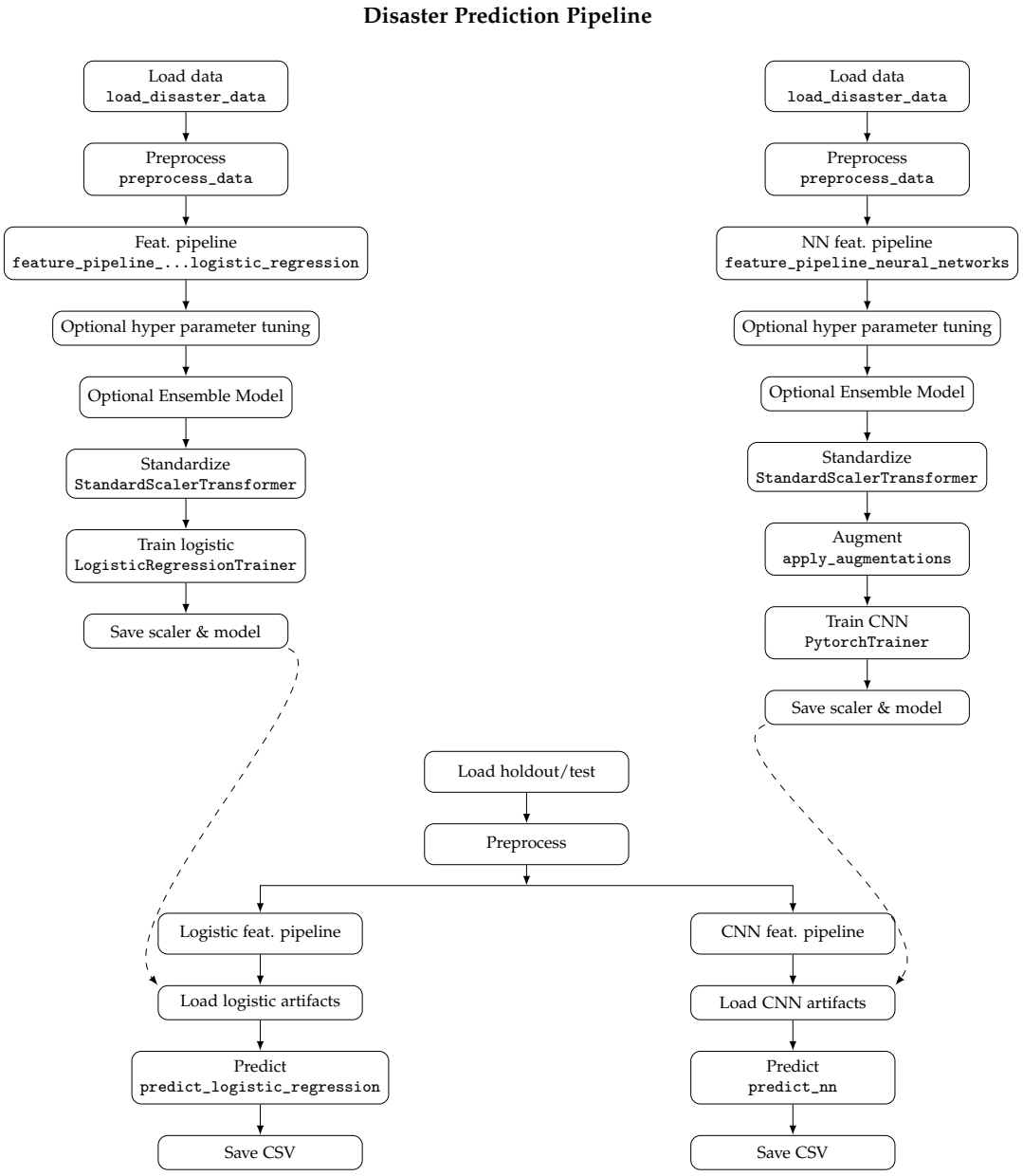

Figure 17: Overview of the disaster prediction training and inference pipeline. Both models follow similar data loading and preprocessing steps but diverge into separate training paths for the Logistic Regression and CNN models. Dashed arrows indicate artifact reuse during prediction.

A.4 Downscaling

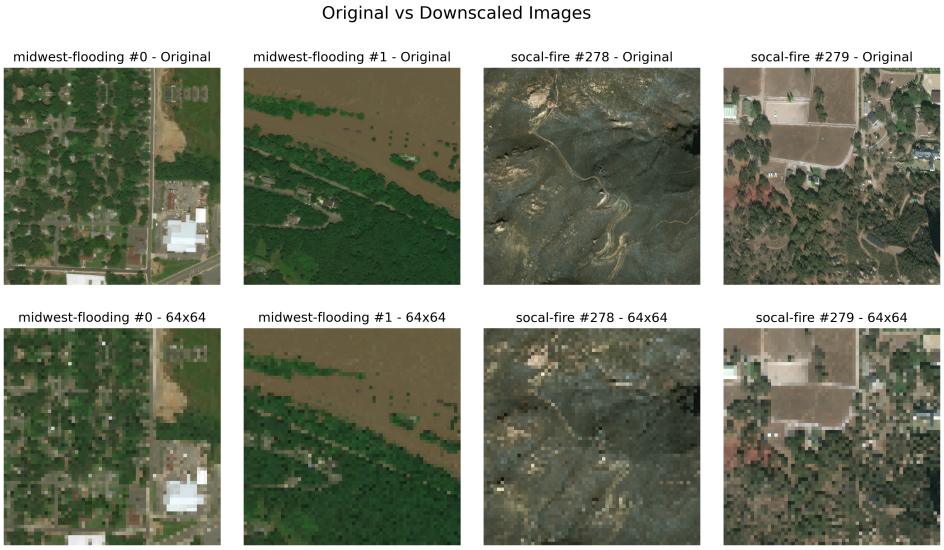

Figure 18: The plot shows 4 original images and their downscaled version used for training of the CNN.

A.5 Augmentation

Figure 19: The plot shows eight transformations based on the first image in 18 illustrating the augmentation used to increase the number of training samples for our CNN models.

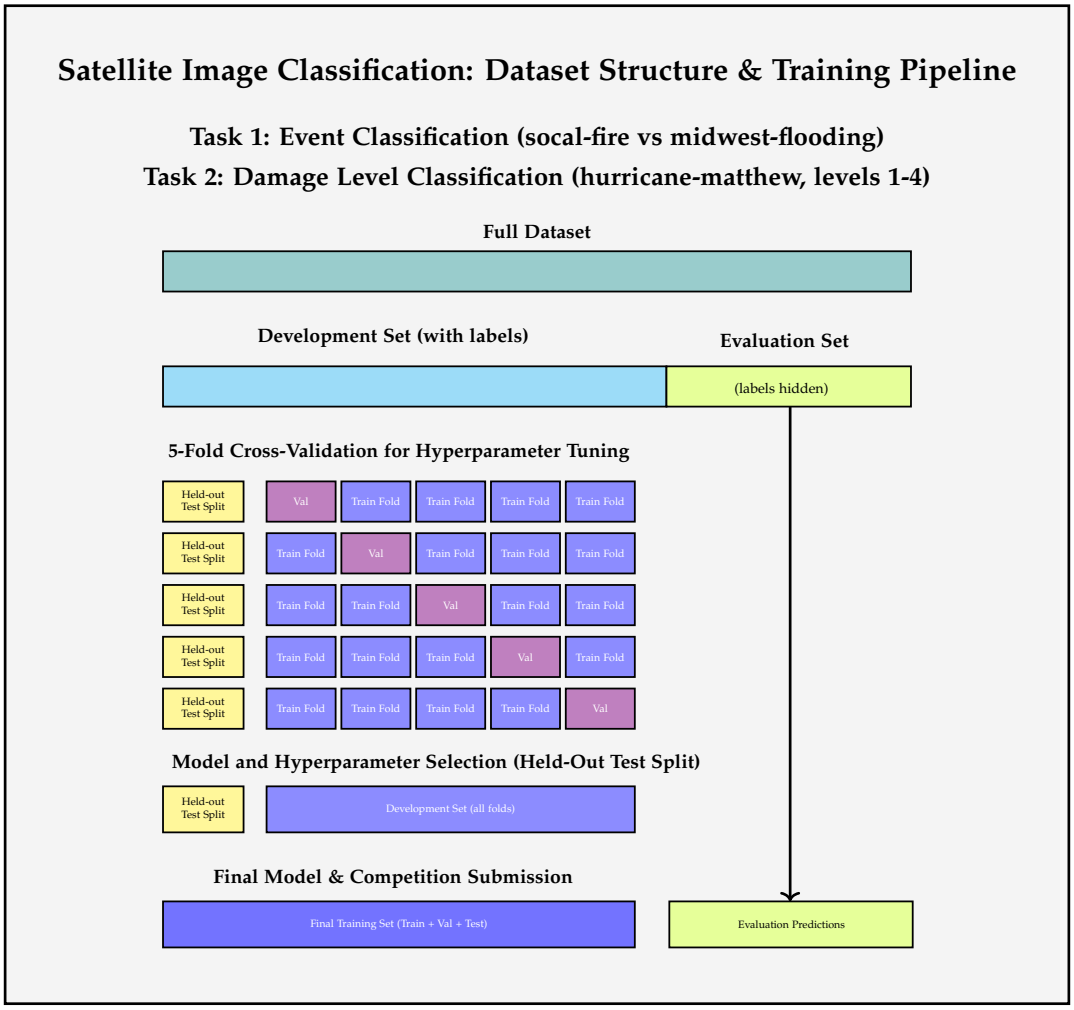

Figure 20: Overall dataset and model training pipeline for satellite image classification. We tune models using 5-fold cross-validation on the development set, with each fold maintaining a validation split. For the damage prediction task we opted against a dedicated test set for the time being given our already limited data (6 samples in minority class) - the samples are more valuable for training. This is reasonable as our best performing models (lightgbm / dinov2 + mlp) work well in the default configuration. The final model is retrained on all available development data before generating predictions on the hidden evaluation set.

A.6 Dataset Structure & Training Pipeline

A.7 Results

A.7.1 Grid Search

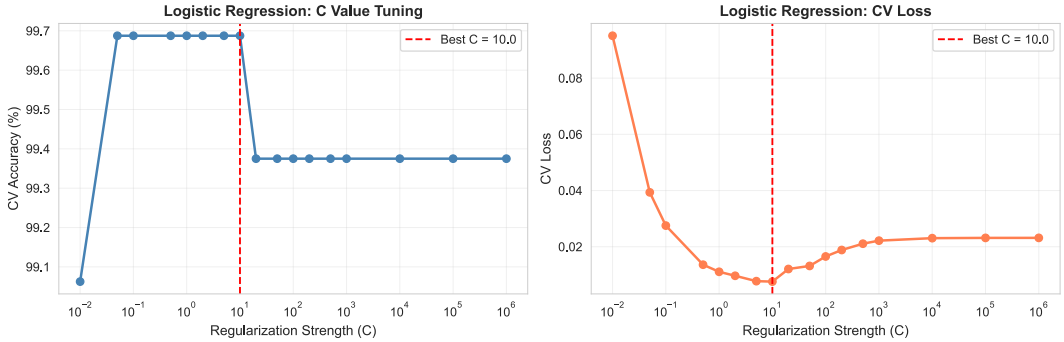

Figure 21: Hyperparameter tuning for Logistic Regression in disaster type classification, showing cross-validation accuracy and loss as functions of regularization strength C. The optimal value achieves the highest accuracy and lowest loss on the validation set.

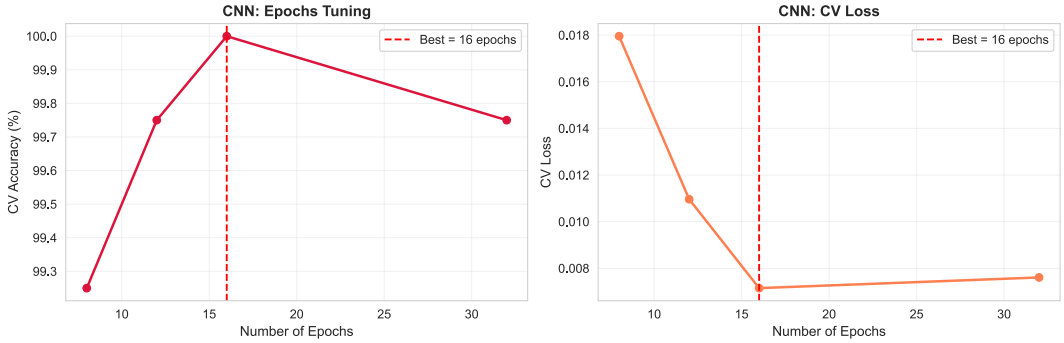

Figure 22: Hyperparameter tuning for CNN in disaster type classification, showing cross-validation accuracy and loss as functions of the number of training epochs. The optimal number of epochs achieves the highest accuracy and lowest loss on the validation set.

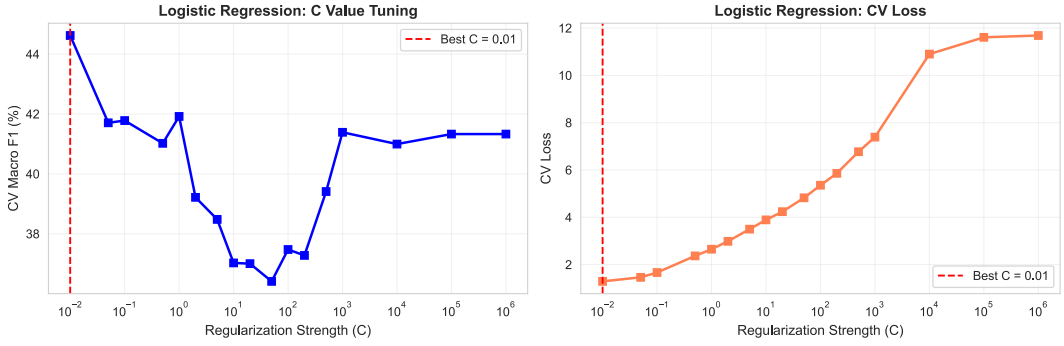

Figure 23: Hyperparameter tuning for Logistic Regression in damage level prediction, showing cross-validation macro F1 score and loss as functions of regularization strength C. The optimal value achieves the highest F1 score and lowest loss on the validation set.

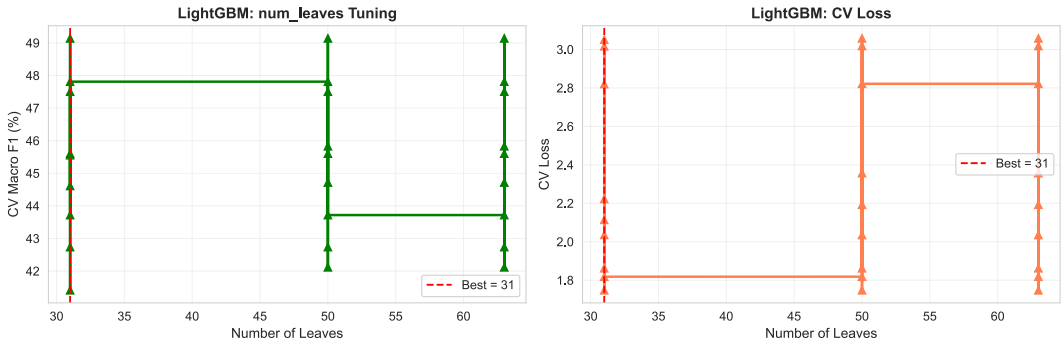

Figure 24: Hyperparameter tuning for LightGBM in damage level prediction, showing cross-validation macro F1 score and loss as functions of the number of leaves. The optimal number of leaves achieves the highest F1 score and lowest loss on the validation set.

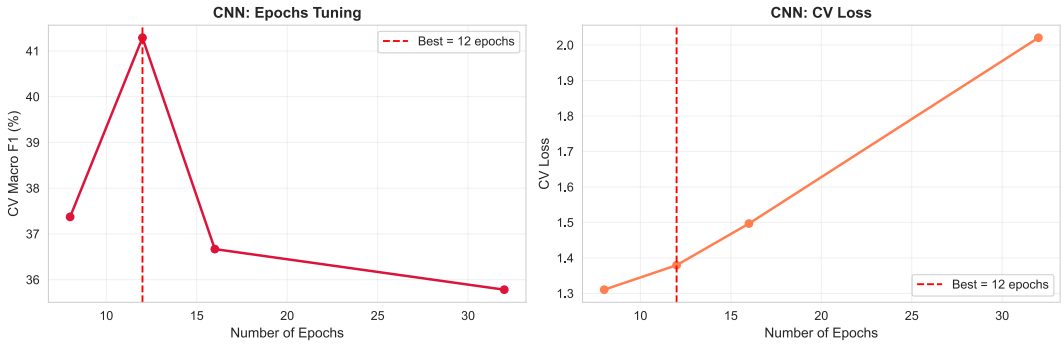

Figure 25: Hyperparameter tuning for CNN in damage level prediction, showing cross-validation macro F1 score and loss as functions of the number of training epochs. The optimal number of epochs achieves the highest F1 score and lowest loss on the validation set.

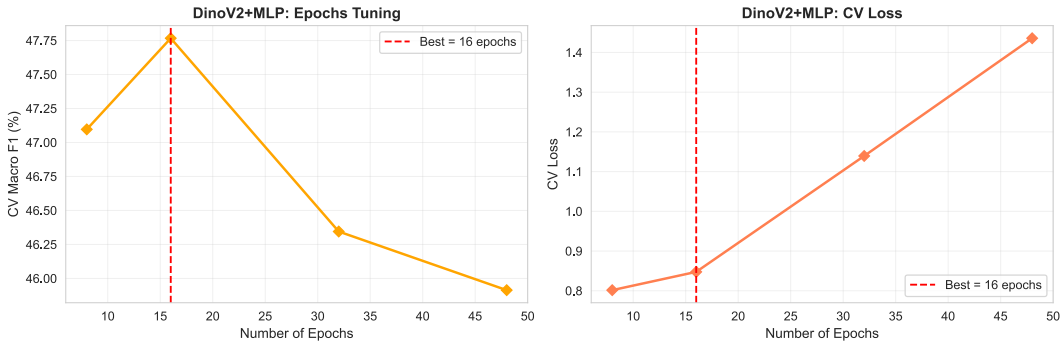

Figure 26: Hyperparameter tuning for DinoV2+MLP in damage level prediction, showing cross-validation macro F1 score and loss as functions of the number of training epochs. The optimal number of epochs achieves the highest F1 score and lowest loss on the validation set.

A.7.2 Disaster Type Classification

Logistic Regression

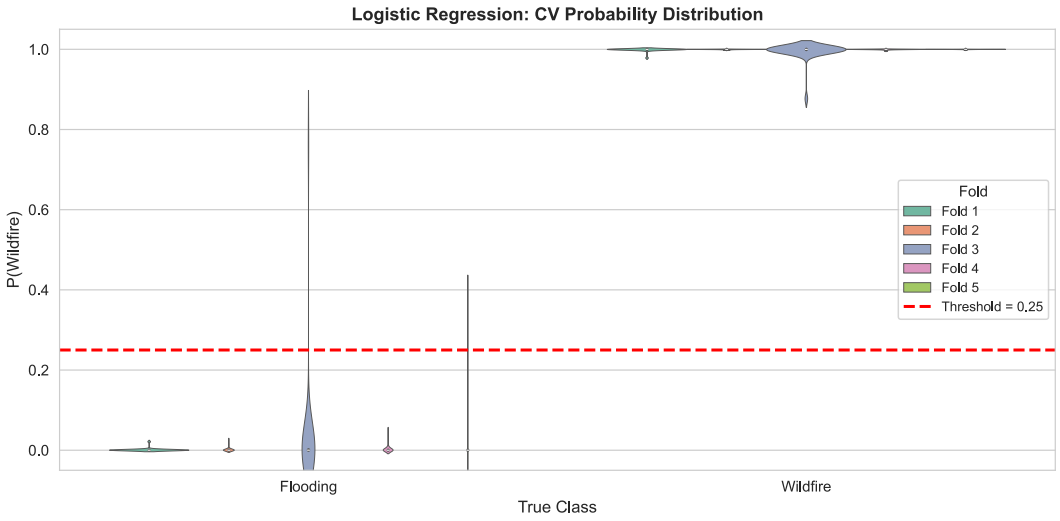

Figure 27: Probability distribution of predicted probabilities by true class label across 5-fold cross-validation for the logistic regression model. Each violin plot shows the distribution for one fold, with colors distinguishing different folds. The red dashed line indicates the decision threshold. Both classes show high predicted probabilities, indicating strong model confidence.

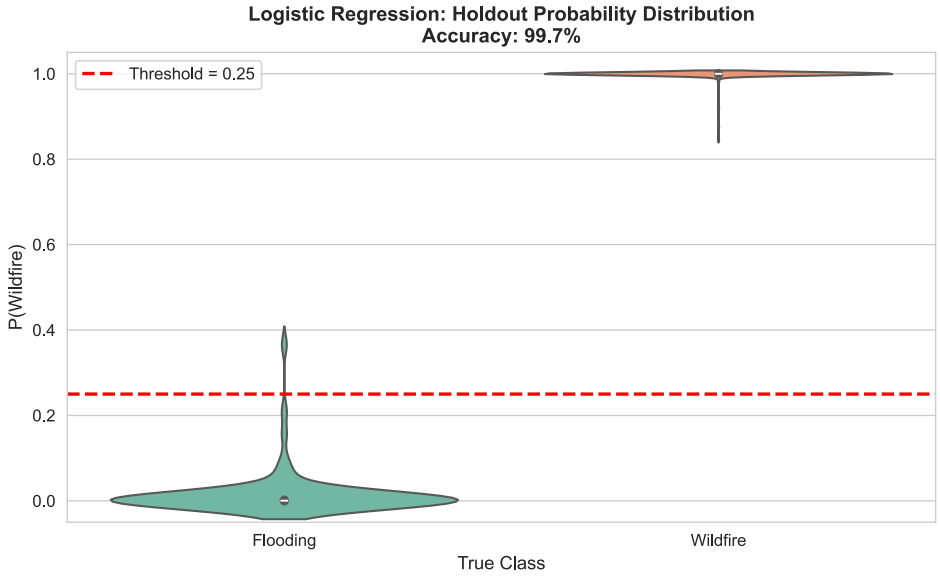

Figure 28: Probability distribution of predicted probabilities by true class label on the holdout set for the logistic regression model. Both classes show concentrated distributions, indicating model confidence. The red dashed line indicates the decision threshold.

Metric	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Macro Average	100.00	100.00	100.00	100.00
Midwest-flooding	100.00	100.00	100.00	100.00
Socal-fire	100.00	100.00	100.00	100.00

Table 3: Disaster classification scores per class at the best decision threshold (at 77%).

Metric	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Macro Average	85.00	55.56	54.63	54.31
Damage Level 0	83.75	49.50	52.00	48.76
Damage Level 1	76.88	70.89	58.79	64.03
Damage Level 2	94.37	20.00	20.00	20.00
Damage Level 3	85.00	81.84	87.71	84.46

Table 4: Damage level classification scores per class at the decision threshold 0.7.

Metric	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Overall	98.75	98.16	99.38	98.76
MACRO AVG	98.75	98.77	98.75	98.75
Class 0	98.75	99.38	98.12	98.74
Class 1	98.75	98.16	99.38	98.76

Table 5: Classification scores after mitigating black bars using color channel pixel value means (Best decision threshold = 0.17).

