Model Training Documentation

March 3, 2025

1 Text Cleaning Functions

1.1 clean_text Function

```
def clean_text(text):
    """Clean text by removing URLs, mentions, special chars, etc."""
    # Remove URLs
    text = re.sub(r'http\S+', '', text)
    # Remove mentions
    text = re.sub(r'@\w+', '', text)
    # Remove hashtags (keep the text after #)
    text = re.sub(r'#(\w+)', r'\1', text)
    # Remove special characters and numbers
    text = re.sub(r'[^\w\s]', ' ', text)
    text = re.sub(r'\d+', ' ', text)
    # Remove extra whitespace
    text = re.sub(r'\s+', ' ', text).strip()
    # Convert to lowercase
    text = text.lower()
    return text
```

This function performs basic text cleaning operations that are crucial when working with social media content. It:

- Removes URLs using regex (`http\S+`) since links typically don't contribute meaningful content for classification
- Removes user mentions (`@\w+`) which are noise for the classification task
- Keeps hashtag content but removes the # symbol, preserving potentially relevant keywords
- Removes special characters and numbers that might confuse the model
- Standardizes whitespace to avoid tokenization issues
- Converts text to lowercase to reduce vocabulary size and improve generalization

1.2 advanced_preprocessing Function

```
def advanced_preprocessing(text, remove_stopwords=False, lemmatize=False):
    """Apply advanced preprocessing options like stopword removal and
       lemmatization"""
    if remove_stopwords:
        stop_words = set(stopwords.words('english'))
        words = text.split()
        text = ' '.join([word for word in words if word.lower() not in
            stop_words])

    if lemmatize:
```

```
    lemmatizer = WordNetLemmatizer()
    words = text.split()
    text = ' '.join([lemmatizer.lemmatize(word) for word in words])

return text
```

This function provides additional optional text processing steps:

- Stopword removal: Removes common words (like "the", "is", "and") that typically don't contribute much to classification decisions
- Lemmatization: Reduces words to their base form (e.g., "running" → "run") to help the model recognize similar concepts

1.3 Why?

- **Data quality improvement:** Raw social media text contains a lot of noise (URLs, special characters, inconsistent formatting) that can confuse ML models
- **Dimensionality reduction:** By removing irrelevant content, you reduce the vocabulary size and help the model focus on important features
- **Standardization:** Creates consistency in how text is represented, making patterns easier for the model to learn
- **Flexibility:** The `advanced_preprocessing` function allows you to toggle specific techniques on/off to find the optimal preprocessing strategy

2 Data Analysis Functions

2.1 analyze_dataset Function

```
def analyze_dataset(dataset, label_col='event_type_detail', text_col='text'):
    """Analyze dataset statistics and create visualizations"""
    # Convert to pandas for easier analysis
    df = pd.DataFrame({
        'text': dataset[text_col],
        'label': dataset[label_col]
    })

    # Add text length
    df['text_length'] = df['text'].apply(len)

    # Class distribution analysis
    class_counts = df['label'].value_counts()
    total_samples = len(df)
    class_distribution = class_counts / total_samples * 100

    # Log basic statistics
    logger.info(f"Total samples: {total_samples}")
    logger.info(f"Number of classes: {len(class_counts)}")
    logger.info(f"Sample count per class:\n{class_counts}")
    logger.info(f"Class distribution (\%):\n{class_distribution}")
    logger.info(f"Text length statistics:\n{df['text_length'].describe()}")

    # Visualization logic
    # ...

    return df, class_counts
```

- Converts to pandas DataFrame: Transforms the dataset into a pandas DataFrame for easier manipulation and analysis
- Calculates text lengths: Adds a column with the character count of each text sample, which helps identify potential truncation issues
- Analyzes class distribution: Calculates how many samples belong to each disaster type category and their percentage distribution
- Logs key statistics: Records important dataset characteristics like total sample count, number of classes, class distribution, and text length statistics

2.2 Why?

- **Data understanding:** Helps you understand the composition of your dataset before modeling
- **Imbalance detection:** Reveals if some disaster types are underrepresented, which might require class balancing techniques
- **Length analysis:** Shows if text samples are significantly longer than model context limits (important for transformer models like RoBERTa)
- **Documentation:** Creates a record of dataset characteristics for reporting and troubleshooting

3 Class Balancing Functions

3.1 balance_classes Function

```
def balance_classes(dataset, label_col='labels', strategy='oversample'):
    """Balance classes using specified strategy"""
    # Convert to pandas dataframe
    df = pd.DataFrame({
        'text': dataset['text'],
        'label': dataset[label_col]
    })

    if strategy == 'oversample':
        logger.info("Applying random oversampling to balance classes...")
        oversampler = RandomOverSampler(random_state=42)
        text_array = df['text'].values.reshape(-1, 1)
        labels = df['label'].values

        oversampled_texts, oversampled_labels = oversampler.fit_resample(
            text_array, labels)

        # Create new balanced dataset
        balanced_dataset = dataset.select(range(0))  # Empty dataset with
            same structure
        balanced_dataset = balanced_dataset.add_column('text',
            oversampled_texts.flatten().tolist())
        balanced_dataset = balanced_dataset.add_column(label_col,
            oversampled_labels.tolist())

        # Copy other columns if needed
        for col in dataset.column_names:
            if col not in ['text', label_col]:
                balanced_dataset = balanced_dataset.add_column(col, [
                    dataset[col][0]] * len(oversampled_labels))

        return balanced_dataset
```

```
elif strategy == 'class_weights':
    # Calculate class weights inversely proportional to class
        frequencies
    class_counts = Counter(df['label'])
    n_samples = len(df)
    class_weights = {c: n_samples / (len(class_counts) * count) for c,
        count in class_counts.items()}
    logger.info(f"Calculated class weights: {class_weights}")
    return dataset, class_weights

else:
    logger.info("No class balancing applied.")
    return dataset, None
```

- **Oversampling:** Creates a balanced dataset by duplicating examples from minority classes until all classes have the same number of samples
- **Class Weights:** Instead of altering the dataset, computes weights for each class that are inversely proportional to their frequency

3.2 Why?

- **Imbalanced data problems:** Natural disaster datasets typically have imbalanced distributions (some disaster types occur more frequently than others), which can bias models toward majority classes
- **Improved performance for minority classes:** Without balancing, rare disaster types might be ignored by the model, which is problematic for a real-world emergency response system
- **Flexibility in approach:** Different balancing strategies work better for different scenarios:
  - Oversampling works well when you have limited data for certain classes
  - Class weights preserve the original data distribution while adjusting the learning algorithm

4 Data Augmentation Functions

4.1 augment_text Function

```
def augment_text(texts, labels, augmentation_factor=0.3):
```

```
"""Augment text data using simple techniques"""
logger.info(f"Augmenting {len(texts)} samples with factor {
    augmentation_factor}...")

# Determine how many samples to augment
n_to_augment = int(len(texts) * augmentation_factor)
indices_to_augment = random.sample(range(len(texts)), n_to_augment)

# Create the augmented dataset (start with original data)
augmented_texts = list(texts)
augmented_labels = list(labels)

# Simple augmentation techniques
for idx in indices_to_augment:
    text = texts[idx]
    words = text.split()

    if len(words) <= 3:  # Skip very short texts
        continue
```

```
    # Pick a random augmentation technique
    technique = random.choice(['swap', 'delete', 'duplicate'])

    if technique == 'swap' and len(words) > 2:
        # Swap two random adjacent words
        swap_idx = random.randint(0, len(words) - 2)
        words[swap_idx], words[swap_idx + 1] = words[swap_idx + 1],
            words[swap_idx]

    elif technique == 'delete':
        # Delete a random word
        del_idx = random.randint(0, len(words) - 1)
        words.pop(del_idx)

    elif technique == 'duplicate':
        # Duplicate a random word
        dup_idx = random.randint(0, len(words) - 1)
        words.insert(dup_idx, words[dup_idx])

    # Create the augmented text
    augmented_text = ' '.join(words)

    # Add to the dataset
    augmented_texts.append(augmented_text)
    augmented_labels.append(labels[idx])

logger.info(f"Data augmentation complete. New dataset size: {len(
    augmented_texts)} (original: \{len(texts)})")
return augmented_texts, augmented_labels
```