Metric	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Overall	99.06	98.79	99.38	99.07
MACRO AVG	99.06	99.09	99.06	99.06
Class 0	99.06	99.39	98.75	99.06
Class 1	99.06	98.79	99.38	99.07

Table 6: Classification scores after mitigating black bars using color channel pixel value medians (Best decision threshold = 0.16).

Metric	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Overall	100	100	100	100
MACRO AVG	100	100	100	100
Class 0	100	100	100	100
Class 1	100	100	100	100

Table 7: Classification scores using mirroring (Best decision threshold = 0.77).

Metric	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Overall	99.38	99.39	99.38	99.37
MACRO AVG	99.38	99.39	99.38	99.37
Class 0	99.38	99.39	99.38	99.37
Class 1	99.38	99.39	99.38	99.37

Table 8: Classification scores without preprocessing (Best decision threshold = 0.46). Due to the class

CNN

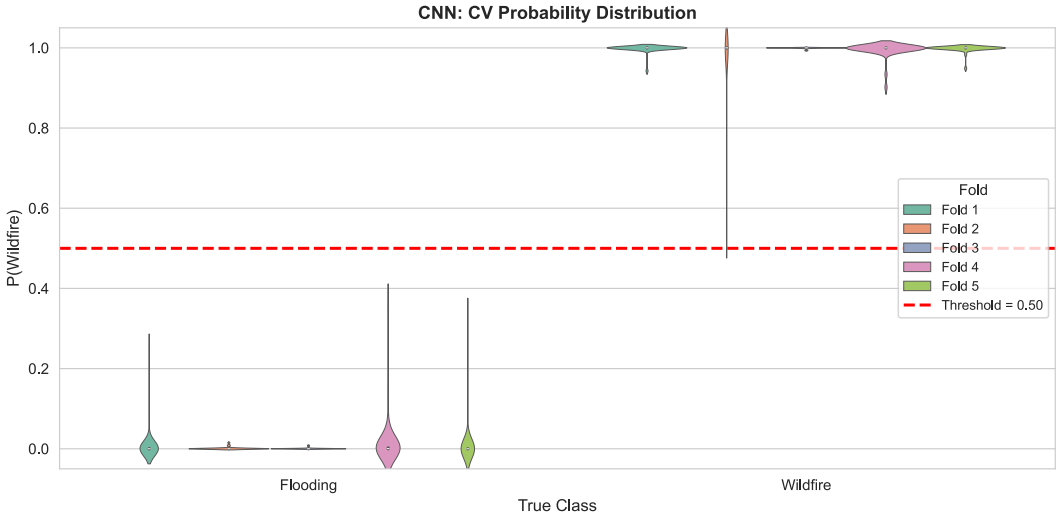

Figure 29: Probability distribution of predicted probabilities by true class label across 5-fold cross-validation for the CNN model. Each violin plot shows the distribution for one fold, with colors distinguishing different folds. The red dashed line indicates the decision threshold at 0.5. Both classes (0: Flooding, 1: Wildfire) show high predicted probabilities near 1.0, indicating strong model confidence.

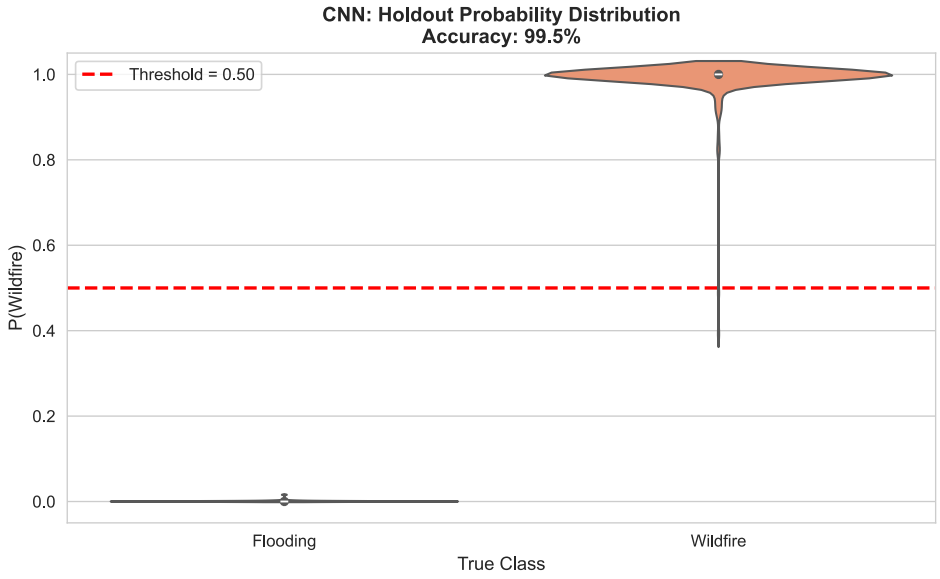

Figure 30: Probability distribution of predicted probabilities by true class label on the holdout set for the CNN model. Both classes show highly concentrated distributions near probability 1.0, indicating strong model confidence. The red dashed line indicates the decision threshold at 0.5.

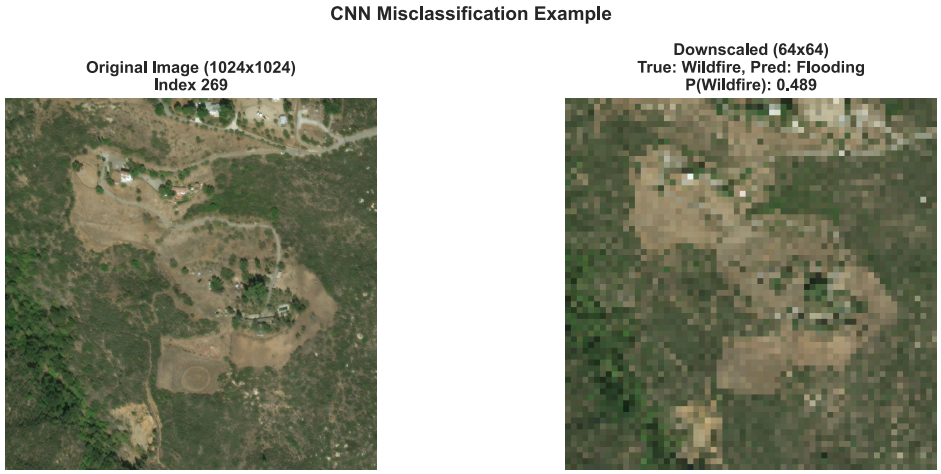

Figure 31: Side-by-side comparison of the original (1024×1024) and downscaled (64×64) images for a sample where the model's prediction differs from the assumed true label. We note that we only assume this is a misclassification, as the holdout set appears to be sorted by disaster type, and we do not have ground truth labels for verification.

A.7.3 Confusion Matrix

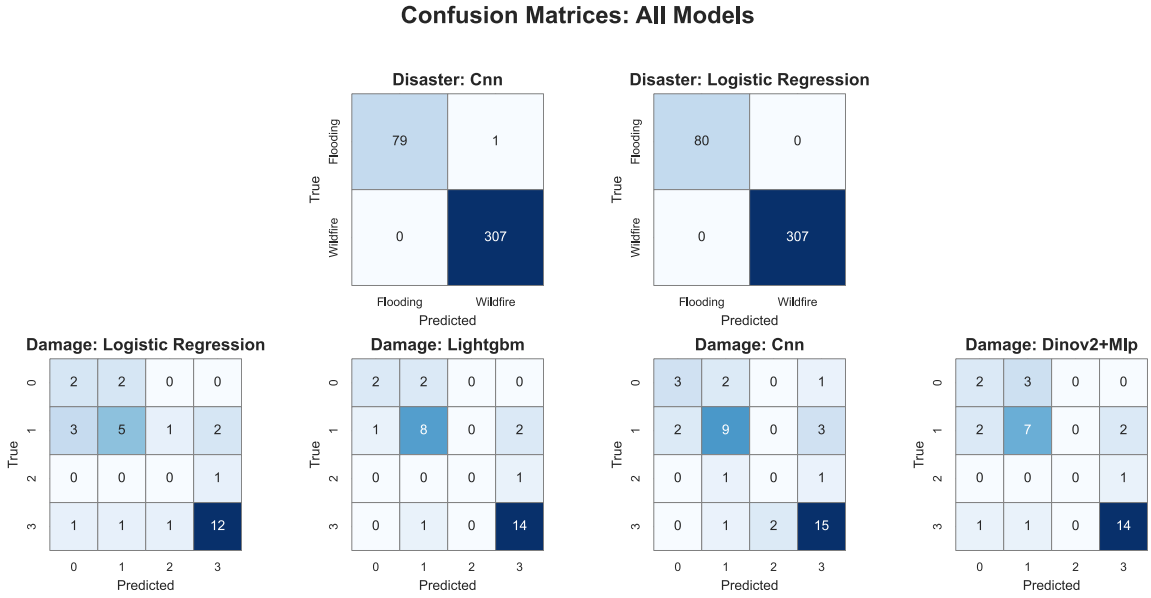

Figure 32: Confusion matrices for all models across disaster type prediction (top row) and damage level prediction (bottom row). For damage prediction models, confusion matrices are aggregated by averaging confusion matrices across all cross-validation folds of the best hyperparameter.

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Exploratory Data Analysis

This notebook explores the satellite imagery dataset for disaster classification and damage assessment.

Contents:

0. Setup & Data Loading

Import required libraries and load the satellite imagery dataset.

In [1]:
```
# Setup paths for notebook to run from analysis/ folder
import sys
from pathlib import Path

ROOT = Path("..").resolve()
sys.path.insert(0, str(ROOT))

# Standard imports
import json
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
import plotly.express as px
from skimage.transform import integral_image
from skimage.feature import haar_like_feature

# Project imports - Constants
from data200.const.const import DATA_DIR, FIGURES_DIR, DISASTER_LIST
from data200.const.schema import DatasetSample
from data200.utils.data import get_images, get_labels

# Project imports - Data loading and preprocessing
from data200.io.load import load_disaster_data
from data200.pipeline.preprocess import preprocess_data
from data200.preprocess.patch import fill_black_bars, fill_black_bars_by_mirror, add_alpha_from_black_bars

# Project imports - Plotting utilities
from data200.plot.image import render_image, render_images, render_image_samples, render_image_interactive
from data200.plot.color import (
    plot_rgb_decomposition,
    render_multiple_black_bar_comparisons,
    plot_black_ratios,
    plot_color_intensity_hist,
    plot_black_ratio_distribute_per_disaster,
    plot_image_region,
    plot_feature_violin_by_disaster,
    plot_histogram_violin_by_disaster,
)

# Project imports - Feature extraction
from data200.utils.feature import (
    get_sobel_features,
    get_gabor_features,
    generate_gabor_kernel,
    get_local_binary_pattern,
    extract_features_by_disaster,
)
from data200.feature.black_pixels import (
    patch_dataset,
    black_bar_ratio_per_disaster,
    find_black_ratios,
    has_black_bars,
    gen_black_ratios_df,
)
from data200.feature.color_based_features import (
    get_color_moments,
    get_color_histogram,
    get_color_entropy,
    get_hsv_histogram,
    get_color_ratios,
)
from data200.feature.structured_features import (
    get_edge_to_area_ratio_sobel,
```

```
    get_edge_to_area_ratio_canny,
    get_connected_component_stats,
    get_corner_count,
)
from data200.feature.texture_based_features import get_wavelet_features, get_haralick_features, get_haar_features
from data200.sample.sample import interleave

# Ensure output directories exist
(FIGURES_DIR / "eda").mkdir(parents=True, exist_ok=True)

print(f"Data directory: {DATA_DIR}")
print(f"Figures directory: {FIGURES_DIR}")

%load_ext autoreload
%autoreload 2
```

```
Data directory: /Users/robinholzi/git/ucb/data200/data200-grad-project/data/satellite-image-data-new
Figures directory: /Users/robinholzi/git/ucb/data200/data200-grad-project/figures
```

0.1 Load Dataset

Load the satellite imagery dataset containing three disaster types: Hurricane Matthew, SoCal Fire, and Midwest Flooding.

In [2]:
```
data = load_disaster_data(path=DATA_DIR)
```

```
Loading train images and labels for hurricane-matthew dataset...
Loading train images and labels for socal-fire dataset...
Loading train images and labels for midwest-flooding dataset...
```

0.2 Verify Image Dimensions

Confirm all images have consistent dimensions (1024×1024×3).

In [3]:
```
print(f"image shape: {data.hurricane_matthew.images[0].shape}")

wrong = 0
for image in data.hurricane_matthew.images:
    if image.shape != (1024,1024,3):
        wrong += 1
for image in data.socal_fire.images:
    if image.shape != (1024,1024,3):
        wrong += 1
for image in data.midwest_flooding.images:
    if image.shape != (1024,1024,3):
        wrong += 1
print(wrong)
```

```
image shape: (1024, 1024, 3)
0
```

0.3 Sample Image Visualization

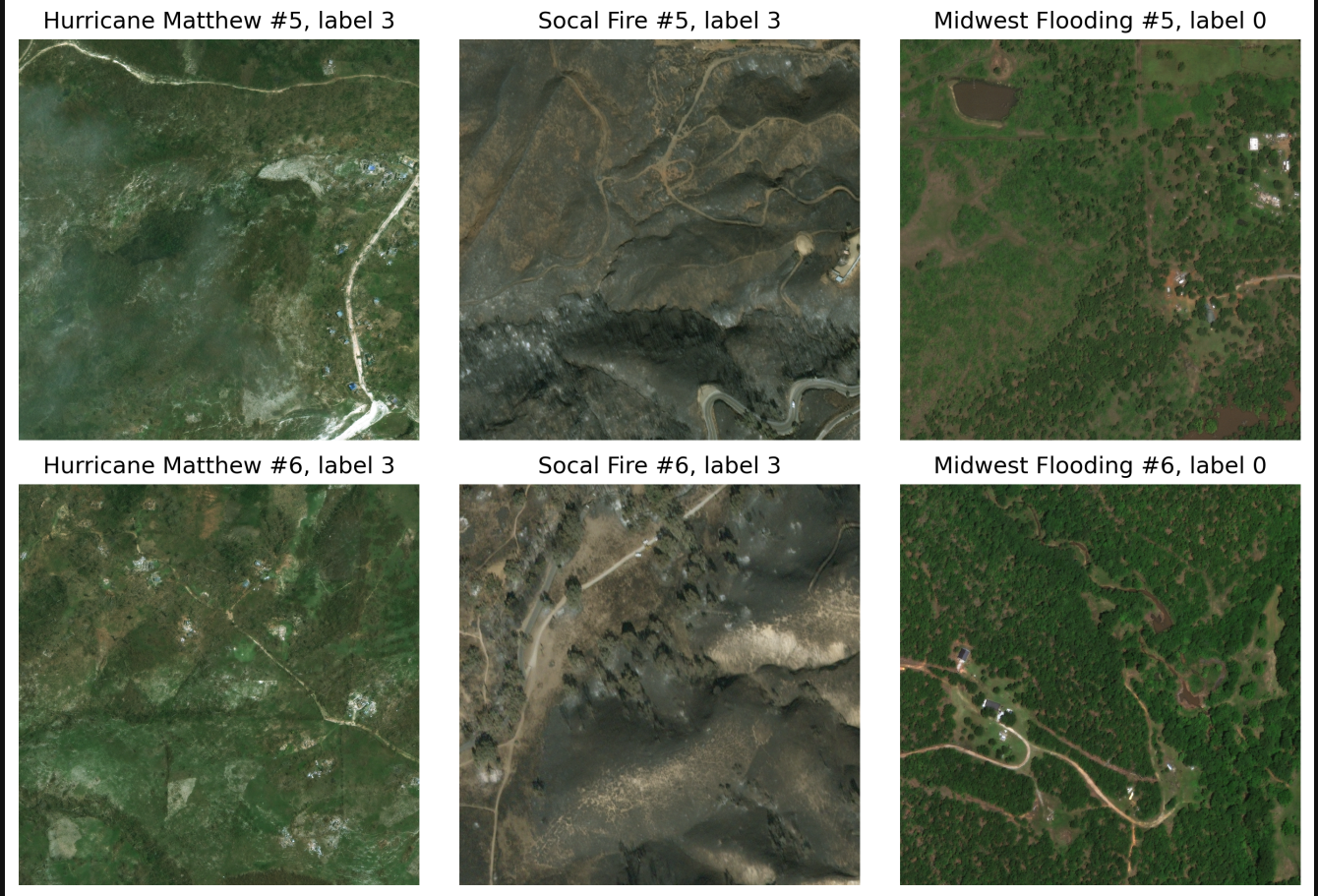
Visualize sample images from each disaster type to understand the data.

In [4]:
```
print(f"image shape: {data.hurricane_matthew.images[0].shape}, dtype", f"{data.hurricane_matthew.images[0].dtype}")
```

```
image shape: (1024, 1024, 3), dtype uint8
```

In [5]:
```
long = False
if long:
    num_images_per_disaster = 100
    start = 0
else:
    num_images_per_disaster = 2
    start = 5

sample_indexes = {
    "hurricane-matthew": list(range(start, start+num_images_per_disaster)),
    "midwest-flooding": list(range(start, start+num_images_per_disaster)),
    "socal-fire": list(range(start, start+num_images_per_disaster)),
}
assert all(
    len(sample_indexes[disaster]) == num_images_per_disaster
    for disaster in DISASTER_LIST
)

# interleave disasters round-robin
samples = [
    data.get(disaster).get_sample(sample_indexes[disaster][idx], dataset=disaster.replace("-", " ").title())
    for idx in range(num_images_per_disaster)
    for disaster in DISASTER_LIST
]

render_image_samples(samples).savefig(FIGURES_DIR / "eda" / "disaster_samples_latex.pdf", dpi=300)
```

```
/Users/robinholzi/git/ucb/data200/data200-grad-project/data200/plot/image.py:96: UserWarning: This figure includes Axes that are not compatible with tight_layout, so results might be incorrect.
  plt.tight_layout()
```



1. Dataset Overview

Explore the basic statistics, class distributions, and characteristics of the satellite imagery dataset.

1.1 Basic Statistics

Summary of dataset dimensions and image properties.

In [6]:
```
structure = data.structure()
overview = data.get_overview()

# All images are 1024x1024x3
structure
```

Out[6]:

	disaster	prediction_task	num_images	width	height	channels	pixels	values
0	hurricane-matthew	damage level	200	1024	1024	3	1048576	3145728
1	socal-fire	disaster type	200	1024	1024	3	1048576	3145728
2	midwest-flooding	disaster type	200	1024	1024	3	1048576	3145728

In [7]:
```
(
    structure["width"].unique(),
    structure["height"].unique(),
    structure["channels"].unique()
)
```

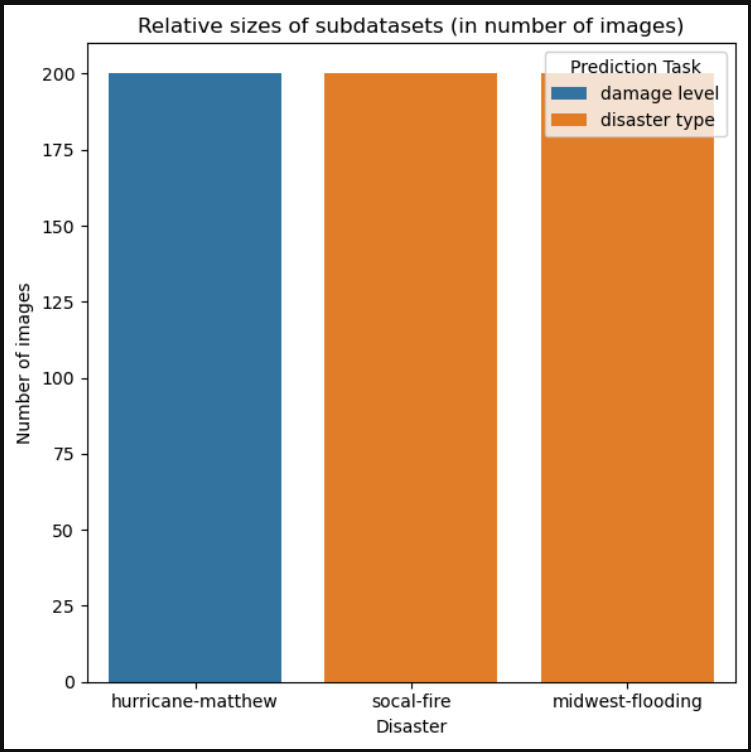
Out[7]:
```
(array([1024]), array([1024]), array([3]))
```

1.2 Images per Disaster Type

Compare the number of images available for each disaster type.

In [8]:
```
plt.figure(figsize=(6, 6))
```

```
# Relative sizes of subdatasets
sns.barplot(
    structure,
    x="disaster",
    y="num_images",
    hue="prediction_task",
)

plt.title("Relative sizes of subdatasets (in number of images)")
plt.xlabel("Disaster")
plt.ylabel("Number of images")
plt.tight_layout()
plt.legend(title='Prediction Task')

# Save as png
plt.savefig(
    FIGURES_DIR / "eda" / "relative_sizes_subdatasets.pdf",
    dpi=300
)
```

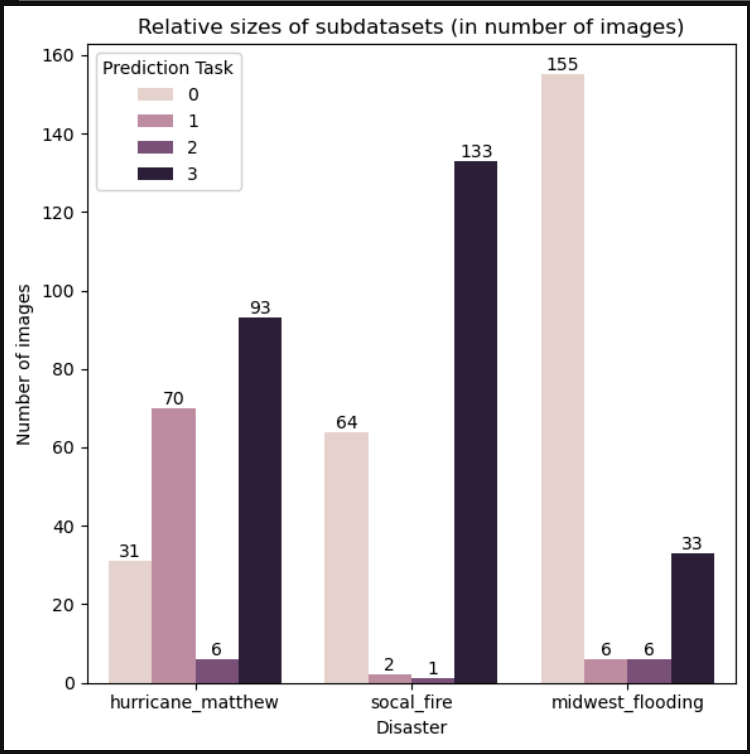


1.3 Damage Label Distribution

Visualize the distribution of damage levels across disaster types.

In [9]:
```
plt.figure(figsize=(6, 6))

ax = sns.countplot(
    overview,
    x="disaster_label",
    hue="damage_label",
)

for container in ax.containers:
    ax.bar_label(container)

plt.title("Relative sizes of subdatasets (in number of images)")
plt.xlabel("Disaster")
plt.ylabel("Number of images")
plt.tight_layout()
plt.legend(title='Damage Level')

plt.title("Relative sizes of subdatasets (in number of images)")
plt.xlabel("Disaster")
plt.ylabel("Number of images")
plt.tight_layout()
plt.legend(title='Prediction Task')

# Save as png
plt.savefig(
    FIGURES_DIR / "eda" / "label_distribution_per_subdataset.pdf",
```

```
    dpi=300
)
```



1.4 Dataset Size Considerations

The datasets are quite small (200 samples per disaster type), which presents challenges for deep learning.

Potential solutions:

1. **Data augmentation**: Random crops, rotations, color jittering, flips, noise addition
2. **Transfer learning**: Use pre-trained models (not pursued to avoid external dependencies)
3. **Classical ML models**: Use hand-crafted features with SVM, Boosted Trees, Random Forests as baselines

2. Missing Data Analysis (Black Bars)

Analyze and handle missing data represented as black bars in satellite images.

2.1 The Problem

Many images have black bars (missing pixels) on the sides, likely due to sensor failure or preprocessing (cloud removal). Different disaster types have different black bar ratios.

2.2 Handling Options

Option	Description	Decision
Drop images	Remove images with black bars	Rejected: Would lose 15-20% of data
Fill with mean	Replace black pixels with image mean	Considered: Simple baseline
Mirror fill	Reflect image content into black regions	**Chosen: Reflects image content naturally**
Mask channel	Add 4th channel indicating valid pixels	Rejected: More complex implementation

2.3 Feature Extraction Strategy

After patching, we extract the following classical features:

Color-based: Color moments, histograms, entropy, HSV, color ratios

Texture-based: Gabor filters, LBP, Sobel edges, Haralick, wavelets

Structural: Edge-to-area ratio, connected components, corner detection

2.4 Black Bar Detection

Analyze the proportion of images with black bars per disaster type.

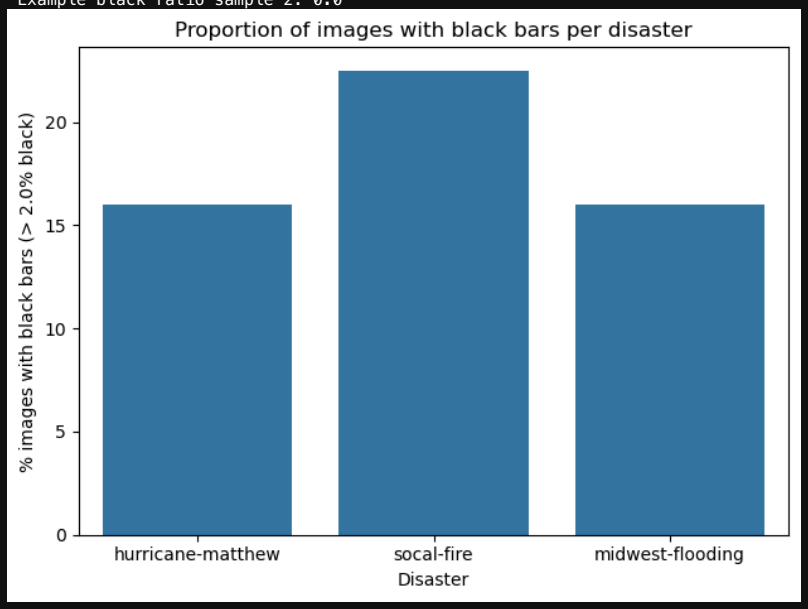
In [10]:
```
black_bar_ratios_per_disaster = {
    disaster: find_black_ratios(data.get(disaster).images)
    for disaster in DISASTER_LIST
}
black_ratios_df = gen_black_ratios_df(black_bar_ratios_per_disaster)
black_ratios_df.head(2)
```

Out[10]:

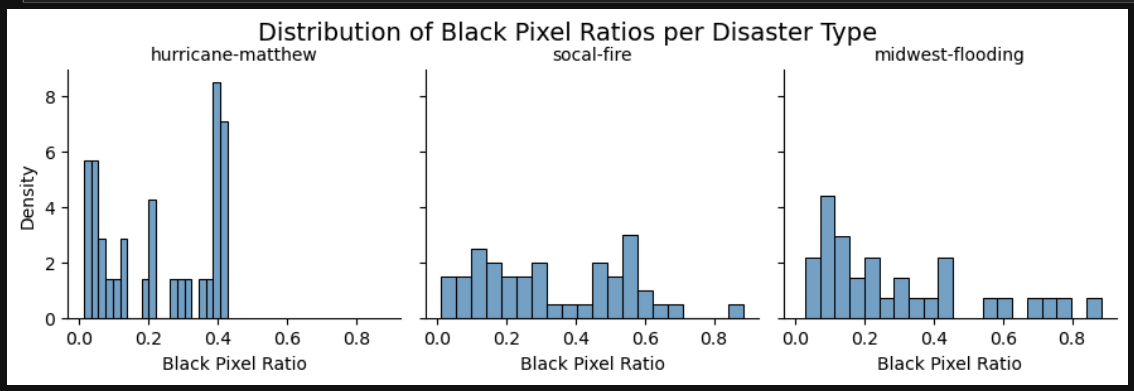
	disaster	sample_idx	black_ratio
0	hurricane-matthew	0	0.0
1	hurricane-matthew	1	0.0

In [11]:
```
plot_black_ratios(black_bar_ratios_per_disaster)
print(
    "Example black ratio sample 0:",
    find_black_ratios(data.hurricane_matthew.images)[0],
)
print(
    "Example black ratio sample 2:",
    find_black_ratios(data.hurricane_matthew.images)[2],
)
```

```
Example black ratio sample 0: 0.0
Example black ratio sample 2: 0.0
```



In [12]:
```
plot_black_ratio_distribute_per_disaster(black_ratios_df).savefig(
        FIGURES_DIR / "eda" / "black_ratio_distribution_per_disaster.pdf",
        dpi=300
    )
```



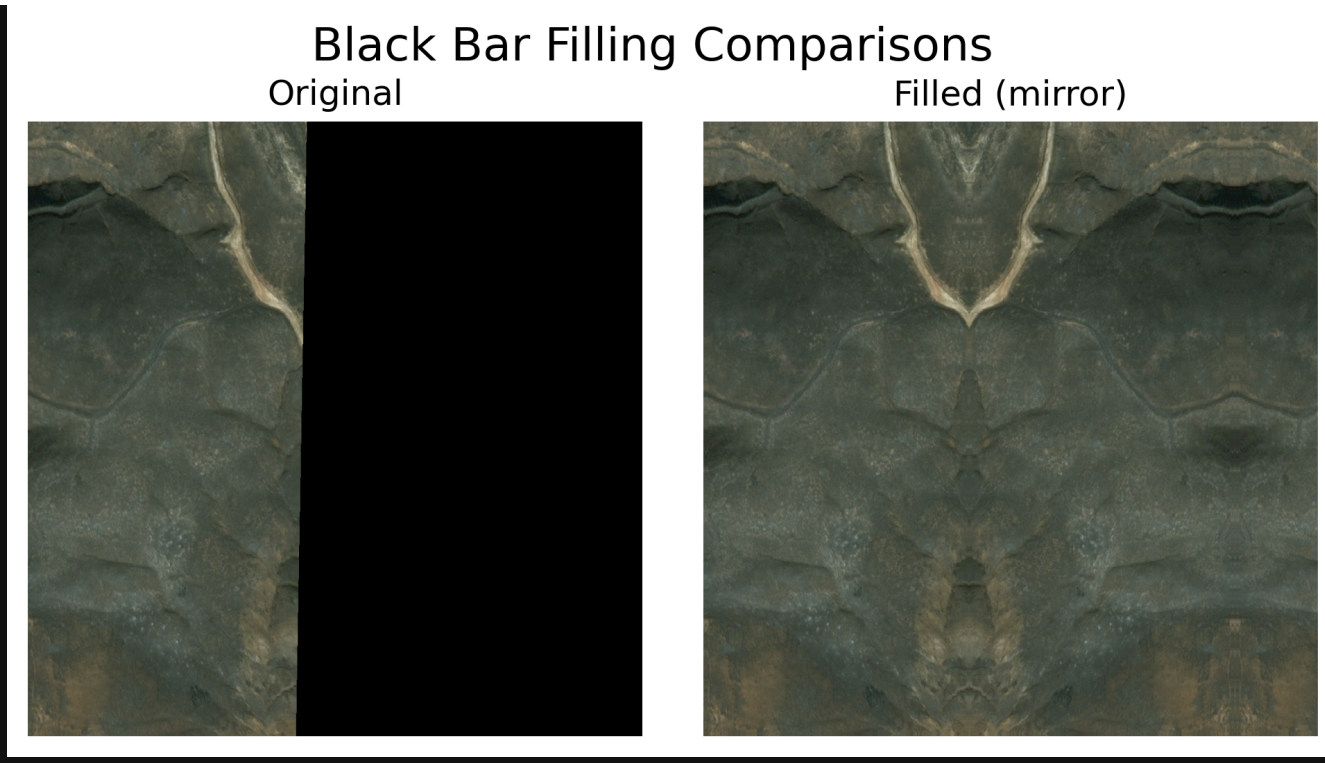
In [13]:
```
black_bar_samples = np.array([
    data.socal_fire.images[i]
    for i, ratio in enumerate(black_bar_ratios_per_disaster["socal-fire"])
    if ratio >= 0.1
])
```

In [14]:
```
offset = 28
num_samples = 1
```

```
subset = black_bar_samples[offset:offset+num_samples]
filled_mean = fill_black_bars(
    subset, method="mean"
)
filled_mirror = fill_black_bars(
    subset, method="mirror"
)
render_multiple_black_bar_comparisons(
    subset,
    filled_mean,
    filled_mirror,
    offset=0,
    num_samples=num_samples
).savefig(
    FIGURES_DIR / "eda" / "black_bar_filling_comparison.pdf",
    dpi=300,
    bbox_inches="tight"
)
render_multiple_black_bar_comparisons(
    subset,
    None,
    filled_mirror,
    offset=0,
    num_samples=num_samples
).savefig(
    FIGURES_DIR / "eda" / "black_bar_filling_comparison_nomean.pdf",
    dpi=300,
    bbox_inches="tight"
)
```

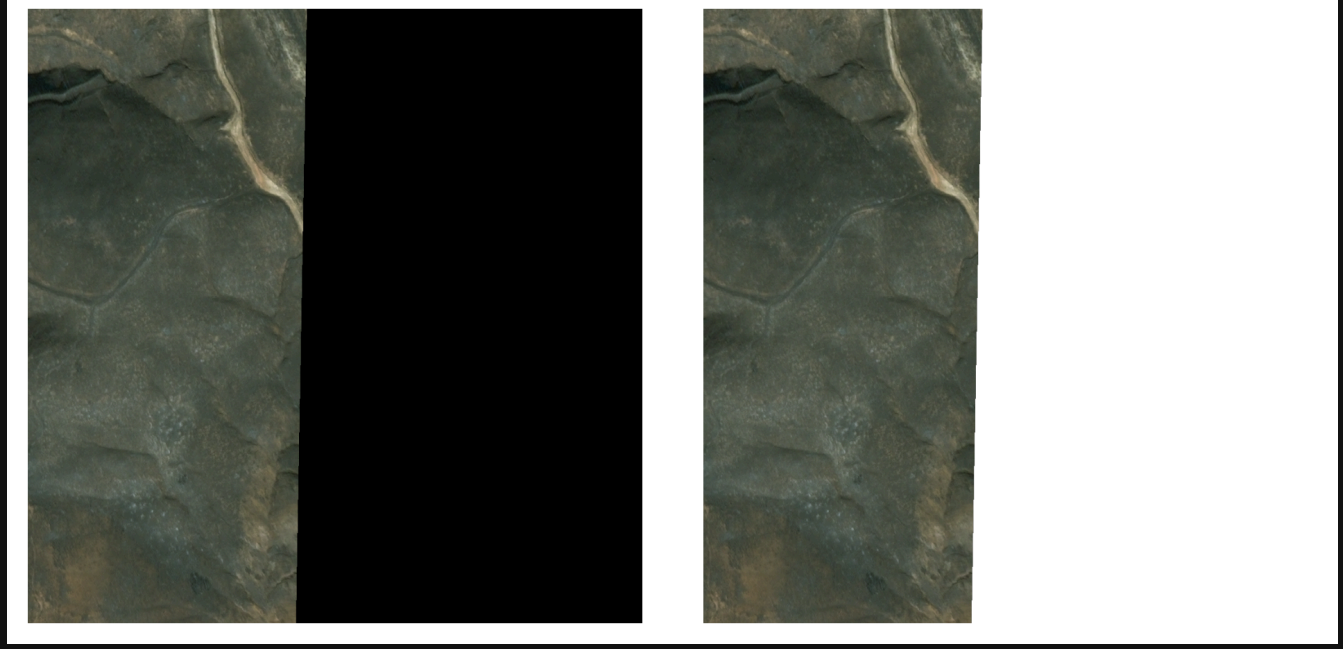
```
/Users/robinholzi/git/ucb/data200/data200-grad-project/data200/plot/image.py:96: UserWarning: This figure includes Axes that are not compatible with tight_layout, so results might be incorrect.
  plt.tight_layout()
```


```
/Users/robinholzi/git/ucb/data200/data200-grad-project/data200/plot/image.py:96: UserWarning: This figure includes Axes that are not compatible with tight_layout, so results might be incorrect.
  plt.tight_layout()
```



In [15]:
```
# Use an image to demonstrate the alpha channel effect
sample_with_black_bars = black_bar_samples[28]

image_with_black_bar_alpha = add_alpha_from_black_bars(
    np.array([sample_with_black_bars])
)
fig = render_images([
    sample_with_black_bars,
    image_with_black_bar_alpha[0],
], labels=["Original", "With Alpha Channel"], ncols=2)
plt.show()
```

```
/Users/robinholzi/git/ucb/data200/data200-grad-project/data200/plot/image.py:96: UserWarning: This figure includes Axes that are not compatible with tight_layout, so results might be incorrect.
  plt.tight_layout()
```



2.5 Apply Patching

Apply mirror-fill patching to all images. All subsequent analysis uses this patched dataset.

In [16]:
```
patched_data = preprocess_data(data)
```

3. Color-based Features

Extract and visualize color-based features that may help distinguish disaster types and damage levels.

3.1 Color Moments

Extract mean, standard deviation, and skewness for each RGB channel to capture color distribution characteristics.

In [17]:
```
# Extract color moments from one sample image
sample_features = get_color_moments(patched_data.hurricane_matthew.images[0])
pd.DataFrame([sample_features])
```

Out[17]:

	r_mean	r_std	r_skew	g_mean	g_std	g_skew	b_mean	b_std	b_skew
0	80.946669	25.259553	1.687784	95.179172	23.573383	1.552585	64.224064	21.924001	2.26661

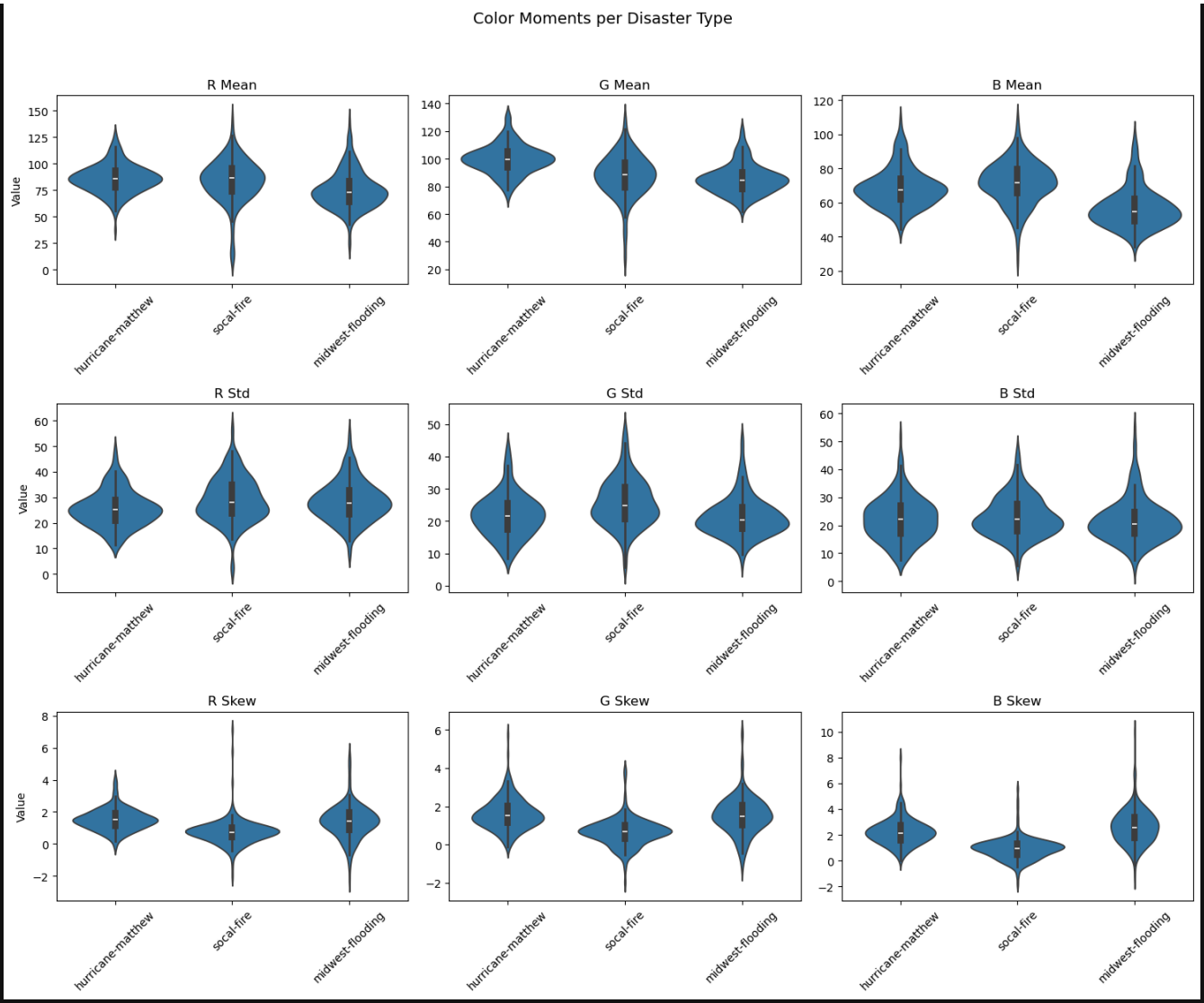
In [18]:
```
# Extract color moments for all disasters
df_color_moments = extract_features_by_disaster(patched_data, get_color_moments)
print(f"Extracted features from {len(df_color_moments)} images")
df_color_moments.head()
```

```
Extracting features: 100%|██████████| 600/600 [00:16<00:00, 36.52it/s]
Extracted features from 600 images
```

Out[18]:

	r_mean	r_std	r_skew	g_mean	g_std	g_skew	b_mean	b_std	b_skew	disaster	label
0	80.946669	25.259553	1.687784	95.179172	23.573383	1.552585	64.224064	21.924001	2.266610	hurricane-matthew	1
1	82.295654	32.486160	1.438341	94.330956	31.130185	1.220090	75.778777	30.406815	1.927453	hurricane-matthew	3
2	96.923233	25.478084	1.496852	104.998304	18.720188	2.213880	71.095031	20.712719	2.505107	hurricane-matthew	1
3	80.765044	11.577415	3.832558	106.896722	8.965433	1.356518	83.332263	8.721872	3.763137	hurricane-matthew	3
4	75.076754	34.162408	1.329201	91.805744	27.319979	2.139990	71.761678	27.859699	2.467230	hurricane-matthew	1

In [19]:
```
# Visualize color moments for all disasters (3x3 grid)
color_features = ['r_mean', 'g_mean', 'b_mean', 'r_std', 'g_std', 'b_std', 'r_skew', 'g_skew', 'b_skew']
plot_feature_violin_by_disaster(
    df_color_moments,
    features=color_features,
    nrows=3,
    suptitle="Color Moments per Disaster Type",
    figsize=(15, 12),
)
plt.show()
```



3.2 Color Histograms

Analyze the distribution of RGB pixel intensities across disaster types.

In [20]:
```
rebuild_hist = False
if rebuild_hist:
    color_intensity_histogram = plot_color_intensity_hist(patched_data, bins=100, images_per_disaster=1000)
    color_intensity_histogram.write_image(
        FIGURES_DIR / "eda" / "color_intensity_histogram.pdf", scale=10.0
    )
```

In [21]:
```
# Extract color histogram from one sample image
sample_img = patched_data.hurricane_matthew.images[0]
sample_features = get_color_histogram(sample_img, bins=32)
pd.DataFrame([sample_features])
```

Out[21]:

	r_hist_0	r_hist_1	r_hist_2	r_hist_3	r_hist_4	r_hist_5	r_hist_6	r_hist_7	r_hist_8	r_hist_9	...	b_hist_22	b_hist_23	b_hist_24	b_hist_2
0	0.000002	0.0	0.000002	0.000225	0.004338	0.020159	0.062877	0.131206	0.18758	0.183578	...	0.000932	0.000514	0.000279	0.00018

1 rows × 96 columns

In [22]:
```
# Extract color histogram for all disasters
df_color_histogram = extract_features_by_disaster(
    patched_data, lambda img: get_color_histogram(img, bins=32)
)
print(f"Extracted features from {len(df_color_histogram)} images")
df_color_histogram.head()
```

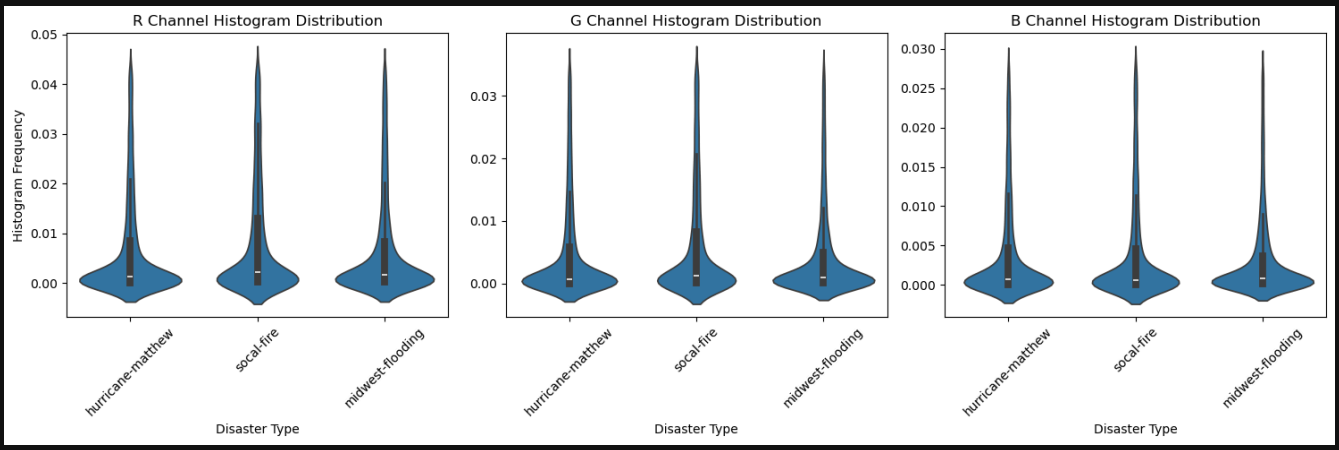
```
Extracting features: 100%|██████████| 600/600 [00:11<00:00, 51.59it/s]
Extracted features from 600 images
```

Out[22]:

	r_hist_0	r_hist_1	r_hist_2	r_hist_3	r_hist_4	r_hist_5	r_hist_6	r_hist_7	r_hist_8	r_hist_9	...	b_hist_24	b_hist_25	b_hist_26
0	0.000002	0.000000	0.000002	2.250671e-04	0.004338	0.020159	0.062877	0.131206	0.187580	0.183578	...	0.000279	0.000185	1.544952e-04
1	0.000002	0.000000	0.000008	4.100800e-05	0.001923	0.062041	0.140810	0.114287	0.126428	0.135360	...	0.003969	0.002934	1.928329e-03
2	0.000000	0.000000	0.000000	0.000000e+00	0.000000	0.000000	0.000018	0.005012	0.056083	0.227024	...	0.000842	0.000485	3.986359e-04
3	0.000000	0.000000	0.000000	9.536743e-07	0.000022	0.000424	0.001400	0.005514	0.087260	0.414827	...	0.000028	0.000013	9.536743e-07
4	0.000033	0.000014	0.000103	1.011648e-01	0.066694	0.022664	0.044926	0.103224	0.161695	0.147786	...	0.003044	0.002165	1.008034e-03

5 rows × 98 columns

In [23]:
```
# Visualize RGB histogram distributions per disaster type using violin plots
plot_histogram_violin_by_disaster(
    df_color_histogram,
    channels=['r', 'g', 'b'],
    hist_prefix='',
    num_bins=32,
    filter_outliers=True,
    iqr_multiplier=0.1,
    save_path=FIGURES_DIR / "eda" / "average_rgb_histograms_per_disaster.pdf",
)
plt.show()
```



3.3 Color Entropy

Measure color diversity entropy (diversity) for each RGB channel.