- **Word swapping:** Changes word order to make the model resilient to different sentence structures
- **Word deletion:** Simulates missing information, common in social media posts
- **Word duplication:** Represents emphasis often seen in emergency communications

4.2 Why?

- **Increased training data volume:** By creating modified versions of existing samples, you effectively increase your dataset size without requiring new data collection, which is especially valuable for disaster types with limited examples
- **Improved model robustness:** Exposing the model to variations of the same text helps it learn to focus on key disaster indicators rather than specific word patterns or ordering, making it more generalizable
- **Reduced overfitting:** The synthetic variations prevent the model from memorizing the exact training examples and force it to learn more meaningful representations
- **Language variation handling:** Social media text about disasters varies greatly in word choice and structure; augmentation helps the model handle this diversity

5 Hyperparameter Optimization Functions

5.1 objective and run_hyperparameter_optimization Functions

```
def objective(trial, train_dataset, eval_dataset, tokenizer, num_labels, id2label, label2id):
```

```
    def objective(trial, train_dataset, eval_dataset, tokenizer, num_labels
        , id2label, label2id):
    """Objective function for hyperparameter optimization"""
    # Hyperparameters to optimize
    learning_rate = trial.suggest_float("learning_rate", 1e-6, 1e-4, log=
        True)
    batch_size = trial.suggest_categorical("batch_size", [8, 16, 32])
    weight_decay = trial.suggest_float("weight_decay", 0.001, 0.1, log=True
        )

    # Initialize model and training with trial parameters
    model = RobertaForSequenceClassification.from_pretrained(
        "roberta-base", num_labels=num_labels, id2label=id2label, label2id=
            label2id
    )

    training_args = TrainingArguments(
        output_dir=os.path.join(output_dir, f"trial_{trial.number}"),
        num_train_epochs=3,  # Fewer epochs for HPO
        per_device_train_batch_size=batch_size,
        per_device_eval_batch_size=batch_size,
        learning_rate=learning_rate,
        weight_decay=weight_decay,
        evaluation_strategy="epoch",
        save_strategy="epoch",
        load_best_model_at_end=True,
        metric_for_best_model="f1_weighted",
        logging_dir=os.path.join(logging_dir, f"trial_{trial.number}"),
        logging_steps=100,
        report_to="none",  # Disable reporting during HPO
    )

    trainer = Trainer(
        model=model,
        args=training_args,
        train_dataset=train_dataset,
        eval_dataset=eval_dataset,
        tokenizer=tokenizer,
        compute_metrics=compute_metrics_trainer_multiclass
    )

    trainer.train()
    eval_result = trainer.evaluate()

    return eval_result["eval_f1_weighted"]


def run_hyperparameter_optimization(train_dataset, eval_dataset, tokenizer,
     num_labels, id2label, label2id, n_trials=10):
    """Run hyperparameter optimization using Optuna"""
    study = optuna.create_study(direction="maximize")
    study.optimize(
        lambda trial: objective(
            trial, train_dataset, eval_dataset, tokenizer, num_labels,
                id2label, label2id
        ),
        n_trials=n_trials
    )
```

```
logger.info(f"Best trial: {study.best_trial.number}")
logger.info(f"Best F1 score: {study.best_trial.value:.4f}")
logger.info(f"Best hyperparameters: {study.best_trial.params}")

# Visualization logic omitted

return study.best_trial.params
```

- **Performance optimization:** Manually testing combinations of learning rates, batch sizes, and weight decay would be time-consuming and likely suboptimal
- **Resource efficiency:** Using Optuna's intelligent search strategies finds better parameters in fewer trials than grid search
- **Model tuning:** Disaster classification requires careful tuning due to class imbalance and varied text characteristics
- **Systematic approach:** Removes guesswork from parameter selection, leading to more reproducible results