In [24]:
```
# Extract color entropy from one sample image
sample_features = get_color_entropy(patched_data.hurricane_matthew.images[0])
pd.DataFrame([sample_features])
```

Out[24]:

	r_entropy	g_entropy	b_entropy
0	6.428279	6.361284	6.036096

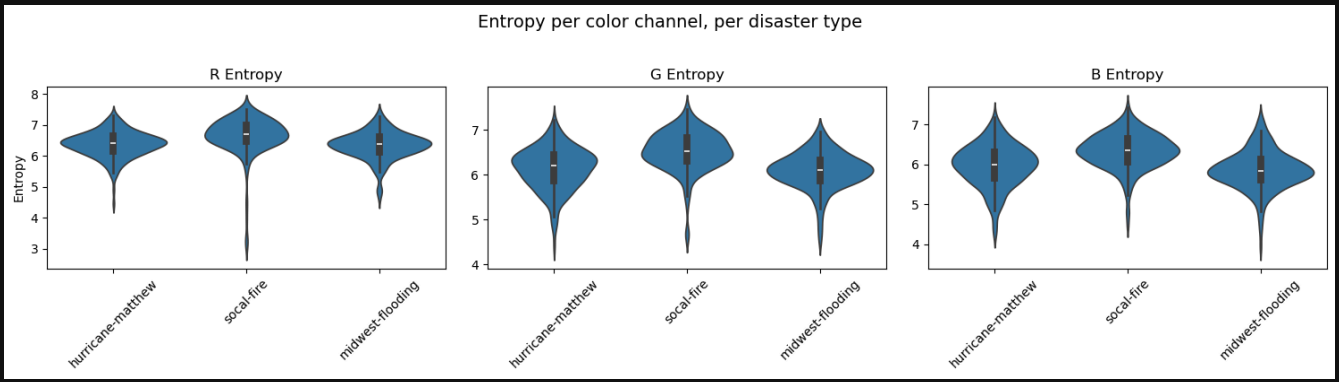
In [25]:
```
# Extract color entropy for all disasters
df_color_entropy = extract_features_by_disaster(patched_data, get_color_entropy)
print(f"Extracted features from {len(df_color_entropy)} images")
df_color_entropy.head()
```

```
Extracting features: 100%|██████████| 600/600 [00:11<00:00, 53.25it/s]
Extracted features from 600 images
```

Out[25]:

	r_entropy	g_entropy	b_entropy	disaster	label
0	6.428279	6.361284	6.036096	hurricane-matthew	1
1	6.721464	6.702422	6.448170	hurricane-matthew	3
2	6.307734	5.850019	5.765490	hurricane-matthew	1
3	4.903666	4.417693	4.279366	hurricane-matthew	3
4	6.673090	6.248124	6.113640	hurricane-matthew	1

In [26]:
```
# Visualize color entropy for all disasters
plot_feature_violin_by_disaster(
    df_color_entropy,
    features=['r_entropy', 'g_entropy', 'b_entropy'],
    ylabel='Entropy',
    suptitle="Entropy per color channel, per disaster type",
    save_path=FIGURES_DIR / "eda" / "color_entropy_violin.pdf",
)
plt.show()
```



3.4 HSV Histograms

Extract histograms in HSV color space (Hue, Saturation, Value).

In [27]:
```
# Extract HSV histogram from one sample image
sample_img = patched_data.hurricane_matthew.images[0]
sample_features = get_hsv_histogram(sample_img, bins=32)
pd.DataFrame([sample_features])
```

Out[27]:

	h_hist_0	h_hist_1	h_hist_2	h_hist_3	h_hist_4	h_hist_5	h_hist_6	h_hist_7	h_hist_8	h_hist_9	...	v_hist_22	v_hist_23	v_hist_24	v_hist_2
0	0.000013	0.000007	0.000105	0.001437	0.011891	0.051447	0.17396	0.305024	0.332318	0.117805	...	0.004493	0.003452	0.002263	0.00

1 rows × 96 columns

In [28]:
```
# Extract HSV histogram for all disasters
df_hsv_histogram = extract_features_by_disaster(
    patched_data, lambda img: get_hsv_histogram(img, bins=32)
)
print(f"Extracted features from {len(df_hsv_histogram)} images")
df_hsv_histogram.head()
```

```
Extracting features: 100%|██████████| 600/600 [00:58<00:00, 10.24it/s]
Extracted features from 600 images
```

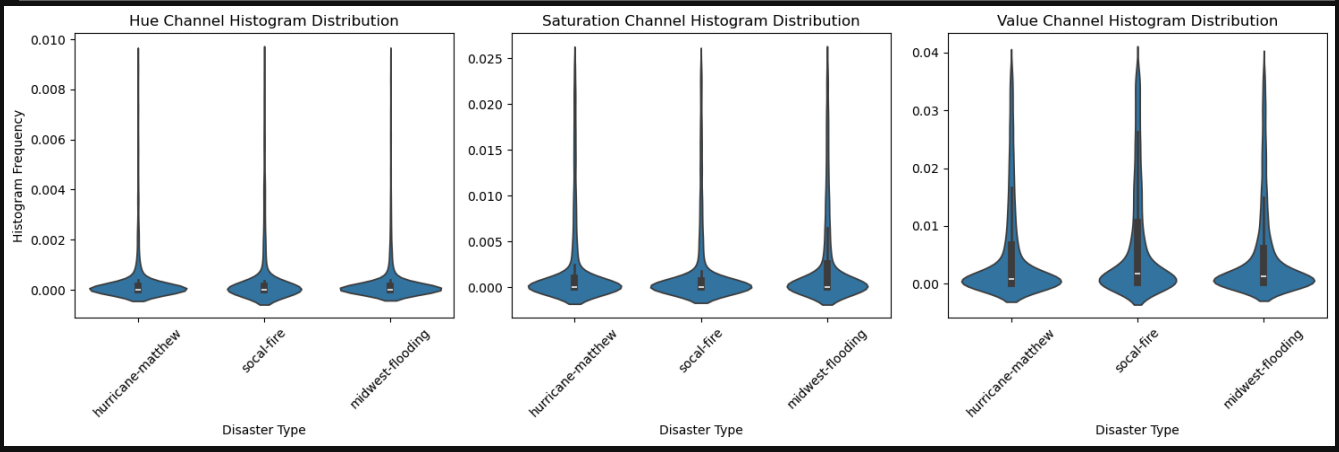
Out[28]:

	h_hist_0	h_hist_1	h_hist_2	h_hist_3	h_hist_4	h_hist_5	h_hist_6	h_hist_7	h_hist_8	h_hist_9	...	v_hist_24	v_hist_25	v_hist_26	v_hist
0	0.000013	0.000007	0.000105	0.001437	0.011891	0.051447	0.173960	0.305024	0.332318	0.117805	...	0.002263	0.001000	0.000452	0.000
1	0.000059	0.000096	0.000547	0.030729	0.135286	0.118480	0.079616	0.060322	0.083125	0.112291	...	0.005197	0.004213	0.002840	0.00
2	0.000412	0.000663	0.000646	0.042691	0.129465	0.131012	0.190145	0.395461	0.107595	0.001067	...	0.002372	0.001224	0.000794	0.000
3	0.000005	0.000000	0.000051	0.000583	0.005885	0.012086	0.019405	0.022624	0.028752	0.047679	...	0.000062	0.000037	0.000013	0.000
4	0.000320	0.000208	0.000467	0.002690	0.010624	0.026950	0.110952	0.238033	0.243384	0.106144	...	0.005957	0.004189	0.002993	0.001

5 rows × 98 columns

In [29]:
```
# Visualize HSV histogram distributions per disaster type using violin plots
plot_histogram_violin_by_disaster(
    df_hsv_histogram,
    channels=['h', 's', 'v'],
    hist_prefix='',
    num_bins=32,
    channel_labels=['Hue', 'Saturation', 'Value'],
    filter_outliers=True,
    iqr_multiplier=0.1,
    save_path=FIGURES_DIR / "eda" / "average_hsv_histograms_per_disaster.pdf",
```

```
)
plt.show()
```



3.5 Color Ratios

Extract R/G, G/B, and R/B ratios.

In [30]:
```
# Extract color ratios from one sample image
sample_features = get_color_ratios(patched_data.hurricane_matthew.images[0])
pd.DataFrame([sample_features])
```

Out[30]:

	r_g_ratio	g_b_ratio	r_b_ratio
0	0.850466	1.481986	1.260379

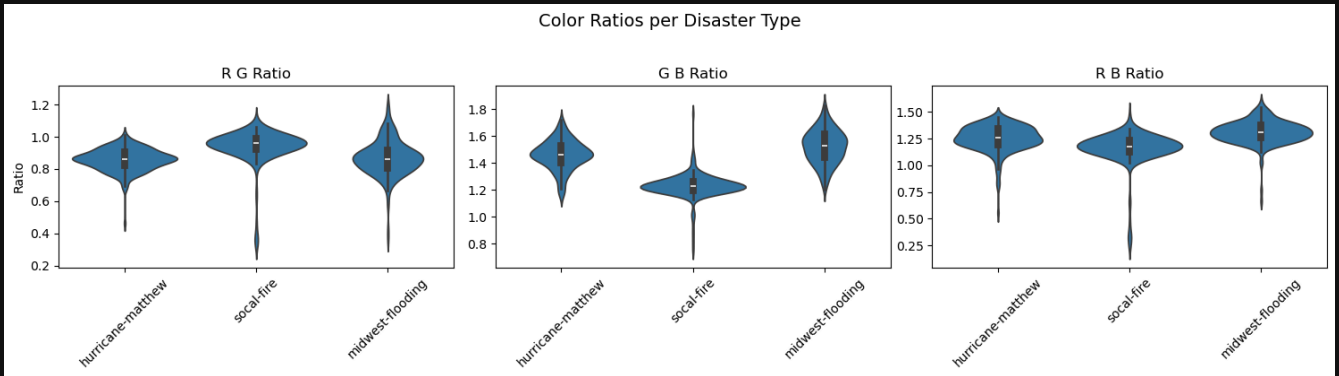
In [31]:
```
# Extract color ratios for all disasters
df_color_ratios = extract_features_by_disaster(patched_data, get_color_ratios)
print(f"Extracted features from {len(df_color_ratios)} images")
df_color_ratios.head()
```

```
Extracting features: 100%|██████████| 600/600 [00:00<00:00, 847.57it/s]
Extracted features from 600 images
```

Out[31]:

	r_g_ratio	g_b_ratio	r_b_ratio	disaster	label
0	0.850466	1.481986	1.260379	hurricane-matthew	1
1	0.872414	1.244820	1.085999	hurricane-matthew	3
2	0.923093	1.476873	1.363291	hurricane-matthew	1
3	0.755543	1.282777	0.969193	hurricane-matthew	3
4	0.817778	1.279314	1.046196	hurricane-matthew	1

In [32]:
```
# Visualize color ratios for all disasters
plot_feature_violin_by_disaster(
    df_color_ratios,
    features=['r_g_ratio', 'g_b_ratio', 'r_b_ratio'],
    ylabel='Ratio',
    suptitle="Color Ratios per Disaster Type",
    save_path=FIGURES_DIR / "eda" / "color_ratios_per_disaster.pdf",
)
plt.show()
```



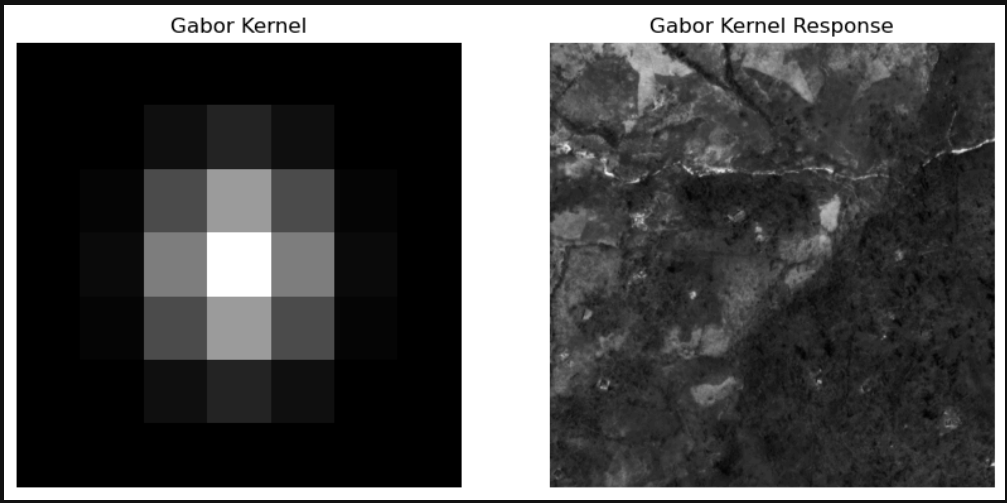
4. Texture & Edge Features

Extract texture and edge-based features that capture structural patterns in the images.

In [33]:
```
sample_dc20 = patched_data.get_random_sample_disaster_classification(10)
sample_dc100 = patched_data.get_random_sample_disaster_classification(50)
sample_dc100 = interleave(sample_dc100,2)
```

4.1 Gabor Filters

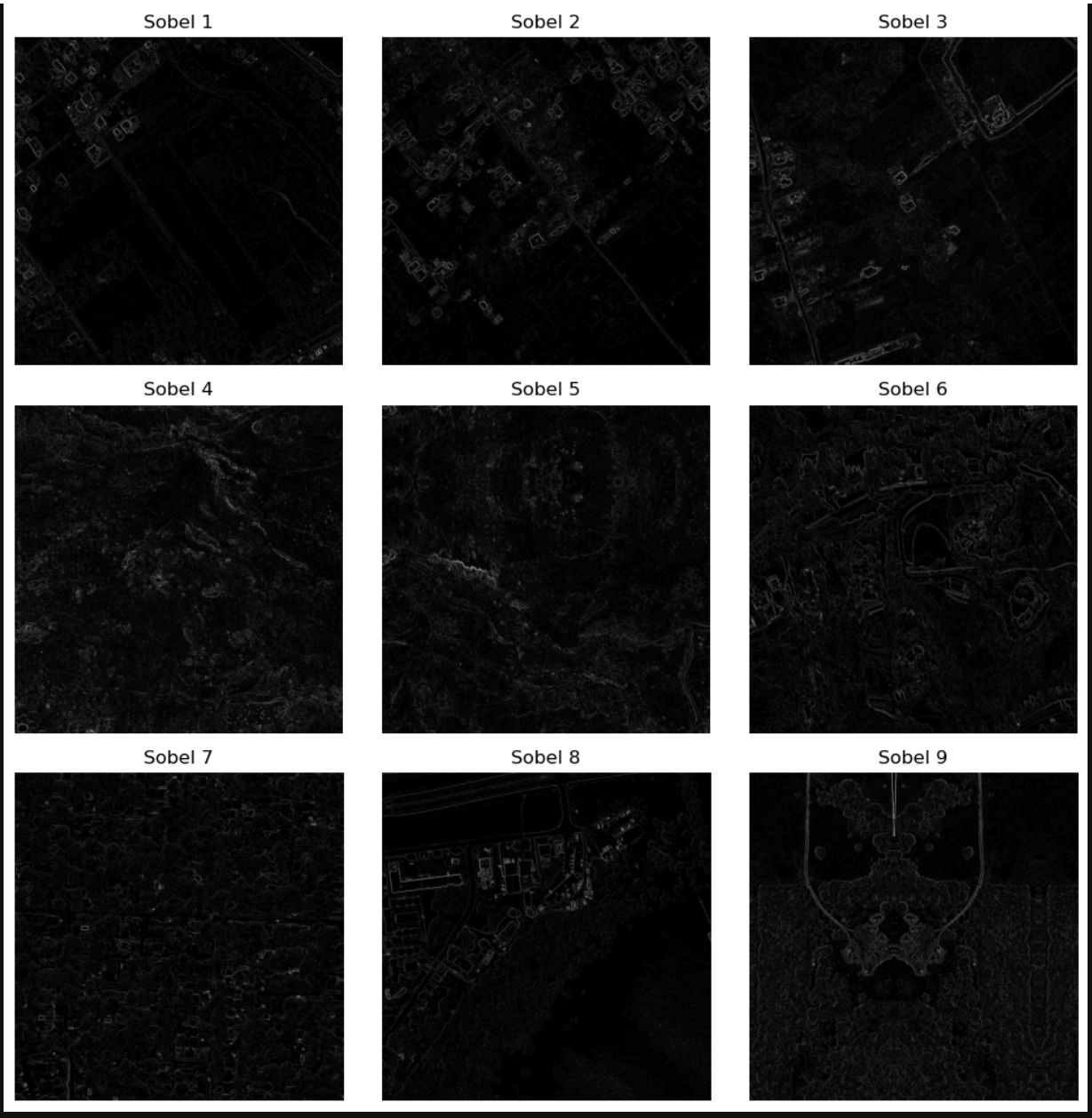
In [34]:
```
sample_img = patched_data.hurricane_matthew.images[0]

theta = 0
sigma = 1.0
frequency = 0.1

kernel = generate_gabor_kernel(theta, sigma, frequency)
gabor = get_gabor_features(sample_img, kernel)

fig, axs = plt.subplots(1, 2, figsize=(10, 5))  # 1 row, 2 columns

# Plot Gabor Kernel
axs[0].imshow(kernel, cmap="gray")
axs[0].axis("off")  # Remove axis
axs[0].set_title("Gabor Kernel")

# Plot Gabor Kernel Response
axs[1].imshow(gabor, cmap="gray")
axs[1].axis("off")  # Remove axis
axs[1].set_title("Gabor Kernel Response")

plt.show()
```



4.2 Sobel Edge Detection

Detect edges using Sobel operators to capture structural boundaries.

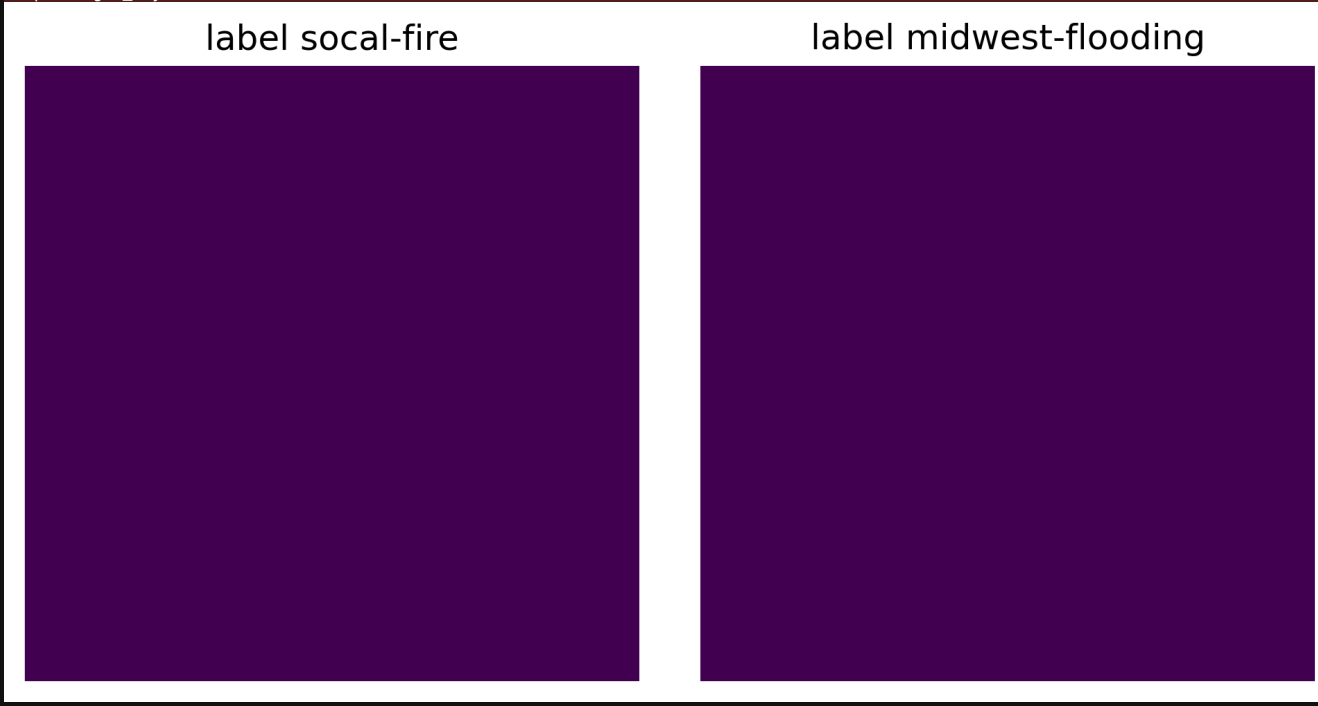
In [35]:
```
fig,axes = plt.subplots(3,3, figsize=(10,10))

for idx, img in enumerate(patched_data.get_random_sample_across_disasters(3)):
    row, col = divmod(idx, 3)  # convert index to row/col
    edges = get_sobel_features(img.image)

    axes[row, col].imshow(edges, cmap="gray")
    axes[row, col].set_title(f"Sobel {idx+1}")
    axes[row, col].axis("off")

plt.tight_layout()
plt.show()
```



In [36]:
```
images_sobel = []
features_fire = []
features_flooding = []

for idx, img in enumerate(sample_dc100):
    sobel = get_sobel_features(img.image)
    images_sobel.append(sobel)

    hist, _ = np.histogram(sobel.ravel(), bins=int(sobel.max() + 1), range=(0, sobel.max() + 1))
    hist = hist / hist.sum()
    img_entropy = -np.sum(hist[hist > 0] * np.log2(hist[hist > 0]))
    img_mean = sobel.mean()
    img_std = sobel.std()
    nonzero_count = np.count_nonzero(sobel)

    fv = np.array([img_entropy, img_mean, img_std, nonzero_count])

    fv = np.append(fv, nonzero_count)
    if idx % 2 == 0:
        features_fire.append(fv)
    else:
        features_flooding.append(fv)

render_images(images_sobel[0:2],ncols=2,labels=['socal-fire','midwest-flooding']);
df_flood = pd.DataFrame(features_flooding)
df_fire = pd.DataFrame(features_fire)


results = pd.DataFrame()
```

```
results['mean flood'] = df_flood.mean()
results['mean fire'] = df_fire.mean()
results['std flood'] = df_flood.std()
results['std fire'] = df_fire.std()
display(results)
```

```
/Users/robinholzi/git/ucb/data200/data200-grad-project/data200/plot/image.py:96: UserWarning: This figure includes Axes that are not compatible with tight_layout, so results might be incorrect.
  plt.tight_layout()
```

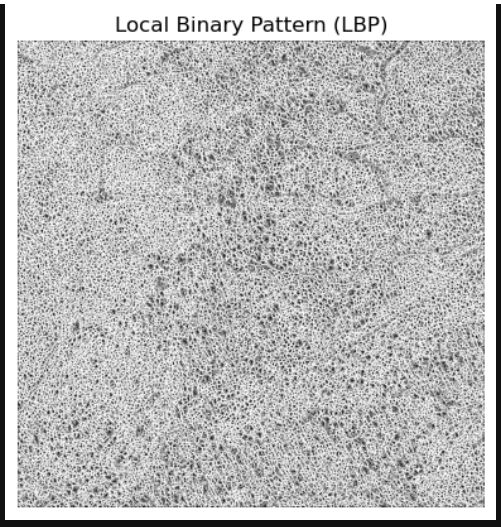


	mean flood	mean fire	std flood	std fire
0	0.000000e+00	0.000000e+00	0.000000	0.000000
1	2.385613e-02	2.447254e-02	0.004938	0.006279
2	2.405656e-02	2.123228e-02	0.005085	0.006318
3	1.048316e+06	1.048418e+06	535.279601	650.734204
4	1.048316e+06	1.048418e+06	535.279601	650.734204

4.3 Local Binary Patterns (LBP)

Capture texture patterns using local binary pattern descriptors.