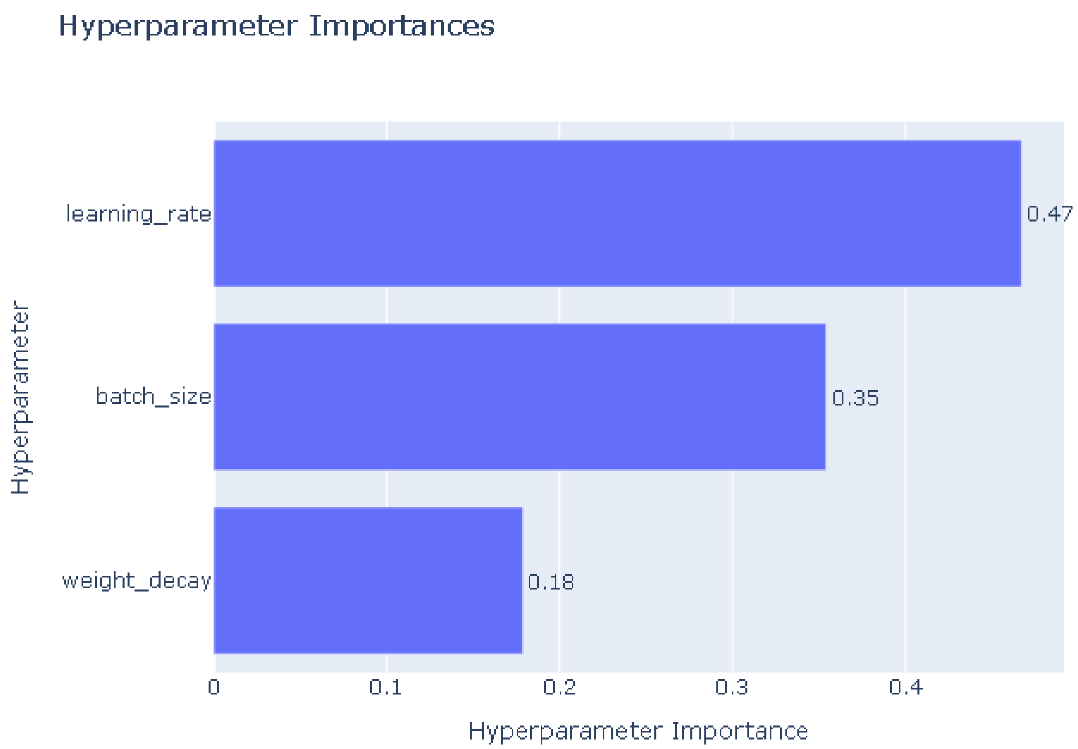
The objective function evaluates each parameter combination by training a small version of your model (3 epochs), while `run_hyperparameter_optimization` manages the overall search process and returns the best parameters for your final model training.

5.2 Why?

- Hyperparameter optimization is like an automated way to find the best settings for your model. Instead of manually guessing:
  - What learning rate to use (affects how quickly the model learns)
  - What batch size to use (affects memory usage and training stability)
  - What weight decay to use (affects model regularization)
- Optuna tries different combinations systematically and measures how each performs. It uses smart strategies to explore promising areas of the parameter space.