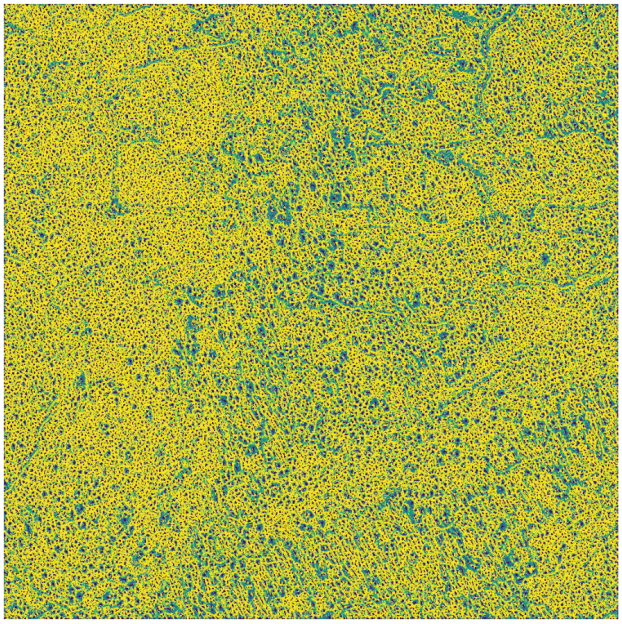
In [37]:
```
lbp = get_local_binary_pattern(sample_dc100[0].image, radius=3)
plt.imshow(lbp, cmap="gray")
plt.axis("off")
plt.title("Local Binary Pattern (LBP)")
plt.show()
```



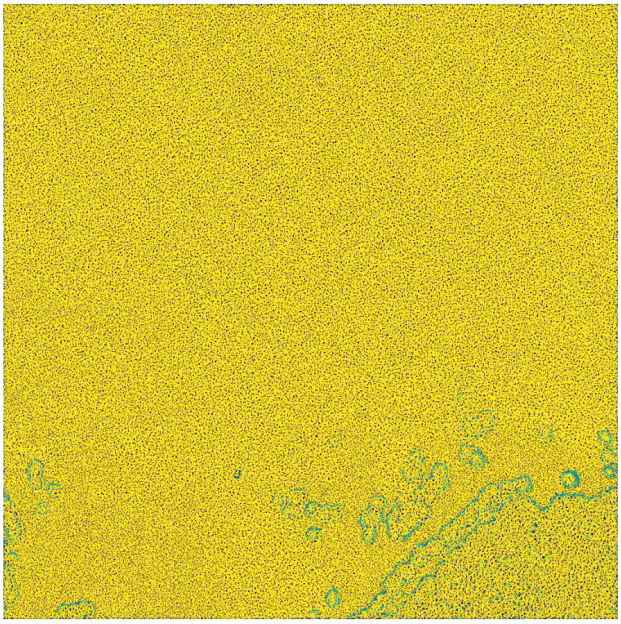
In [38]:
```
images_lbp = []
features_fire = []
features_flooding = []

for idx, img in enumerate(sample_dc100):
    lbp = get_local_binary_pattern(img.image, radius=3)
    images_lbp.append(lbp)

    hist, _ = np.histogram(lbp.ravel(), bins=int(lbp.max() + 1), range=(0, lbp.max() + 1))
    hist = hist / hist.sum()
    img_entropy = -np.sum(hist[hist > 0] * np.log2(hist[hist > 0]))
    img_mean = lbp.mean()
    img_std = lbp.std()
    nonzero_count = np.count_nonzero(lbp)

    fv = np.array([img_entropy, img_mean, img_std, nonzero_count])

    fv = np.append(fv, nonzero_count)
    if idx % 2 == 0:
        features_fire.append(fv)
    else:
        features_flooding.append(fv)

render_images(images_lbp[0:2],ncols=2,labels=['socal-fire','midwest-flooding']);
df_flood = pd.DataFrame(features_flooding)
df_fire = pd.DataFrame(features_fire)


results = pd.DataFrame()
results['mean flood'] = df_flood.mean()
results['mean fire'] = df_fire.mean()
results['std flood'] = df_flood.std()
results['std fire'] = df_fire.std()
display(results)
```

```
/Users/robinholzi/git/ucb/data200/data200-grad-project/data200/plot/image.py:96: UserWarning: This figure includes Axes that are not compatible with tight_layout, so results might be incorrect.
  plt.tight_layout()
```

label socal-fire

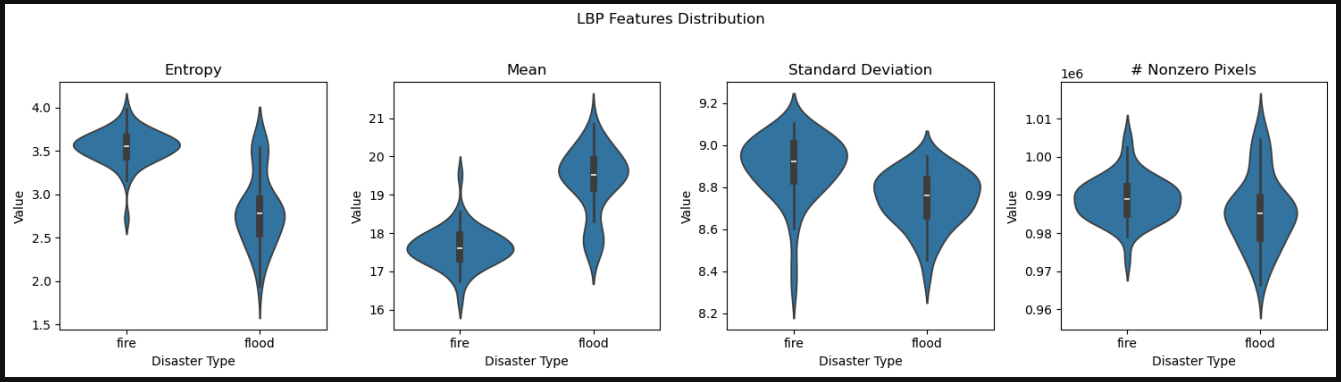


label midwest-flooding



	mean flood	mean fire	std flood	std fire
0	2.813866	3.544877	0.413570	0.197876
1	19.366262	17.620881	0.857580	0.513790
2	8.741378	8.892735	0.130338	0.155433
3	985719.180000	988952.760000	9519.055183	5859.863569
4	985719.180000	988952.760000	9519.055183	5859.863569

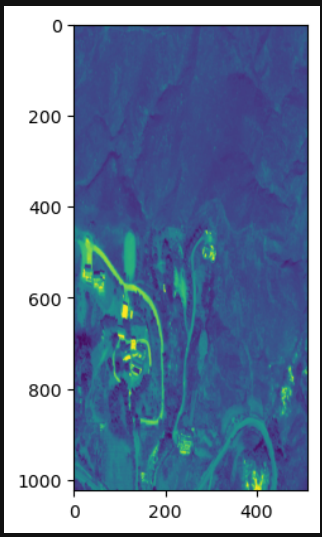
In [39]:
```
fig, axes = plt.subplots(1,4, figsize=(15, 4))
axes = axes.flatten()
features = range(4)
labels = ['Entropy', 'Mean', 'Standard Deviation', '# Nonzero Pixels']

for ax, feature_nr, lbl in zip(axes, features, labels):
    df_plot = pd.DataFrame({
        'value': list(df_fire[feature_nr]) + list(df_flood[feature_nr]),
        'disaster': ['fire'] * len(df_fire) + ['flood'] * len(df_flood)
    })
    sns.violinplot(data=df_plot, x='disaster', y='value', ax=ax)
    ax.set_title(f'{lbl}')
    ax.set_xlabel('Disaster Type')
    ax.set_ylabel('Value')

fig.suptitle("LBP Features Distribution", y=1.03)
plt.tight_layout()
fig.savefig(
    FIGURES_DIR / "eda" / "lbp_features_distribution.pdf",
    dpi=300,
    bbox_inches="tight"
)
plt.show()
```



4.4 Wavelet Features

Extract multi-scale frequency information using wavelet transforms.

In [40]:
```
wvf = get_wavelet_features(patched_data.socal_fire.images[2])

cA=wvf['cA']
cA = cA.mean(axis=2)

plt.imshow(np.array(cA));
```

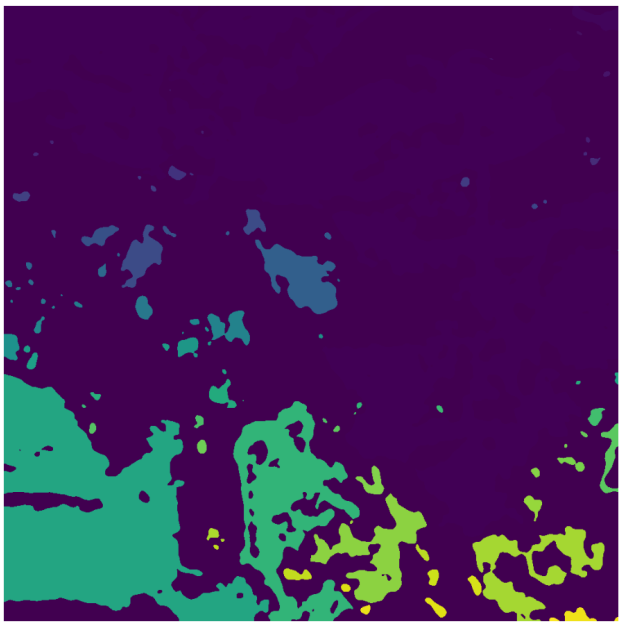


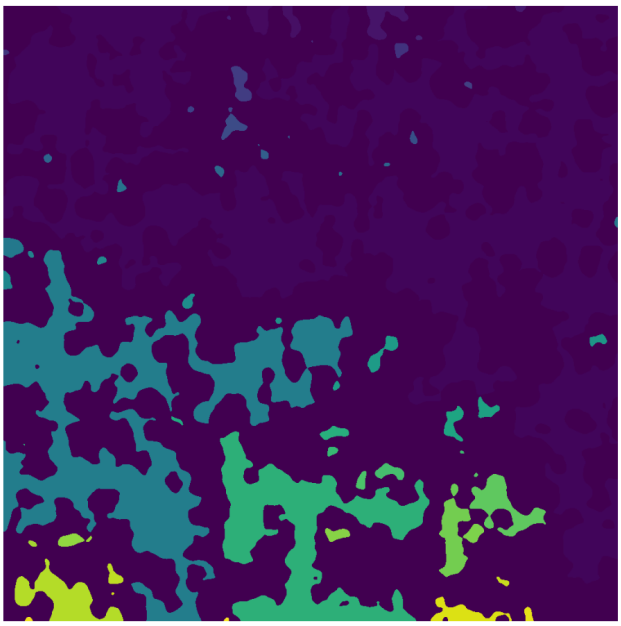
4.5 Haralick Features

Compute texture statistics from gray-level co-occurrence matrices.

In [41]:
```
images_hrk = []
features_fire = []
features_flooding = []

for idx, img in enumerate(sample_dc100):
    labeled_img, feature = get_haralick_features(img.image)
    images_hrk.append(labeled_img)

    nonzero_count = labeled_img.size - np.count_nonzero(labeled_img)
    haralick_keys = sorted([k for k in feature.keys() if k.startswith("haralick_")])
    fv = np.array([feature[k] for k in haralick_keys])
    fv = np.append(fv, nonzero_count)
    if idx % 2 == 0:
        features_fire.append(fv)
    else:
        features_flooding.append(fv)

fig = render_images(images_hrk[2:4], ncols=2, labels=['socal-fire', 'midwest-flooding'])
fig.savefig(
    FIGURES_DIR / "eda" / "haralick_labeled_images.pdf",
    dpi=300,
    bbox_inches="tight"
)
df_flood = pd.DataFrame(features_flooding)
df_fire = pd.DataFrame(features_fire)

results = pd.DataFrame()
results['mean flood'] = df_flood.mean()
results['mean fire'] = df_fire.mean()
results['std flood'] = df_flood.std()
results['std fire'] = df_fire.std()
display(results)
```

```
/Users/robinholzi/git/ucb/data200/data200-grad-project/data200/plot/image.py:96: UserWarning: This figure includes Axes that are not compatible with tight_layout, so results might be incorrect.
  plt.tight_layout()
```





	mean flood	mean fire	std flood	std fire
0	0.454409	0.388047	0.069457	0.050189
1	99.531738	32.086856	268.337908	32.597979
2	0.182221	0.178960	0.081719	0.047351
3	-0.909922	-0.920013	0.025407	0.018664
4	0.967283	0.979501	0.019157	0.014279
5	0.948192	0.962132	0.019432	0.014038
6	825.004538	434.567148	2126.196713	480.977739
7	0.985714	0.985416	0.007083	0.004187
8	15.965200	19.652894	20.870706	13.379647
9	3200.486413	1706.181738	8239.515114	1893.349856
10	1.731700	1.977741	0.403311	0.382089
11	1.761782	2.005946	0.416324	0.388485
12	0.013581	0.014707	0.010758	0.025148
13	589915.220000	550730.860000	124682.030144	58716.232298

The different features have different distributions.

In [42]:
```
component_stats_data = []

for idx, (s, transf) in enumerate(zip(sample_dc100, images_hrk)):
    features = get_connected_component_stats(s.image)
    disaster = "socal-fire" if idx % 2 == 0 else "midwest-flooding"
    features['disaster'] = disaster
    features['label'] = s.label
    component_stats_data.append(features)

df_component_stats = pd.DataFrame(component_stats_data)
print(f"Extracted features from {len(df_component_stats)} images")
```

```
Extracted features from 100 images
```

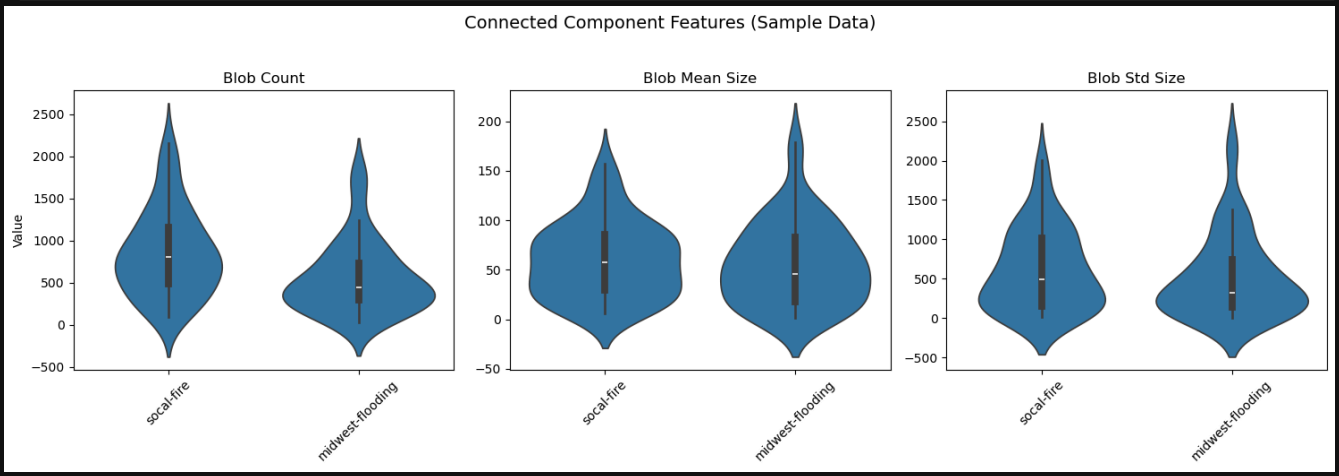
In [43]:
```
df_component_stats.head(100)
```

Out[43]:

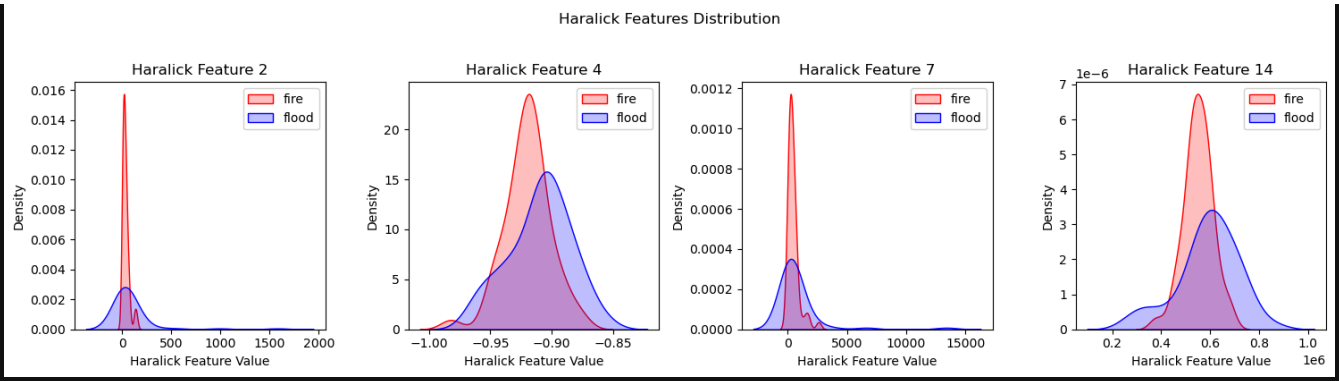
	blob_count	blob_mean_size	blob_std_size	disaster	label
0	808	16.227723	60.891277	socal-fire	3
1	5129	1.283291	1.596165	midwest-flooding	3
2	858	38.500000	230.216272	socal-fire	3
3	698	46.277937	142.962746	midwest-flooding	0
4	921	74.819761	487.684954	socal-fire	3
...	...	...	...	...	...
95	788	18.039340	116.051351	midwest-flooding	3
96	149	17.530201	55.688438	socal-fire	3
97	239	117.158996	1308.493001	midwest-flooding	0
98	1232	124.956981	845.383393	socal-fire	0
99	913	63.210296	863.530019	midwest-flooding	0

100 rows × 5 columns

In [44]:
```python
# Visualize connected component stats (sample data from Haralick exploration)
fig = plot_feature_violin_by_disaster(
    df_component_stats,
    features=['blob_count', 'blob_mean_size', 'blob_std_size'],
    ylabel='Value',
    suptitle="Connected Component Features (Sample Data)",
    figsize=(15, 5),
    filter_outliers=True,
)
fig.savefig(
    FIGURES_DIR / "eda" / "connected_component_features.pdf",
    dpi=300,
    bbox_inches="tight"
)
plt.show()
```



In [45]:
```python
fig, axes = plt.subplots(1,4, figsize=(15, 4))
axes = axes.flatten()
features = [1,3,6,13]

for ax, feature_nr in zip(axes,features):
    sns.kdeplot(df_fire[feature_nr], ax=ax, fill=True, color='red',label='fire')
    sns.kdeplot(df_flood[feature_nr], ax=ax, fill=True, color='blue',label='flood')
    ax.set_title(f'Haralick Feature {feature_nr+1}')
    ax.set_xlabel(f'Haralick Feature Value')
    ax.set_ylabel('Density')
    ax.legend()

fig.suptitle("Haralick Features Distribution", y=1.03)
plt.tight_layout()
fig.savefig(
    FIGURES_DIR / "eda" / "haralick_features_distribution.pdf",
    dpi=300,
    bbox_inches="tight"
)
plt.show()
```



4.6 Haar-like Features

Extract rectangular Haar-like features commonly used in object detection.