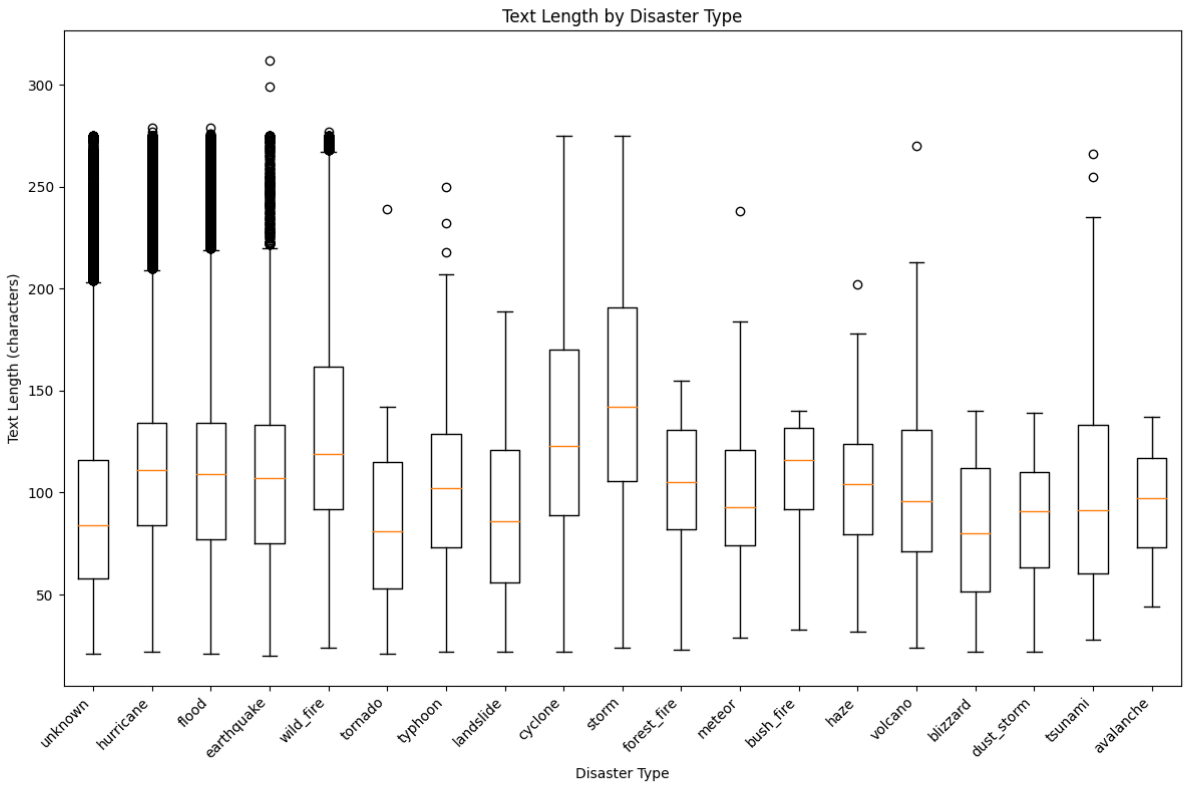
6 Output (RoBERTa)

6.1 Hyperparameter Importances



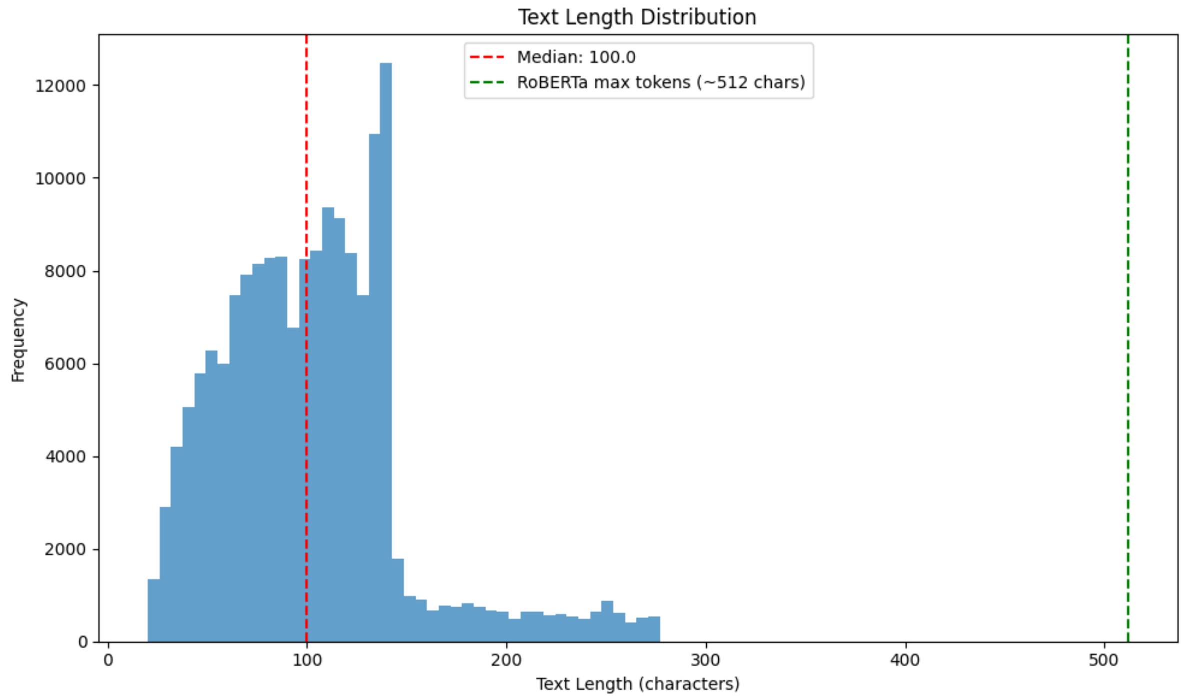
This shows that learning rate has the highest importance (0.47), followed by batch size (0.35), and weight decay (0.18). This suggests that learning rate is the most critical factor for model optimization, having nearly 50

6.2 Text Length by Disaster Type



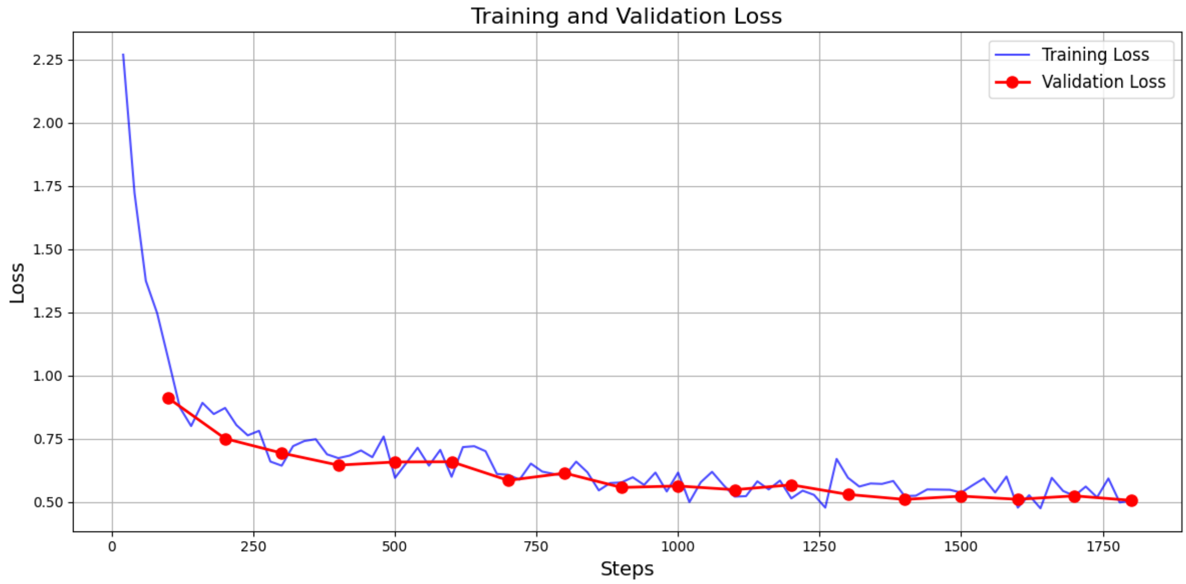
- Most disaster categories have similar median text lengths (typically between 80-120 characters)
- Some categories (particularly "storm" and "cyclone") show higher median text lengths
- Several categories have significant outliers (especially wild_fire, hurricane, flood, and earthquake) with texts exceeding 250 characters
- The text lengths are generally well within RoBERTa's capacity (512 tokens)