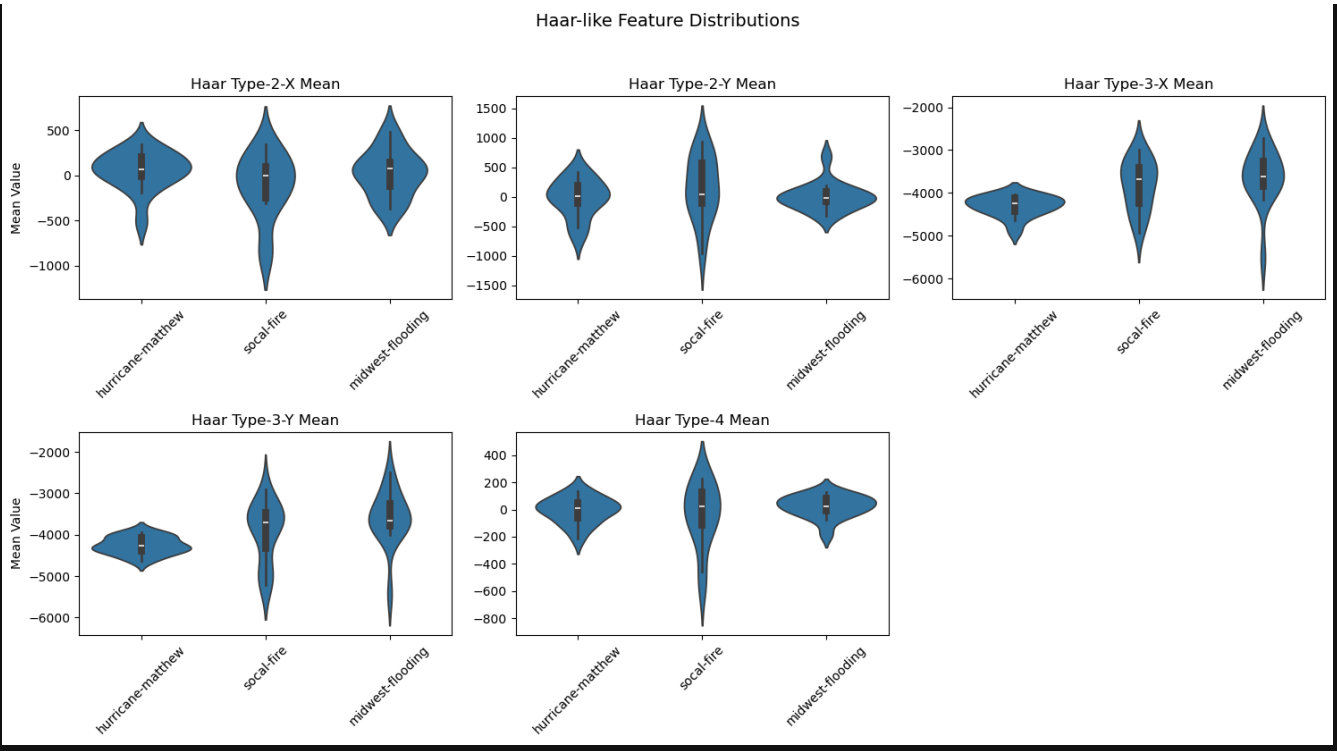
In [46]:
```
# Extract Haar-like features from a random sample (computationally expensive)
# Note: Images are downsampled to 32x32 patches for efficiency
n_samples_per_disaster = 15  # Use subset for speed

haar_data = []
for disaster in DISASTER_LIST:
    images = patched_data.get(disaster).images
    labels = patched_data.get(disaster).labels
    # Random sample
    indices = np.random.choice(len(images), min(n_samples_per_disaster, len(images)), replace=False)
    for idx in indices:
        features = get_haar_features(images[idx])
        features['disaster'] = disaster
        features['label'] = labels[idx]
        haar_data.append(features)

df_haar = pd.DataFrame(haar_data)
print(f"Extracted Haar features from {len(df_haar)} images ({n_samples_per_disaster} per disaster)")
df_haar.head()
```

```
Extracted Haar features from 45 images (15 per disaster)
```

Out[46]:

	haar_type-2-x_mean	haar_type-2-x_std	haar_type-2-x_max	haar_type-2-y_mean	haar_type-2-y_std	haar_type-2-y_max	haar_type-3-x_mean	haar_type-3-x_std	haar_type-3-x_max	haar_type-3-y_mean	haar_type-3-y_std	ha
0	341.863281	867.197165	6277	282.422289	672.137130	4629	-4095.517723	4260.740924	-53	-3939.690220	4064.747393	
1	99.169907	387.740891	1828	-0.157301	258.384937	1024	-4312.193434	4278.900704	-70	-4376.840863	4417.625267	
2	-25.989864	633.122256	4114	11.664551	494.141581	2277	-4128.510239	4210.132836	-17	-4014.817723	3990.367666	
3	181.402654	613.565523	4421	39.354063	229.898003	1687	-4428.174334	4602.728089	-76	-4312.975115	4335.256133	
4	258.843424	534.792263	3589	382.704812	915.182142	5738	-4166.074242	4196.309824	-66	-4243.226768	4359.765578	

In [47]:
```
# Visualize Haar feature distributions (mean statistics)
haar_mean_features = [col for col in df_haar.columns if col.startswith('haar_') and '_mean' in col]
plot_feature_violin_by_disaster(
    df_haar,
    features=haar_mean_features,
    ylabel='Mean Value',
    suptitle="Haar-like Feature Distributions",
    nrows=2,
    save_path=FIGURES_DIR / "eda" / "haar_features_per_disaster.pdf",
)
plt.show()
```



5. Structural Features

Extract features that capture the structural composition and geometric properties of images.

5.1 Edge-to-Area Ratio

Measure proportion of edge pixels (Sobel and Canny variants).

In [48]:
```
# Extract edge ratios from one sample image
sample_sobel = get_edge_to_area_ratio_sobel(patched_data.hurricane_matthew.images[0])
sample_canny = get_edge_to_area_ratio_canny(patched_data.hurricane_matthew.images[0])
sample_features = {**sample_sobel, **sample_canny}
pd.DataFrame([sample_features])
```

Out[48]:

	edge_ratio_sobel	edge_ratio_canny
0	0.02152	0.105304

In [49]:
```
# Extract edge ratios for all disasters
def get_edge_ratios(img):
    """Combine Sobel and Canny edge ratio features."""
    return {**get_edge_to_area_ratio_sobel(img), **get_edge_to_area_ratio_canny(img)}

df_edge_ratio = extract_features_by_disaster(patched_data, get_edge_ratios)
print(f"Extracted features from {len(df_edge_ratio)} images")
df_edge_ratio.head()
```

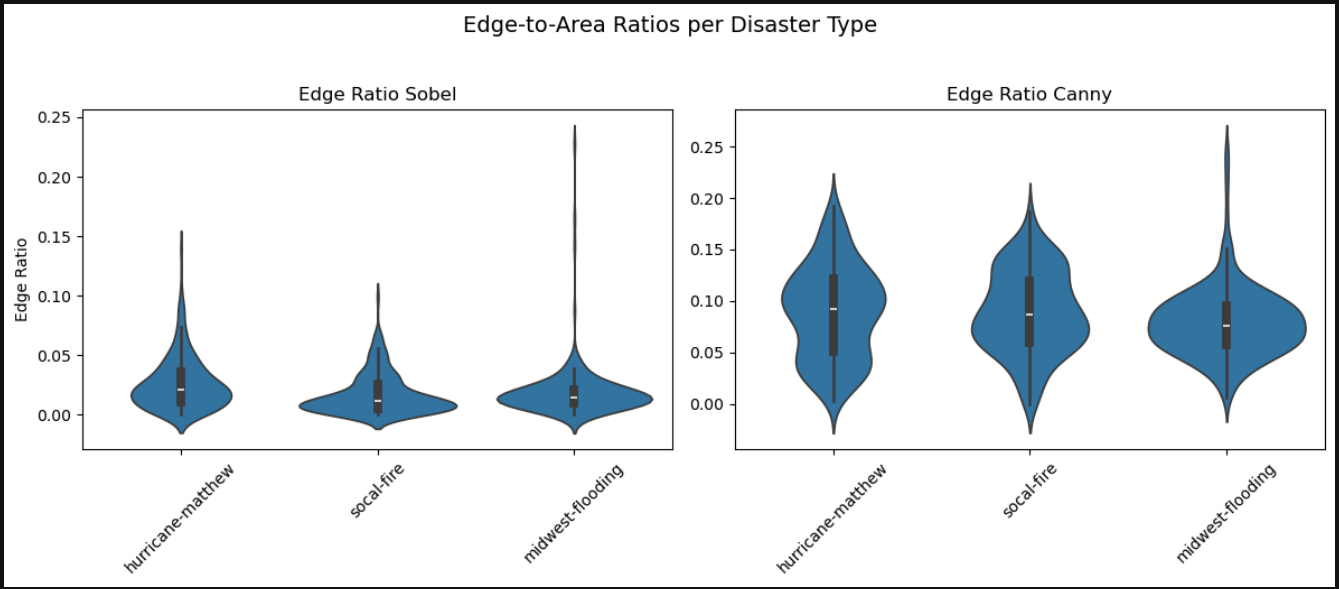
```
Extracting features: 100%|██████████| 600/600 [00:39<00:00, 15.12it/s]
Extracted features from 600 images
```

Out[49]:

	edge_ratio_sobel	edge_ratio_canny	disaster	label
0	0.021520	0.105304	hurricane-matthew	1
1	0.033147	0.090958	hurricane-matthew	3
2	0.014235	0.044187	hurricane-matthew	1
3	0.004337	0.015178	hurricane-matthew	3
4	0.033848	0.090000	hurricane-matthew	1

In [50]:
```
# Visualize edge ratios for all disasters
plot_feature_violin_by_disaster(
    df_edge_ratio,
    features=['edge_ratio_sobel', 'edge_ratio_canny'],
    ylabel='Edge Ratio',
    suptitle="Edge-to-Area Ratios per Disaster Type",
    figsize=(12, 5),
    save_path=FIGURES_DIR / "eda" / "edge_ratios_per_disaster.pdf",
```

```
)
plt.show()
```



5.2 Connected Components

Count and measure blobs/connected components.

In [51]:
```
# Extract connected component stats from one sample image
sample_features = get_connected_component_stats(patched_data.hurricane_matthew.images[0])
pd.DataFrame([sample_features])
```

Out[51]:

	blob_count	blob_mean_size	blob_std_size
0	3580	22.222067	312.727558

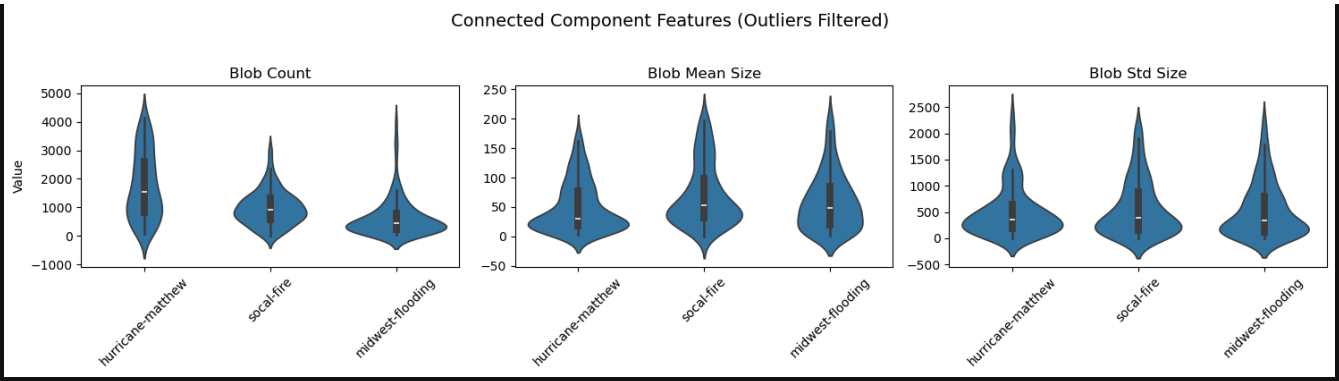
In [52]:
```
# Extract connected component stats for all disasters
df_component_stats = extract_features_by_disaster(patched_data, get_connected_component_stats)
print(f"Extracted features from {len(df_component_stats)} images")
df_component_stats.head()
```

```
Extracting features: 100%|██████████| 600/600 [00:16<00:00, 36.77it/s]
Extracted features from 600 images
```

Out[52]:

	blob_count	blob_mean_size	blob_std_size	disaster	label
0	3580	22.222067	312.727558	hurricane-matthew	1
1	3774	25.851086	727.705226	hurricane-matthew	3
2	725	118.084138	1266.159183	hurricane-matthew	1
3	356	47.426966	471.685583	hurricane-matthew	3
4	1025	86.920976	1335.470351	hurricane-matthew	1

In [53]:
```
# Visualize connected component stats for all disasters (with outlier filtering)
plot_feature_violin_by_disaster(
    df_component_stats,
    features=['blob_count', 'blob_mean_size', 'blob_std_size'],
    ylabel='Value',
    suptitle="Connected Component Features (Outliers Filtered)",
    filter_outliers=True,
    save_path=FIGURES_DIR / "eda" / "connected_component_stats_per_disaster.pdf",
)
plt.show()
```



5.3 Corner Detection

Count corners using goodFeaturesToTrack.

In [54]:
```
# Extract corner count from one sample image
sample_features = get_corner_count(patched_data.hurricane_matthew.images[0])
pd.DataFrame([sample_features])
```

Out[54]:

	corner_count
0	3872

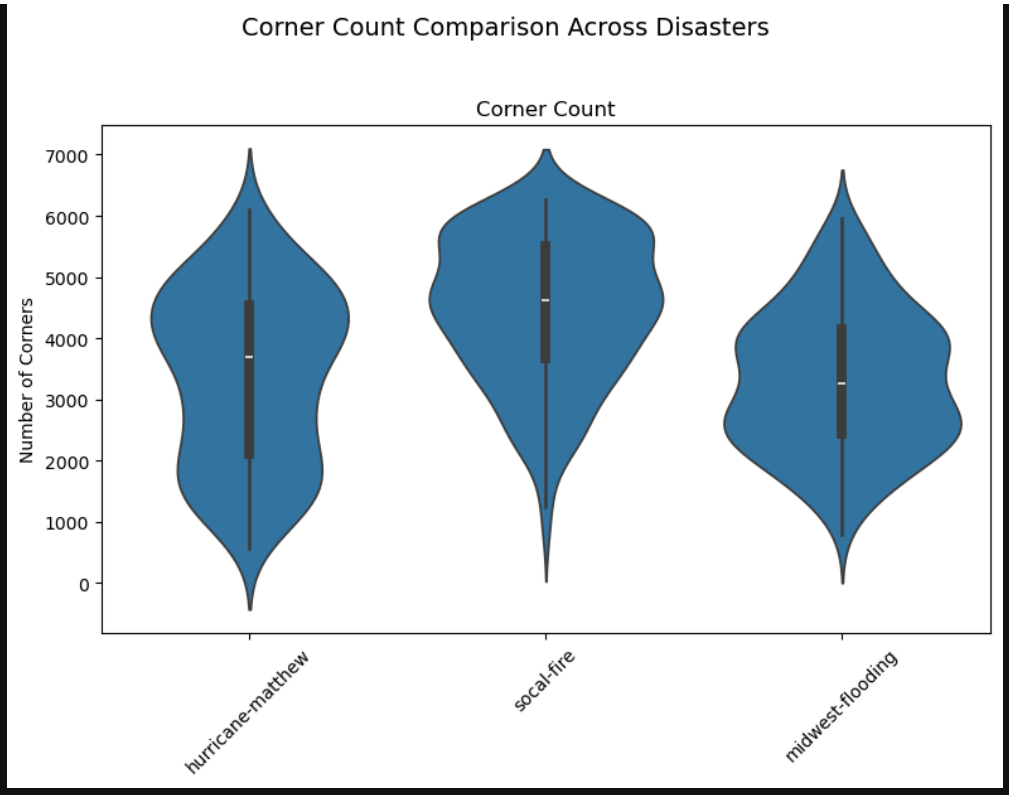
In [55]:
```
# Extract corner counts for all disasters
df_corner_count = extract_features_by_disaster(patched_data, get_corner_count)
print(f"Extracted features from {len(df_corner_count)} images")
df_corner_count.head()
```

```
Extracting features: 100%|██████████| 600/600 [00:07<00:00, 78.50it/s]
Extracted features from 600 images
```

Out[55]:

	corner_count	disaster	label
0	3872	hurricane-matthew	1
1	3015	hurricane-matthew	3
2	2608	hurricane-matthew	1
3	566	hurricane-matthew	3
4	1684	hurricane-matthew	1

In [56]:
```
# Visualize corner counts for all disasters
plot_feature_violin_by_disaster(
    df_corner_count,
    features=['corner_count'],
    ylabel='Number of Corners',
    suptitle="Corner Count Comparison Across Disasters",
    figsize=(8, 6),
)
plt.show()
```


Corner Count Comparison Across Disasters
Corner Count
Number of Corners
7000
6000
5000
4000
3000
2000
1000
0
hurricane-matthew
socal-fire
midwest-flooding

disaster_prediction.py

```python
"""
Training and prediction pipeline for disaster type prediction.

Run via `pixi run disaster-prediction --help`

E.g.:

# With hyper-parameter tuning (model selection: logistic_regression or cnn)
pixi run disaster-prediction fit \
   --model logistic_regression \
   --no-skip-cross-validation

# For prediction on unlabeled test set
pixi run disaster-prediction predict \
   --model logistic_regression
"""

import json
import warnings
from pathlib import Path
from typing import Literal, get_args

import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim
import typer
from data200.const.const import (
    CNN_AUGMENTATIONS,
    DATA_DIR,
    DISASTER_TYPE_PREDICTIONS_PATH,
    MODEL_ARTIFACTS_DIR_DISASTER_PREDICTION,
)
from data200.evaluate.cross_validation import k_fold_cross_validation
from data200.evaluate.evaluator import BasicCrossValidationEvaluator
from data200.evaluate.grid_search import (
    grid_search_cross_validation,
    grid_search_decision_threshold,
)
from data200.feature.transform import (
    IdentityTransformer,
    StandardScalerTransformer,
    convert_to_image_tensor,
    convert_to_trainable_tensor,
)
from data200.io.load import (
    load_disaster_data,
)
from data200.io.save import save_predictions
from data200.model.classic.logistic import LogisticRegressionTrainer
from data200.model.nn.architecture.cnn import CNNClassifier
from data200.model.nn.ensemble import EnsembleTrainer
from data200.model.nn.pytorch import PytorchTrainer, PytorchTrainingConfig
from data200.pipeline.config import NNConfig
from data200.pipeline.feature import (
    feature_pipeline_flood_fire_logistic_regression,
    feature_pipeline_flood_fire_neural_networks,
)
from data200.pipeline.preprocess import preprocess_data
from data200.preprocess.augmentation import apply_augmentations
from data200.sample.sample import BalancedUpsampler, IdentitySampler
from data200.utils.device import get_device
from data200.utils.utils import set_seed
from pydantic import BaseModel

app = typer.Typer()

DisasterTypeModel = Literal["logistic_regression", "cnn"]
DISASTER_TYPE_MODELS = list(get_args(DisasterTypeModel))

SEED = 42

TRANSFORMER_PATHS: dict[DisasterTypeModel, Path] = {
```

```
    model: MODEL_ARTIFACTS_DIR_DISASTER_PREDICTION / f"{model}_scaler.json"
    for model in DISASTER_TYPE_MODELS
}
TRAINER_CONFIG_PATHS = {
    model: MODEL_ARTIFACTS_DIR_DISASTER_PREDICTION / f"{model}_trainer_config.json"
    for model in DISASTER_TYPE_MODELS
}
MODEL_PATHS = {
    model: MODEL_ARTIFACTS_DIR_DISASTER_PREDICTION / f"{model}_model.json"
    for model in DISASTER_TYPE_MODELS
}
EVAL_RESULTS_PATHS = {
    model: MODEL_ARTIFACTS_DIR_DISASTER_PREDICTION
    / f"{model}_grid_search_eval_results.json"
    for model in DISASTER_TYPE_MODELS
}

# ------------------------------------------------------------------------------------ #
#                                       TRAINING                                       #
# ------------------------------------------------------------------------------------ #


# ------------------------------------ LOGISTIC ------------------------------------ #


def fit_logistic_regression(
    data_path: Path = DATA_DIR,
    skip_cross_validation: bool = True,
    train_ensemble: bool = True,  # More robust 99.5% - 100% accuracy
):
    """Fit logistic regression model for disaster type prediction."""
    model = "logistic_regression"

    # Load the data
    data = load_disaster_data(path=data_path)

    # Preprocess the data, overwrite to save memory
    data = preprocess_data(data)

    # ------------------------------ FEATURE ENGINEERING ------------------------------ #

    trainable_dataset = feature_pipeline_flood_fire_logistic_regression(data)
    del data

    # -------------------------- CROSS VALIDATION AND TRAINING -------------------------- #

    print(f"Training {model} model...")
    transformer = StandardScalerTransformer()

    # logistic regression is sensitive to duplicates, so we use identity sampler
    sampler = IdentitySampler()

    trainer_grid = {
        # smaller C = stronger regularization
        C: LogisticRegressionTrainer(C=C)
        for C in [
            0.01,
            0.05,
            0.1,
            0.5,
            1.0,
            2.0,
            5.0,
            10.0,
            20.0,
            50.0,
            100.0,
            200.0,
            500.0,
            1000.0,
            10_000.0,
            100_000.0,
            1_000_000.0,
        ]
    }

    if not skip_cross_validation:
```

```
        # Tune hyperparameters via grid search cross-validation
        eval_results, (best_name, best_trainer), test_metrics, _ = (
            grid_search_cross_validation(
                data=trainable_dataset,
                trainer_grid=trainer_grid,
                # loss: lower is better
                fn_find_best_metric=lambda m: min(m.keys(), key=lambda t: m[t].loss),
                k_folds=5,
                test_split=0.2,
                sampler=sampler,
                transformer=transformer,
                fn_augment=None,
                seed=SEED,
            )
        )

        # Manual override to select middle of indifferent Cs
        best_name = 10.0
        best_trainer = trainer_grid[best_name]

        # Tune decision-threshold via grid search cross-validation
        thresholds_grid = list(np.arange(0.05, 0.96, 0.01))
        eval_results_dt, prob_distributions, best_threshold, test_metrics_dt = (
            grid_search_decision_threshold(
                data=trainable_dataset,
                trainer=best_trainer,
                thresholds_grid=thresholds_grid,
                fn_find_best_metric=lambda m: max(
                    m.keys(),
                    key=lambda t: m[t].accuracy,  # accuracy: higher is better
                ),
                k_folds=5,
                test_split=0.2,
                sampler=sampler,
                transformer=transformer,
                fn_augment=None,
                seed=SEED,
            )
        )

        # Manual override to select reasonable threshold
        best_threshold = 0.5

        # Save eval results
        EVAL_RESULTS_PATHS[model].write_text(
            json.dumps(
                {
                    "hyperparameter_tuning": {
                        name: eval_results[name].model_dump()
                        for name in eval_results.keys()
                    },
                    "best_hyperparameters": best_name,
                    "test_metrics": test_metrics.model_dump(),
                    "decision_threshold_tuning": {
                        thresh: eval_results_dt[thresh].model_dump()
                        for thresh in eval_results_dt.keys()
                    },
                    "best_decision_threshold": best_threshold,
                    "test_metrics_dt": test_metrics_dt.model_dump(),
                    "prob_distributions_cv": {
                        int(cls): [probs.tolist() for probs in fold_probs]
                        for cls, fold_probs in prob_distributions.items()
                    },
                }
            )
        )

    else:
        print("Skipping cross-validation as requested.")

        # hard coded from previous grid searches
        best_name = 10.0
        best_trainer = trainer_grid[best_name]

    if train_ensemble:
        # Ensemble by averaging predictions from 5 models with different seeds
        print("Ensembling via averaging predictions from 5 models...")
```

```
228
229         ensemble_trainer = EnsembleTrainer(
230             submodels=[LogisticRegressionTrainer(C=best_name) for _ in range(5)],
231             bootstrap_samples=True,  # needed for classical models
232             stratified_bootstrap=True,
233         )
234
235     else:
236         print("Not ensembling, using best trainer directly.")
237         ensemble_trainer = best_trainer
238
239     # Final validation through cross validation
240     # Validating ensemble performance (average over 5 folds)
241     evaluator = BasicCrossValidationEvaluator(
242         loss_func="cross_entropy", track_prob_distributions=True
243     )
244     k_fold_cross_validation(
245         data=trainable_dataset,
246         index_subset=trainable_dataset.original_indexes,  # all data
247         trainer=ensemble_trainer,
248         k=5,
249         sampler=sampler,
250         transformer=transformer,
251         fn_augment=None,
252         evaluator=evaluator,
253         seed=SEED,
254         print_folds=True,
255     )
256
257     # Train final model on all data for best generalization
258     set_seed(SEED)
259     ensemble_trainer.reset_model()
260
261     # Use full trainable dataset
262     X, y = trainable_dataset.X, trainable_dataset.y
263
264     X_sampled, y_sampled = sampler.sample(X, y, seed=SEED)
265     class_counts = np.bincount(y_sampled)
266
267     # Standardize features (typically done after up/down sampling)
268     transformer.reset()
269     X_sampled_scaled = transformer.fit_transform(X_sampled)
270
271     ensemble_trainer.fit(X_sampled_scaled, y_sampled)
272     print(f"Trained final model on {X.shape[0]} samples [{class_counts}]")
273
274     # ------------------------------- PERSIST ARTIFACTS ------------------------------- #
275
276     print("Saving trained artifacts...")
277     MODEL_ARTIFACTS_DIR_DISASTER_PREDICTION.mkdir(parents=True, exist_ok=True)
278     transformer.save(TRANSFORMER_PATHS[model])
279     ensemble_trainer.save_model(MODEL_PATHS[model])
280
281
282 # ---------------------------------------- CNN ---------------------------------------- #
283 class PytorchTrainerConfig(BaseModel):
284     """Configuration for PyTorch trainer."""
285
286     target_image_size: int = 64
287     num_epochs: int = 4
288     batch_size: int = 32
289     lr: float = 0.001
290     conv_channels: list[int] = [64, 32]
291
292
293 def build_trainer(config: PytorchTrainerConfig) -> PytorchTrainer:
294     """Build a PyTorch trainer based on the given configuration."""
295
296     def model_factory() -> nn.Module:
297         return CNNClassifier(
298             in_channels=3,
299             num_classes=2,
300             conv_channels=config.conv_channels,
301         )
302
303     return PytorchTrainer(
304         model_factory=model_factory,
```

```
        optimizer_factory=lambda m: optim.Adam(m.parameters(), lr=config.lr),
        criterion=nn.CrossEntropyLoss(),
        config=PytorchTrainingConfig(
            num_epochs=config.num_epochs,
            batch_size=config.batch_size,
            device=get_device(),
        ),
    )


def fit_cnn_model(
    data_path: Path = DATA_DIR,
    skip_cross_validation: bool = True,
    train_ensemble: bool = True,  # bumps from ~99% - 100%
):
    """Fit CNN model for disaster type prediction."""
    model = "cnn"

    # Load the data
    data = load_disaster_data(path=data_path)

    # Preprocess the data, overwrite to save memory
    data = preprocess_data(data)

    # ------------------------------ FEATURE ENGINEERING ------------------------------ #

    target_image_size = 64
    trainable_dataset = feature_pipeline_flood_fire_neural_networks(
        data,
        nn_config=NNConfig(
            image_size=target_image_size,
            in_channels=3,
            num_classes=2,
        ),
    )
    del data

    def fn_augment(X_tr, y_tr) -> tuple[torch.Tensor, torch.Tensor]:
        X_tr, y_tr = apply_augmentations(
            images=convert_to_image_tensor(X_tr).numpy(),
            labels=y_tr.numpy(),
            augmentations=CNN_AUGMENTATIONS,
        )[2:]
        return convert_to_trainable_tensor(torch.tensor(X_tr)), torch.tensor(y_tr)

    # ---------------------------------- TRAINING ---------------------------------- #

    print("Training CNN model...")

    # CNNs don't need standardization
    transformer = IdentityTransformer()
    sampler = BalancedUpsampler()

    if not skip_cross_validation:
        trainer_config_grid = {
            repr(
                (
                    num_epochs,
                    batch_size,
                    lr,
                    conv_channels,
                )
            ): PytorchTrainerConfig(
                target_image_size=target_image_size,
                num_epochs=num_epochs,
                batch_size=batch_size,
                lr=lr,
                conv_channels=conv_channels,
            )
            for (num_epochs, batch_size, lr, conv_channels) in (
                [
                    (num_epochs, batch_size, lr, conv_channels)
                    for num_epochs in [8, 12, 16, 32]
                    for batch_size in [16, 32, 64]
                    for lr in [0.0005, 0.0001, 0.0005]
                    for conv_channels in [[64, 32], [128, 64], [64, 64, 32]]
                ]
```

```
            )
        }

        trainer_grid = {
            name: build_trainer(config) for name, config in trainer_config_grid.items()
        }

        eval_results, (best_name, best_trainer), test_metrics, prob_distributions = (
            grid_search_cross_validation(
                data=trainable_dataset,
                trainer_grid=trainer_grid,
                fn_find_best_metric=lambda m: min(m.keys(), key=lambda t: m[t].loss),
                k_folds=5,
                # no separate test holdout needed for decision threshold tuning
                test_split=None,
                sampler=sampler,
                transformer=transformer,
                fn_augment=fn_augment,
                seed=SEED,
            )
        )
        best_trainer_config = trainer_config_grid[best_name]

        # Save eval results
        eval_results_dict = {
            name: eval_results[name].model_dump() for name in eval_results.keys()
        }
        if prob_distributions:
            eval_results_dict["prob_distributions_cv"] = {
                int(cls): [probs.tolist() for probs in fold_probs]
                for cls, fold_probs in prob_distributions.items()
            }
        EVAL_RESULTS_PATHS[model].write_text(json.dumps(eval_results_dict))

        # Save best trainer config
        TRAINER_CONFIG_PATHS[model].write_text(best_trainer_config.model_dump_json())

    else:
        print("Skipping cross-validation as requested.")

        # Load best trainer config from previous grid search
        best_trainer_config = PytorchTrainerConfig.model_validate_json(
            TRAINER_CONFIG_PATHS[model].read_text()
        )
        best_trainer = build_trainer(best_trainer_config)

    if train_ensemble:
        # Ensemble by averaging predictions from 5 models with different seeds
        print("Ensembling via averaging predictions from 5 models...")

        ensemble_trainer = EnsembleTrainer(
            submodels=[build_trainer(best_trainer_config) for _ in range(5)],
            bootstrap_samples=False,  # seeding is usually enough for deep NN
        )

    else:
        print("Not ensembling, using best trainer directly.")
        ensemble_trainer = best_trainer

    # Final validation through cross validation
    # Validating ensemble performance (average over 5 folds)
    evaluator = BasicCrossValidationEvaluator(
        loss_func="cross_entropy", track_prob_distributions=True
    )
    k_fold_cross_validation(
        data=trainable_dataset,
        index_subset=trainable_dataset.original_indexes,  # all data
        trainer=ensemble_trainer,
        k=5,
        sampler=sampler,
        transformer=transformer,
        fn_augment=None,
        evaluator=evaluator,
        seed=SEED,
        print_folds=True,
    )

```

```
    # Train final model on all data for best generalization
    set_seed(SEED)
    ensemble_trainer.reset_model()

    # Use full trainable dataset
    X, y = trainable_dataset.X, trainable_dataset.y

    # Apply augmentations to all data
    X, y = fn_augment(X, y)

    # Sampling to balance classes
    # X_sampled, y_sampled = sampler.sample(X, y, seed=SEED)
    X_sampled, y_sampled = X, y
    class_counts = np.bincount(y_sampled)

    # Standardize features (typically done after up/down sampling)
    transformer.reset()
    X_sampled_scaled = transformer.fit_transform(X_sampled)

    ensemble_trainer.fit(X_sampled_scaled, y_sampled, X_val=None, y_val=None)
    print(f"Trained final model on {X.shape[0]} samples [{class_counts}]")

    # ------------------------------ PERSIST ARTIFACTS ------------------------------ #

    print("Saving trained artifacts...")
    MODEL_ARTIFACTS_DIR_DISASTER_PREDICTION.mkdir(parents=True, exist_ok=True)
    transformer.save(TRANSFORMER_PATHS[model])
    ensemble_trainer.save_model(MODEL_PATHS[model])


# ---------------------------------------------------------------------------------- #
#                                      PREDICT                                       #
# ---------------------------------------------------------------------------------- #

# ------------------------------------ LOGISTIC ------------------------------------ #


def predict_logistic_regression(data_path: Path = DATA_DIR):
    """Predict disaster types using logistic regression model."""
    model = "logistic_regression"

    # Load model
    print("Loading trained artifacts...")
    transformer = StandardScalerTransformer()
    transformer.load(TRANSFORMER_PATHS[model])
    decision_threshold = 0.5  # Tuned in training

    pred_model = EnsembleTrainer(
        submodels=[LogisticRegressionTrainer() for _ in range(5)],
        bootstrap_samples=True,
        stratified_bootstrap=True,
    )
    pred_model.load_model(MODEL_PATHS[model])

    # Load holdout data
    print("Loading holdout data...")
    data = load_disaster_data(path=data_path, split="test")

    # Preprocess holdout data, overwrite to save memory
    data = preprocess_data(data)

    # ------------------------------ FEATURE ENGINEERING ------------------------------ #

    predictable_dataset = feature_pipeline_flood_fire_logistic_regression(data)

    # ---------------------------------- RUN INFERENCE ---------------------------------- #

    X_holdout = predictable_dataset.X
    X_holdout_scaled = transformer.transform(X_holdout)

    # Training was on balanced data, but output needs to reflect original class imbalance
    y_prob_holdout = pred_model.predict_proba(X_holdout_scaled)[:, 1]
    y_pred_holdout = (y_prob_holdout >= decision_threshold).astype(np.uint8)

    # Save results to CSV
    save_predictions(
        y_pred_holdout,
```

```
        DISASTER_TYPE_PREDICTIONS_PATH.with_name(
            f"{DISASTER_TYPE_PREDICTIONS_PATH.stem}_{model}.csv",
        ),
    )
    print("Holdout predictions saved")


# ---------------------------------------- CNN ---------------------------------------- #


def predict_cnn(data_path: Path = DATA_DIR):
    """Predict disaster types using CNN model."""
    model = "cnn"

    # Load model
    print("Loading trained artifacts...")
    transformer = IdentityTransformer()
    transformer.load(TRANSFORMER_PATHS[model])

    best_trainer_config = PytorchTrainerConfig.model_validate_json(
        TRAINER_CONFIG_PATHS[model].read_text()
    )
    pred_model = EnsembleTrainer(
        submodels=[build_trainer(best_trainer_config) for _ in range(5)],
        bootstrap_samples=False,  # seeding is usually enough for deep NN
    )
    pred_model.load_model(MODEL_PATHS[model])

    # Load holdout data
    print("Loading holdout data...")
    data = load_disaster_data(path=data_path, split="test")

    # Preprocess holdout data, overwrite to save memory
    data = preprocess_data(data)

    # ------------------------------ FEATURE ENGINEERING ------------------------------ #

    predictable_dataset = feature_pipeline_flood_fire_neural_networks(
        data,
        nn_config=NNConfig(
            image_size=64,
            in_channels=3,
            num_classes=2,
        ),
    )

    # ---------------------------------- RUN INFERENCE ---------------------------------- #

    X_holdout = predictable_dataset.X
    X_holdout_scaled = transformer.transform(X_holdout)

    # TODO: test time augmentation
    y_prob_holdout = pred_model.predict_proba(X_holdout_scaled)[:, 1]
    y_pred_holdout = (y_prob_holdout >= 0.5).astype(np.uint8)

    # Save results to CSV
    save_predictions(
        y_pred_holdout,
        DISASTER_TYPE_PREDICTIONS_PATH.with_name(
            f"{DISASTER_TYPE_PREDICTIONS_PATH.stem}_{model}.csv",
        ),
    )
    print("Holdout predictions saved")


# ------------------------------------------------------------------------------------- #
#                                          CLI                                          #
# ------------------------------------------------------------------------------------- #


@app.command()
def fit(
    data_path: Path = DATA_DIR,
    model: DisasterTypeModel = "logistic_regression",
    skip_cross_validation: bool = True,
):
    """Fit disaster type prediction model."""
```

```
    if model == "logistic_regression":
        fit_logistic_regression(
            data_path=data_path, skip_cross_validation=skip_cross_validation
        )
    else:
        fit_cnn_model(data_path=data_path, skip_cross_validation=skip_cross_validation)


@app.command()
def predict(
    data_path: Path = DATA_DIR,
    model: DisasterTypeModel = "logistic_regression",
):
    """Predict disaster types using trained model."""

    if model == "logistic_regression":
        predict_logistic_regression(data_path=data_path)
    else:
        predict_cnn(data_path=data_path)


if __name__ == "__main__":
    warnings.filterwarnings("ignore", category=UserWarning)

    print("Using device:", get_device())
    app()

```

damage_prediction.py

```python
"""
Training and prediction pipeline for damage level prediction.

Run via `pixi run damage-prediction --help`

E.g.:

# With hyper-parameter tuning (model selection: logistic_regression or cnn)
pixi run damage-prediction fit \
   --model logistic_regression \
   --no-skip-cross-validation

# For prediction on unlabeled test set
pixi run damage-prediction predict \
   --model logistic_regression
"""

import json
from pathlib import Path
from typing import Literal, get_args

import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim
import typer
from data200.const.const import (
    CNN_AUGMENTATIONS,
    DAMAGE_LEVEL_PREDICTIONS_PATH,
    DATA_DIR,
    MODEL_ARTIFACTS_DIR_DAMAGE_PREDICTION,
)
from data200.evaluate.cross_validation import k_fold_cross_validation
from data200.evaluate.evaluator import BasicCrossValidationEvaluator
from data200.evaluate.grid_search import (
    grid_search_cross_validation,
)
from data200.evaluate.loss import SoftF1Loss
from data200.feature.transform import (
    IdentityTransformer,
    StandardScalerTransformer,
    convert_to_image_tensor,
    convert_to_trainable_tensor,
)
from data200.io.load import (
    load_disaster_data,
)
from data200.io.save import save_predictions
from data200.model.classic.lightgbm import LightGBMTrainer
from data200.model.classic.logistic import LogisticRegressionTrainer
from data200.model.nn.architecture.cnn import CNNClassifier
from data200.model.nn.architecture.mlp import MLPClassifier
from data200.model.nn.ensemble import EnsembleTrainer
from data200.model.nn.pytorch import PytorchTrainer, PytorchTrainingConfig
from data200.pipeline.config import NNConfig
from data200.pipeline.feature import (
    feature_pipeline_hurricane_dinov2,
    feature_pipeline_hurricane_logistic_regression,
    feature_pipeline_hurricane_neural_networks,
)
from data200.pipeline.preprocess import preprocess_data
from data200.preprocess.augmentation import apply_augmentations
from data200.sample.sample import BalancedUpsampler
from data200.utils.device import get_device
from data200.utils.utils import set_seed
from pydantic import BaseModel

app = typer.Typer()

DamageLevelModel = Literal["logistic_regression", "lightgbm", "dinov2+mlp", "cnn"]
DAMAGE_LEVEL_MODELS = list(get_args(DamageLevelModel))

TRANSFORMER_PATHS: dict[DamageLevelModel, Path] = {
```

```python
    model: MODEL_ARTIFACTS_DIR_DAMAGE_PREDICTION / f"{model}_scaler.json"
    for model in DAMAGE_LEVEL_MODELS
}
TRAINER_CONFIG_PATHS = {
    model: MODEL_ARTIFACTS_DIR_DAMAGE_PREDICTION / f"{model}_trainer_config.json"
    for model in DAMAGE_LEVEL_MODELS
}
MODEL_PATHS = {
    model: MODEL_ARTIFACTS_DIR_DAMAGE_PREDICTION / f"{model}_model.json"
    for model in DAMAGE_LEVEL_MODELS
}
EVAL_RESULTS_PATHS = {
    model: MODEL_ARTIFACTS_DIR_DAMAGE_PREDICTION
    / f"{model}_grid_search_eval_results.json"
    for model in DAMAGE_LEVEL_MODELS
}

SEED = 42


def serialize_prob_distributions(prob_dist: dict) -> dict:
    """Convert prob_distributions dict to JSON-serializable format."""
    if prob_dist is None:
        return None
    return {int(k): [arr.tolist() for arr in v] for k, v in prob_dist.items()}


# ---------------------------------------------------------------------------- #
#                                     TRAINING                                 #
# ---------------------------------------------------------------------------- #


class PytorchTrainerConfig(BaseModel):
    """Configuration for PyTorch trainer."""

    target_image_size: int = 64
    num_epochs: int = 4
    batch_size: int = 32
    lr: float = 0.001

    conv_channels: list[int] = [64, 32]
    """Channels per conv layer in CNN model."""

    hidden_layers: list[int] = [128]
    """Hidden layer sizes for MLP model."""

    num_classes: int = 4
    loss: Literal[
        "cross_entropy", "balanced_cross_entropy", "weighted_cross_entropy"
    ] = "cross_entropy"


def build_trainer(
    kind: Literal["dinov2+mlp", "cnn"],
    config: PytorchTrainerConfig,
    class_weights: torch.Tensor | None = None,
) -> PytorchTrainer:
    """Build a PyTorch trainer based on the given configuration."""

    def model_factory() -> nn.Module:
        if kind == "dinov2+mlp":
            return MLPClassifier(
                in_channels=1,
                height=config.target_image_size,
                width=1,
                num_classes=config.num_classes,
                hidden_layers=config.hidden_layers,
            )
        elif kind == "cnn":
            return CNNClassifier(
                in_channels=3,
                num_classes=config.num_classes,
                conv_channels=config.conv_channels,
            )
        else:
            raise ValueError(f"Unknown model kind: {kind}")