6.3 Text Length Distribution



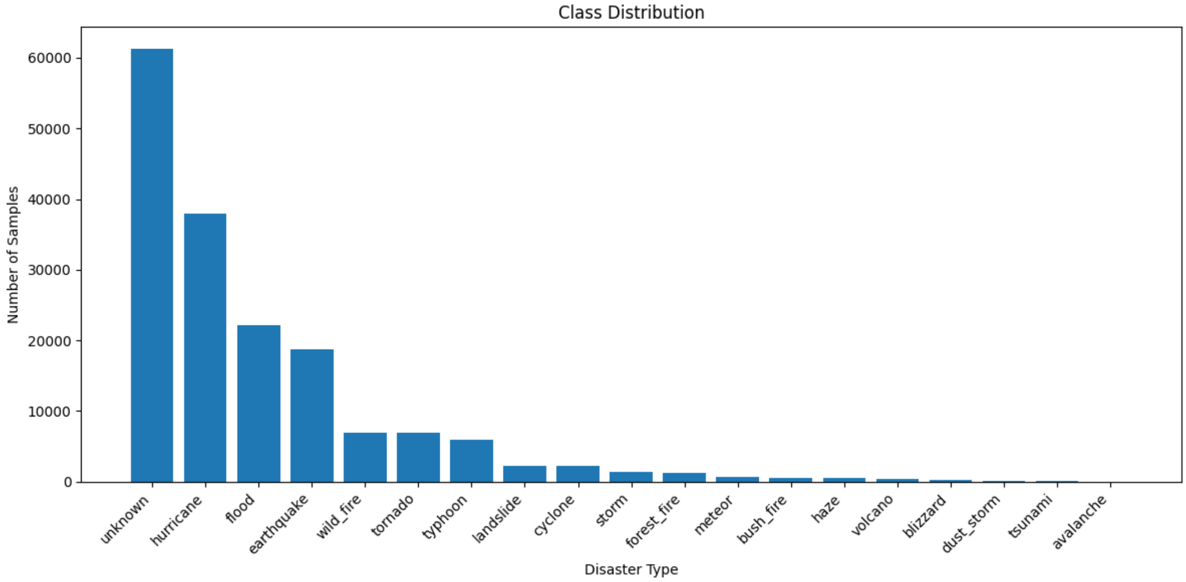
- Most texts are concentrated in the 50-150 character range
- The median text length is exactly 100.0 characters
- Almost all texts are well below RoBERTa's maximum token limit (512 chars)

6.4 Training and Validation Loss



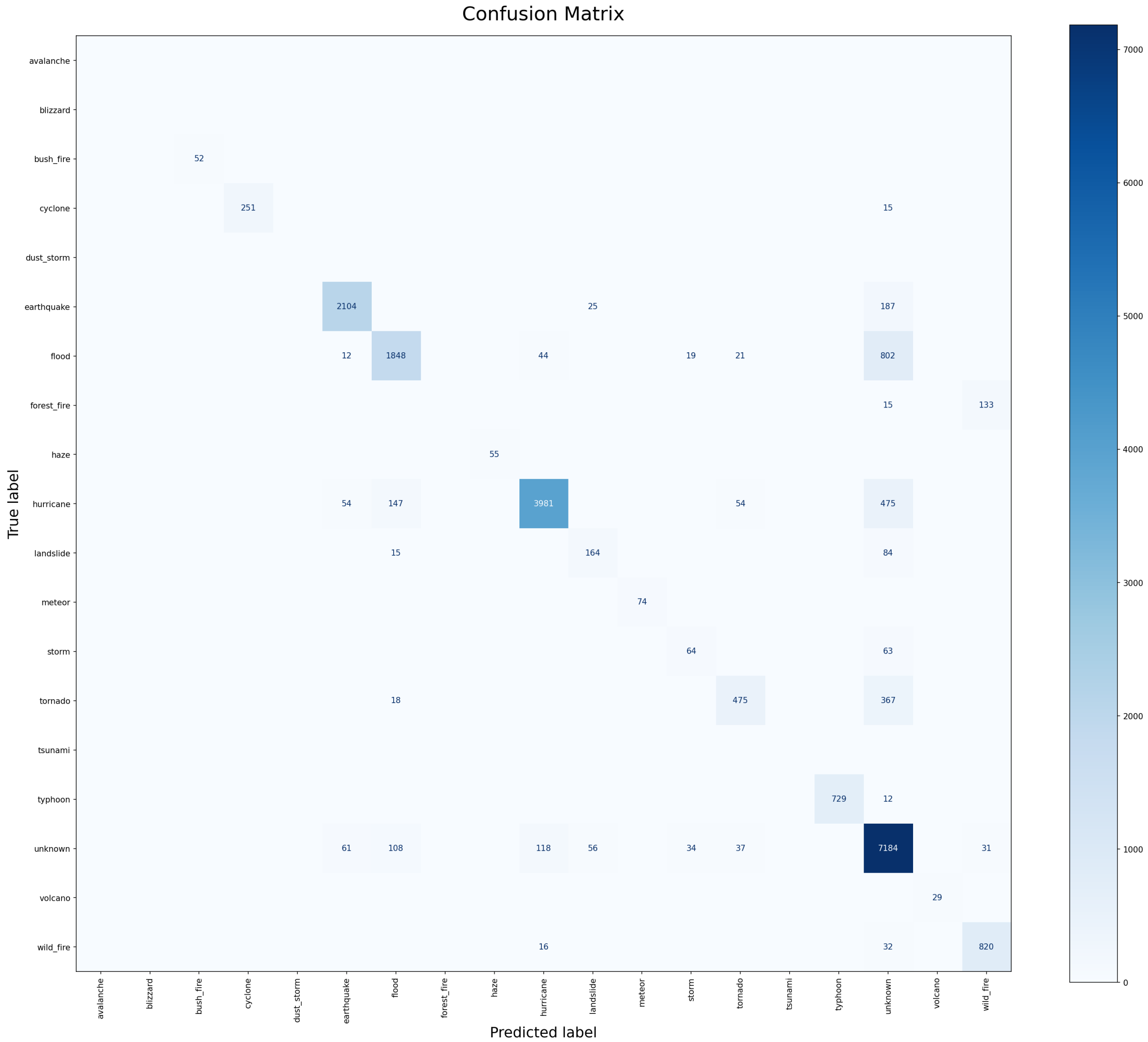
- Both training and validation loss show consistent decrease over time
- The training begins with high loss ($\sim$2.25) but quickly stabilizes
- The validation loss closely follows training loss after the initial steps