```

```
    device = get_device()

    if config.loss == "cross_entropy":
        criterion = nn.CrossEntropyLoss()
    elif config.loss == "balanced_cross_entropy":
        criterion = SoftF1Loss()
    elif config.loss == "weighted_cross_entropy":
        if class_weights is None:
            raise ValueError(
                "class_weights must be provided for weighted_cross_entropy"
            )
        normalized_weights = class_weights / class_weights.sum()
        criterion = nn.CrossEntropyLoss(weight=normalized_weights.float().to(device))
    else:
        raise ValueError(f"Unknown loss type: {config.loss}")

    return PytorchTrainer(
        model_factory=model_factory,
        optimizer_factory=lambda m: optim.Adam(m.parameters(), lr=config.lr),
        criterion=criterion,
        config=PytorchTrainingConfig(
            num_epochs=config.num_epochs, batch_size=config.batch_size, device=device
        ),
    )


# ------------------------------------ LOGISTIC ------------------------------------ #


def fit_logistic_regression(
    data_path: Path = DATA_DIR,
    skip_cross_validation: bool = True,
    train_ensemble: bool = True,  # Consistently +5-10% F1 score on every fold
):
    """Fit logistic regression model for damage level prediction."""

    model = "logistic_regression"
    print(f"Training {model} model...")

    # Load the data
    data = load_disaster_data(path=data_path)

    # Preprocess the data, overwrite to save memory
    data = preprocess_data(data)

    # ------------------------------ FEATURE ENGINEERING ------------------------------ #

    trainable_dataset = feature_pipeline_hurricane_logistic_regression(data)
    del data

    # -------------------------- CROSS VALIDATION AND TRAINING -------------------------- #

    print(f"Training {model} model...")
    transformer = StandardScalerTransformer()

    # Even though logistic regression is sensitive to duplicate samples,
    # empirically it seems to help with class imbalance here.
    sampler = BalancedUpsampler()

    trainer_grid = {
        # smaller C = stronger regularization
        C: LogisticRegressionTrainer(C=C, max_iter=1000)
        for C in [
            0.01,
            0.05,
            0.1,
            0.5,
            1.0,
            2.0,
            5.0,
            10.0,
            20.0,
            50.0,
            100.0,
            200.0,
            500.0,
            1000.0,
```

```
            10_000.0,
            100_000.0,
            1_000_000.0,
        ]
    }

    if not skip_cross_validation:
        # Tune hyperparameters via grid search cross-validation
        eval_results, (best_name, best_trainer), _, prob_distributions = (
            grid_search_cross_validation(
                data=trainable_dataset,
                trainer_grid=trainer_grid,
                # f1: higher is better
                fn_find_best_metric=lambda m: max(
                    m.keys(), key=lambda t: m[t].f1_score_macro
                ),
                k_folds=5,
                # 20% test / 20% val split removes too many samples
                # of the minority classes (only 6 samples in class 2)
                test_split=None,
                sampler=sampler,
                transformer=transformer,
                fn_augment=None,
                seed=42,
            )
        )

        # Manual override
        # best_name =
        # best_trainer = trainer_grid[best_name]

        # Save eval results
        EVAL_RESULTS_PATHS[model].write_text(
            json.dumps(
                {
                    "hyperparameter_tuning": {
                        name: eval_results[name].model_dump()
                        for name in eval_results.keys()
                    },
                    "best_hyperparameters": best_name,
                    "test_metrics": None,
                    "prob_distributions_cv": serialize_prob_distributions(
                        prob_distributions
                    ),
                }
            )
        )

    else:
        print("Skipping cross-validation as requested.")

        # hard coded from previous grid searches
        best_name = 0.05
        best_trainer = trainer_grid[best_name]

    if train_ensemble:
        # Ensemble by averaging predictions from 5 models with different seeds
        print("Ensembling via averaging predictions from 5 models...")

        ensemble_trainer = EnsembleTrainer(
            submodels=[
                LogisticRegressionTrainer(C=best_name, max_iter=1000) for _ in range(5)
            ],
            bootstrap_samples=True,  # needed for classical models
            stratified_bootstrap=True,
        )

    else:
        print("Not ensembling, using best trainer directly.")
        ensemble_trainer = best_trainer

    # Final validation through cross validation
    # Validating ensemble performance (average over 5 folds)
    evaluator = BasicCrossValidationEvaluator(
        loss_func="cross_entropy", track_prob_distributions=True
    )
    k_fold_cross_validation(
```

```
        data=trainable_dataset,
        index_subset=trainable_dataset.original_indexes,  # all data
        trainer=ensemble_trainer,
        k=5,
        sampler=sampler,
        transformer=transformer,
        fn_augment=None,
        evaluator=evaluator,
        seed=SEED,
        print_folds=True,
    )

    # Train final model on all data for best generalization
    # Use ensemble for final model
    set_seed(SEED)
    ensemble_trainer.reset_model()

    # Use full trainable dataset
    X, y = trainable_dataset.X, trainable_dataset.y

    X_sampled, y_sampled = sampler.sample(X, y, seed=SEED)
    class_counts = np.bincount(y_sampled)

    # Standardize features (typically done after up/down sampling)
    transformer.reset()
    X_sampled_scaled = transformer.fit_transform(X_sampled)

    ensemble_trainer.fit(X_sampled_scaled, y_sampled)
    print(f"Trained final model on {X.shape[0]} samples [{class_counts}]")

    # ------------------------------ PERSIST ARTIFACTS ------------------------------ #

    print("Saving trained artifacts...")
    MODEL_ARTIFACTS_DIR_DAMAGE_PREDICTION.mkdir(parents=True, exist_ok=True)
    transformer.save(TRANSFORMER_PATHS[model])
    ensemble_trainer.save_model(MODEL_PATHS[model])


# ------------------------------------ LIGHTGBM ------------------------------------ #


def fit_lightgbm(
    data_path: Path = DATA_DIR,
    skip_cross_validation: bool = True,
    train_ensemble: bool = True,  # Consistently +5-10% F1 score on every fold
):
    """Fit LightGBM model for damage level prediction."""

    model = "lightgbm"
    print(f"Training {model} model...")

    # Load the data
    data = load_disaster_data(path=data_path)

    # Preprocess the data, overwrite to save memory
    data = preprocess_data(data)

    # ------------------------------ FEATURE ENGINEERING ------------------------------ #

    trainable_dataset = feature_pipeline_hurricane_logistic_regression(data)
    del data

    # -------------------------- CROSS VALIDATION AND TRAINING -------------------------- #

    print(f"Training {model} model...")
    transformer = StandardScalerTransformer()

    sampler = BalancedUpsampler()

    trainer_grid = {
        (
            "lightgbm_" + str(params).strip().replace(" ", "").replace("'", "")
        ): LightGBMTrainer(num_classes=len(np.unique(trainable_dataset.y)), **params)
        for params in [
            {"objective": "multiclassova", "class_weight": "balanced"},
            {"objective": "multiclassova", "class_weight": None},
            *[
```

```
                {
                    "objective": "multiclassova",
                    "class_weight": "balanced",
                    "num_leaves": num_leaves,
                    "max_depth": max_depth,
                    "min_child_samples": min_child_samples,
                }
                for num_leaves in [31, 50, 63]
                for max_depth in [6, 8, 10]
                for min_child_samples in [1, 5, 10]
            ],
        ]
    }

    if not skip_cross_validation:
        # Tune hyperparameters via grid search cross-validation
        eval_results, (best_name, best_trainer), _, prob_distributions = (
            grid_search_cross_validation(
                data=trainable_dataset,
                trainer_grid=trainer_grid,
                # f1: higher is better
                fn_find_best_metric=lambda m: max(
                    m.keys(), key=lambda t: m[t].f1_score_macro
                ),
                k_folds=5,
                # 20% test / 20% val split removes too many samples
                # of the minority classes (only 6 samples in class 2)
                test_split=None,
                sampler=sampler,
                transformer=transformer,
                fn_augment=None,
                seed=42,
            )
        )

        # Manual override
        # best_name =
        # best_trainer = trainer_grid[best_name]

        # Save eval results
        EVAL_RESULTS_PATHS[model].write_text(
            json.dumps(
                {
                    "hyperparameter_tuning": {
                        name: eval_results[name].model_dump()
                        for name in eval_results.keys()
                    },
                    "best_hyperparameters": best_name,
                    "test_metrics": None,
                    "prob_distributions_cv": serialize_prob_distributions(
                        prob_distributions
                    ),
                }
            )
        )

    else:
        print("Skipping cross-validation as requested.")

        # hard coded from previous grid searches
        best_name = "lightgbm_{objective:multiclassova,class_weight:balanced}"
        best_trainer = trainer_grid[best_name]

    if train_ensemble:
        # Ensemble by averaging predictions from 5 models with different seeds
        print("Ensembling via averaging predictions from 5 models...")

        ensemble_trainer = EnsembleTrainer(
            submodels=[
                LightGBMTrainer(
                    num_classes=len(np.unique(trainable_dataset.y)),
                    objective="multiclassova",
                    class_weight="balanced",
                )
                for _ in range(5)
            ],
            bootstrap_samples=True,  # needed for classical models
```

```
            stratified_bootstrap=True,
        )

    else:
        print("Not ensembling, using best trainer directly.")
        ensemble_trainer = best_trainer

    # Final validation through cross validation
    # Validating ensemble performance (average over 5 folds)
    evaluator = BasicCrossValidationEvaluator(
        loss_func="cross_entropy", track_prob_distributions=True
    )
    k_fold_cross_validation(
        data=trainable_dataset,
        index_subset=trainable_dataset.original_indexes,  # all data
        trainer=ensemble_trainer,
        k=5,
        sampler=sampler,
        transformer=transformer,
        fn_augment=None,
        evaluator=evaluator,
        seed=SEED,
        print_folds=True,
    )

    # Train final model on all data for best generalization
    # Use ensemble for final model
    set_seed(SEED)
    ensemble_trainer.reset_model()

    # Train final model on all data for best generalization
    set_seed(SEED)
    ensemble_trainer.reset_model()

    # Use full trainable dataset
    X, y = trainable_dataset.X, trainable_dataset.y

    X_sampled, y_sampled = sampler.sample(X, y, seed=SEED)
    class_counts = np.bincount(y_sampled)

    # Standardize features (typically done after up/down sampling)
    transformer.reset()
    X_sampled_scaled = transformer.fit_transform(X_sampled)

    ensemble_trainer.fit(X_sampled_scaled, y_sampled)
    print(f"Trained final model on {X.shape[0]} samples [{class_counts}]")

    # ---------------------------------- PERSIST ARTIFACTS ---------------------------------- #

    print("Saving trained artifacts...")
    MODEL_ARTIFACTS_DIR_DAMAGE_PREDICTION.mkdir(parents=True, exist_ok=True)
    transformer.save(TRANSFORMER_PATHS[model])
    ensemble_trainer.save_model(MODEL_PATHS[model])


# ------------------------------------ DINOV2+MLP ------------------------------------ #


def fit_mlp_dinov2(
    data_path: Path = DATA_DIR,
    skip_cross_validation: bool = True,
    augment: bool = True,
    train_ensemble: bool = True,
):
    """Fit dinov2+mlp model for damage level prediction."""
    model = "dinov2+mlp"
    print(f"Training {model} model on top of dinov2 embeddings...")

    # Load the data
    data = load_disaster_data(path=data_path)

    # Preprocess the data, overwrite to save memory
    data = preprocess_data(data)

    # ---------------------------------- FEATURE ENGINEERING ---------------------------------- #

    trainable_dataset = feature_pipeline_hurricane_dinov2(
```

```
        dataset_dir=data_path, data=data, augment=augment
    )
    del data

    # ------------------------- CROSS VALIDATION AND TRAINING ------------------------ #

    sampler = BalancedUpsampler()
    num_classes = len(np.unique(trainable_dataset.y))

    # With standandization performs significantly better here than without
    transformer = StandardScalerTransformer()

    if not skip_cross_validation:
        trainer_config_grid = {
            repr(
                (num_epochs, batch_size, lr, hidden_layers, loss)
            ): PytorchTrainerConfig(
                target_image_size=trainable_dataset.X.shape[1],
                num_epochs=num_epochs,
                batch_size=batch_size,
                lr=lr,
                hidden_layers=hidden_layers,
                num_classes=num_classes,
                loss=loss,
            )
            for (num_epochs, batch_size, lr, hidden_layers, loss) in (
                [
                    (num_epochs, batch_size, lr, hidden_layers, loss)
                    for num_epochs in [8, 16, 32, 48]
                    for batch_size in [32, 64]
                    for lr in [0.0001, 0.00005]
                    for hidden_layers in [[128], [128, 64], [256], [64, 32]]
                    for loss in ["cross_entropy"]
                ]
            )
        }

        trainer_grid = {
            name: build_trainer(
                model, config, class_weights=torch.tensor([31, 70, 6, 93])
            )
            for name, config in trainer_config_grid.items()
        }

        eval_results, (best_name, best_trainer), _, prob_distributions = (
            grid_search_cross_validation(
                data=trainable_dataset,
                trainer_grid=trainer_grid,
                fn_find_best_metric=lambda m: max(
                    m.keys(), key=lambda t: m[t].f1_score_macro
                ),
                k_folds=5,
                # 20% test / 20% val split removes too many samples
                # of the minority classes (only 6 samples in class 2)
                test_split=None,
                sampler=sampler,
                transformer=transformer,
                # Augmentation already applied before during feature pipeline
                fn_augment=None,
                seed=42,
            )
        )
        best_trainer_config = trainer_config_grid[best_name]

        # Save eval results
        EVAL_RESULTS_PATHS[model].write_text(
            json.dumps(
                {
                    "hyperparameter_tuning": {
                        name: eval_results[name].model_dump()
                        for name in eval_results.keys()
                    },
                    "best_hyperparameters": best_name,
                    "prob_distributions_cv": serialize_prob_distributions(
                        prob_distributions
                    ),
                }
```

```
            )
        )

        # Save best trainer config
        TRAINER_CONFIG_PATHS[model].write_text(best_trainer_config.model_dump_json())

    else:
        print("Skipping cross-validation as requested.")

        # Load best trainer config from previous grid search
        best_trainer_config = PytorchTrainerConfig.model_validate_json(
            TRAINER_CONFIG_PATHS[model].read_text()
        )
        best_trainer = build_trainer(model, best_trainer_config)

    if train_ensemble:
        # Ensemble by averaging predictions from 5 models with different seeds
        print("Ensembling via averaging predictions from 5 models...")

        ensemble_trainer = EnsembleTrainer(
            submodels=[build_trainer(model, best_trainer_config) for _ in range(5)],
            bootstrap_samples=True,
            stratified_bootstrap=True,
        )

    else:
        print("Not ensembling, using best trainer directly.")
        ensemble_trainer = best_trainer

    # Final validation through cross validation
    # Validating ensemble performance (average over 5 folds)
    evaluator = BasicCrossValidationEvaluator(
        loss_func="cross_entropy", track_prob_distributions=True
    )
    k_fold_cross_validation(
        data=trainable_dataset,
        index_subset=trainable_dataset.original_indexes,  # all data
        trainer=ensemble_trainer,
        k=5,
        sampler=sampler,
        transformer=transformer,
        fn_augment=None,
        evaluator=evaluator,
        seed=SEED,
        print_folds=True,
    )

    # Train final model on all data for best generalization
    set_seed(SEED)
    ensemble_trainer.reset_model()

    # Use full trainable dataset
    X, y = trainable_dataset.X, trainable_dataset.y

    # No additional data augmentation

    # Sampling to balance classes
    X_sampled, y_sampled = sampler.sample(X, y, seed=SEED)
    class_counts = np.bincount(y_sampled)

    # Standardize features (typically done after up/down sampling)
    transformer.reset()
    X_sampled_scaled = transformer.fit_transform(X_sampled)

    ensemble_trainer.fit(X_sampled_scaled, y_sampled, X_val=None, y_val=None)
    print(
        f"Trained final model on {X_sampled_scaled.shape[0]} samples; [{class_counts}]"
    )

    # ------------------------------ PERSIST ARTIFACTS ------------------------------ #

    print("Saving trained artifacts...")
    MODEL_ARTIFACTS_DIR_DAMAGE_PREDICTION.mkdir(parents=True, exist_ok=True)
    transformer.save(TRANSFORMER_PATHS[model])
    ensemble_trainer.save_model(MODEL_PATHS[model])

```

```python
# ---------------------------------------- CNN ---------------------------------------- #


def fit_cnn_model(
    data_path: Path = DATA_DIR,
    skip_cross_validation: bool = True,
    train_ensemble: bool = True,  # Consistently +1-2% F1 score average, better stability with bootstrap sampling
):
    """Fit CNN model for damage level prediction."""

    model = "cnn"

    # Load the data
    data = load_disaster_data(path=data_path)

    # Preprocess the data, overwrite to save memory
    data = preprocess_data(data)

    # ------------------------------ FEATURE ENGINEERING ------------------------------ #

    target_image_size = 64
    trainable_dataset = feature_pipeline_hurricane_neural_networks(
        data,
        nn_config=NNConfig(
            image_size=target_image_size,
            in_channels=3,
            num_classes=2,
        ),
    )
    del data

    def fn_augment(X_tr, y_tr) -> tuple[torch.Tensor, torch.Tensor]:
        X_tr, y_tr = apply_augmentations(
            images=convert_to_image_tensor(X_tr).numpy(),
            labels=y_tr.numpy(),
            augmentations=CNN_AUGMENTATIONS,
        )[2:]
        return convert_to_trainable_tensor(torch.tensor(X_tr)), torch.tensor(y_tr)

    # ---------------------------------- TRAINING ----------------------------------- #

    print("Training CNN model...")

    # CNNs don't need standardization
    transformer = IdentityTransformer()
    sampler = BalancedUpsampler()

    if not skip_cross_validation:
        trainer_config_grid = {
            repr(
                (
                    num_epochs,
                    batch_size,
                    lr,
                    conv_channels,
                )
            ): PytorchTrainerConfig(
                target_image_size=target_image_size,
                num_epochs=num_epochs,
                batch_size=batch_size,
                lr=lr,
                conv_channels=conv_channels,
            )
            for (num_epochs, batch_size, lr, conv_channels) in (
                [
                    (num_epochs, batch_size, lr, conv_channels)
                    for num_epochs in [8, 12, 16, 32]
                    for batch_size in [16, 32, 64]
                    for lr in [0.0005, 0.0001, 0.0005]
                    for conv_channels in [[64, 32], [128, 64], [64, 64, 32]]
                ]
            )
        }

        trainer_grid = {
            name: build_trainer(model, config)
            for name, config in trainer_config_grid.items()
```

```
        }

        eval_results, (best_name, best_trainer), _, prob_distributions = (
            grid_search_cross_validation(
                data=trainable_dataset,
                trainer_grid=trainer_grid,
                fn_find_best_metric=lambda m: max(
                    m.keys(), key=lambda t: m[t].f1_score_macro
                ),
                k_folds=5,
                # 20% test / 20% val split removes too many samples
                # of the minority classes (only 6 samples in class 2)
                test_split=None,
                sampler=sampler,
                transformer=transformer,
                fn_augment=fn_augment,
                seed=42,
            )
        )
        best_trainer_config = trainer_config_grid[best_name]

        # Save eval results
        EVAL_RESULTS_PATHS[model].write_text(
            json.dumps(
                {
                    "hyperparameter_tuning": {
                        name: eval_results[name].model_dump()
                        for name in eval_results.keys()
                    },
                    "best_hyperparameters": best_name,
                    "prob_distributions_cv": serialize_prob_distributions(
                        prob_distributions
                    ),
                }
            )
        )

        # Save best trainer config
        TRAINER_CONFIG_PATHS[model].write_text(best_trainer_config.model_dump_json())

    else:
        print("Skipping cross-validation as requested.")

        # Load best trainer config from previous grid search
        best_trainer_config = PytorchTrainerConfig.model_validate_json(
            TRAINER_CONFIG_PATHS[model].read_text()
        )
        best_trainer = build_trainer(model, best_trainer_config)

    if train_ensemble:
        # Ensemble by averaging predictions from 5 models with different seeds
        print("Ensembling via averaging predictions from 5 models...")

        ensemble_trainer = EnsembleTrainer(
            submodels=[build_trainer(model, best_trainer_config) for _ in range(5)],
            bootstrap_samples=True,
            stratified_bootstrap=True,
        )

    else:
        print("Not ensembling, using best trainer directly.")
        ensemble_trainer = best_trainer

    # Final validation through cross validation
    # Validating ensemble performance (average over 5 folds)
    evaluator = BasicCrossValidationEvaluator(
        loss_func="cross_entropy", track_prob_distributions=True
    )
    k_fold_cross_validation(
        data=trainable_dataset,
        index_subset=trainable_dataset.original_indexes,  # all data
        trainer=ensemble_trainer,
        k=5,
        sampler=sampler,
        transformer=transformer,
        fn_augment=None,
        evaluator=evaluator,
```

```
        seed=SEED,
        print_folds=True,
    )

    # Train final model on all data for best generalization
    # Use ensemble for final model
    set_seed(SEED)
    ensemble_trainer.reset_model()

    # Use full trainable dataset
    X, y = trainable_dataset.X, trainable_dataset.y

    # Apply augmentations to all data
    X, y = fn_augment(X, y)

    # Sampling to balance classes
    # X_sampled, y_sampled = sampler.sample(X, y, seed=SEED)
    X_sampled, y_sampled = X, y
    class_counts = np.bincount(y_sampled)

    # Standardize features (typically done after up/down sampling)
    transformer.reset()
    X_sampled_scaled = transformer.fit_transform(X_sampled)

    ensemble_trainer.fit(X_sampled_scaled, y_sampled, X_val=None, y_val=None)
    print(f"Trained final model on {X.shape[0]} samples [{class_counts}]")

    # ------------------------------- PERSIST ARTIFACTS ------------------------------- #

    print("Saving trained artifacts...")
    MODEL_ARTIFACTS_DIR_DAMAGE_PREDICTION.mkdir(parents=True, exist_ok=True)
    transformer.save(TRANSFORMER_PATHS[model])
    ensemble_trainer.save_model(MODEL_PATHS[model])


# ============================================================================== #
#                                       PREDICT                                  #
# ============================================================================== #

# ------------------------------------ LOGISTIC ------------------------------------ #


def predict_logistic_regression(data_path: Path = DATA_DIR):
    """Predict damage level using logistic regression model."""
    model = "logistic_regression"

    # Load model
    print("Loading trained artifacts...")
    transformer = StandardScalerTransformer()
    transformer.load(TRANSFORMER_PATHS[model])

    pred_model = EnsembleTrainer(
        submodels=[LogisticRegressionTrainer() for _ in range(5)],
        bootstrap_samples=True,
        stratified_bootstrap=True,
    )
    pred_model.load_model(MODEL_PATHS[model])

    # Load holdout data
    print("Loading holdout data...")
    data = load_disaster_data(path=data_path, split="test")

    # Preprocess holdout data, overwrite to save memory
    data = preprocess_data(data)

    # ------------------------------- FEATURE ENGINEERING ------------------------------- #

    predictable_dataset = feature_pipeline_hurricane_logistic_regression(data)

    # --------------------------------- RUN INFERENCE --------------------------------- #

    X_holdout = predictable_dataset.X
    X_holdout_scaled = transformer.fit_transform(X_holdout)
    y_pred_holdout = pred_model.predict(X_holdout_scaled)

    # Save results to CSV
    save_predictions(
```

```
        y_pred_holdout,
        DAMAGE_LEVEL_PREDICTIONS_PATH.with_name(
            f"{DAMAGE_LEVEL_PREDICTIONS_PATH.stem}_{model}.csv",
        ),
    )
    print("Holdout predictions saved")


def predict_lightgbm(data_path: Path = DATA_DIR):
    """Predict damage level using LightGBM model."""

    model = "lightgbm"

    # Load model
    print("Loading trained artifacts...")
    transformer = StandardScalerTransformer()
    transformer.load(TRANSFORMER_PATHS[model])

    pred_model = EnsembleTrainer(
        submodels=[LightGBMTrainer(num_classes=4) for _ in range(5)],
        bootstrap_samples=True,
        stratified_bootstrap=True,
    )
    pred_model.load_model(MODEL_PATHS[model])

    # Load holdout data
    print("Loading holdout data...")
    data = load_disaster_data(path=data_path, split="test")

    # Preprocess holdout data, overwrite to save memory
    data = preprocess_data(data)

    # ------------------------------ FEATURE ENGINEERING ------------------------------ #

    predictable_dataset = feature_pipeline_hurricane_logistic_regression(data)

    # --------------------------------- RUN INFERENCE --------------------------------- #

    X_holdout = predictable_dataset.X
    X_holdout_scaled = transformer.fit_transform(X_holdout)
    y_pred_holdout = pred_model.predict(X_holdout_scaled)

    # Save results to CSV
    save_predictions(
        y_pred_holdout,
        DAMAGE_LEVEL_PREDICTIONS_PATH.with_name(
            f"{DAMAGE_LEVEL_PREDICTIONS_PATH.stem}_{model}.csv",
        ),
    )
    print("Holdout predictions saved")


def predict_mlp_dinov2(data_path: Path = DATA_DIR):
    """Predict damage level using dinov2+mlp model."""

    model = "dinov2+mlp"

    # Load model
    print("Loading trained artifacts...")
    transformer = StandardScalerTransformer()
    transformer.load(TRANSFORMER_PATHS[model])

    best_trainer_config = PytorchTrainerConfig.model_validate_json(
        TRAINER_CONFIG_PATHS[model].read_text()
    )
    pred_model = EnsembleTrainer(
        submodels=[
            build_trainer(
                model, best_trainer_config, class_weights=torch.tensor([31, 70, 6, 93])
            )
            for _ in range(5)
        ],
        bootstrap_samples=True,
        stratified_bootstrap=True,
    )
    pred_model.load_model(MODEL_PATHS[model])

```

```
    # Load holdout data
    print("Loading holdout data...")
    data = load_disaster_data(path=data_path, split="test")

    # Preprocess holdout data, overwrite to save memory
    data = preprocess_data(data)

    # ------------------------------ FEATURE ENGINEERING ------------------------------ #

    predictable_dataset = feature_pipeline_hurricane_dinov2(
        dataset_dir=data_path, data=data, augment=False
    )

    # ---------------------------------- RUN INFERENCE ---------------------------------- #

    X_holdout = predictable_dataset.X
    X_holdout_scaled = transformer.transform(X_holdout)

    y_pred_holdout = pred_model.predict(X_holdout_scaled)

    # Save results to CSV
    save_predictions(
        y_pred_holdout,
        DAMAGE_LEVEL_PREDICTIONS_PATH.with_name(
            f"{DAMAGE_LEVEL_PREDICTIONS_PATH.stem}_{model}.csv",
        ),
    )
    print(
        f"Holdout predictions saved to {DAMAGE_LEVEL_PREDICTIONS_PATH.stem}_{model}.csv"
    )


def predict_cnn(data_path: Path = DATA_DIR):
    """Predict damage level using CNN model."""

    model = "cnn"

    # Load model
    print("Loading trained artifacts...")
    transformer = IdentityTransformer()
    transformer.load(TRANSFORMER_PATHS[model])

    best_trainer_config = PytorchTrainerConfig.model_validate_json(
        TRAINER_CONFIG_PATHS[model].read_text()
    )
    pred_model = EnsembleTrainer(
        submodels=[build_trainer(model, best_trainer_config) for _ in range(5)],
        bootstrap_samples=True,
        stratified_bootstrap=True,
    )
    pred_model.load_model(MODEL_PATHS[model])

    # Load holdout data
    print("Loading holdout data...")
    data = load_disaster_data(path=data_path, split="test")

    # Preprocess holdout data, overwrite to save memory
    data = preprocess_data(data)

    # ------------------------------ FEATURE ENGINEERING ------------------------------ #

    predictable_dataset = feature_pipeline_hurricane_neural_networks(
        data,
        nn_config=NNConfig(
            image_size=64,
            in_channels=3,
            num_classes=2,
        ),
    )

    # ---------------------------------- RUN INFERENCE ---------------------------------- #

    X_holdout = predictable_dataset.X
    X_holdout_scaled = transformer.transform(X_holdout)

    # TODO: test time augmentation
    y_pred_holdout = pred_model.predict(X_holdout_scaled)
```

```
    # Save results to CSV
    save_predictions(
        y_pred_holdout,
        DAMAGE_LEVEL_PREDICTIONS_PATH.with_name(
            f"{DAMAGE_LEVEL_PREDICTIONS_PATH.stem}_{model}.csv",
        ),
    )
    print("Holdout predictions saved")


# ---------------------------------------------------------------------------------------- #
#                                          CLI                                             #
# ---------------------------------------------------------------------------------------- #


@app.command()
def fit(
    data_path: Path = DATA_DIR,
    model: DamageLevelModel = "logistic_regression",
    skip_cross_validation: bool = True,
):
    """Fit damage level prediction model."""

    if model == "logistic_regression":
        fit_logistic_regression(
            data_path=data_path, skip_cross_validation=skip_cross_validation
        )
    elif model == "lightgbm":
        fit_lightgbm(data_path=data_path, skip_cross_validation=skip_cross_validation)
    elif model == "dinov2+mlp":
        fit_mlp_dinov2(data_path=data_path, skip_cross_validation=skip_cross_validation)
    elif model == "cnn":
        fit_cnn_model(data_path=data_path, skip_cross_validation=skip_cross_validation)
    else:
        raise NotImplementedError(f"Training for model {model} not implemented.")


@app.command()
def predict(
    data_path: Path = DATA_DIR, model: DamageLevelModel = "logistic_regression"
):
    """Predict damage levels using trained model."""

    if model == "logistic_regression":
        predict_logistic_regression(data_path=data_path)
    elif model == "lightgbm":
        predict_lightgbm(data_path=data_path)
    elif model == "dinov2+mlp":
        predict_mlp_dinov2(data_path=data_path)
    elif model == "cnn":
        predict_cnn(data_path=data_path)
    else:
        raise NotImplementedError(f"Prediction for model {model} not implemented.")


if __name__ == "__main__":
    print("Using device:", get_device())
    app()
```