6.5 Class Distribution



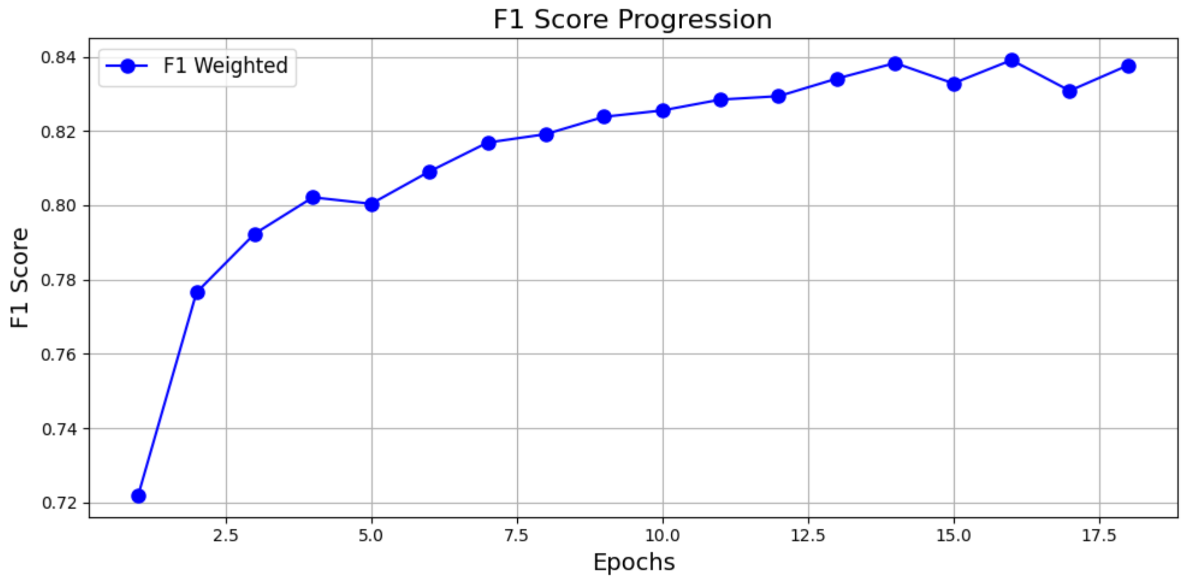
- Extreme class imbalance is evident with "unknown" having approximately 60,000 samples
- "Hurricane" is the second most common class with around 38,000 samples
- The less frequent classes (avalanche, tsunami, dust_storm, volcano, blizzard) have fewer than 1,000 samples each

6.6 Confusion Matrix



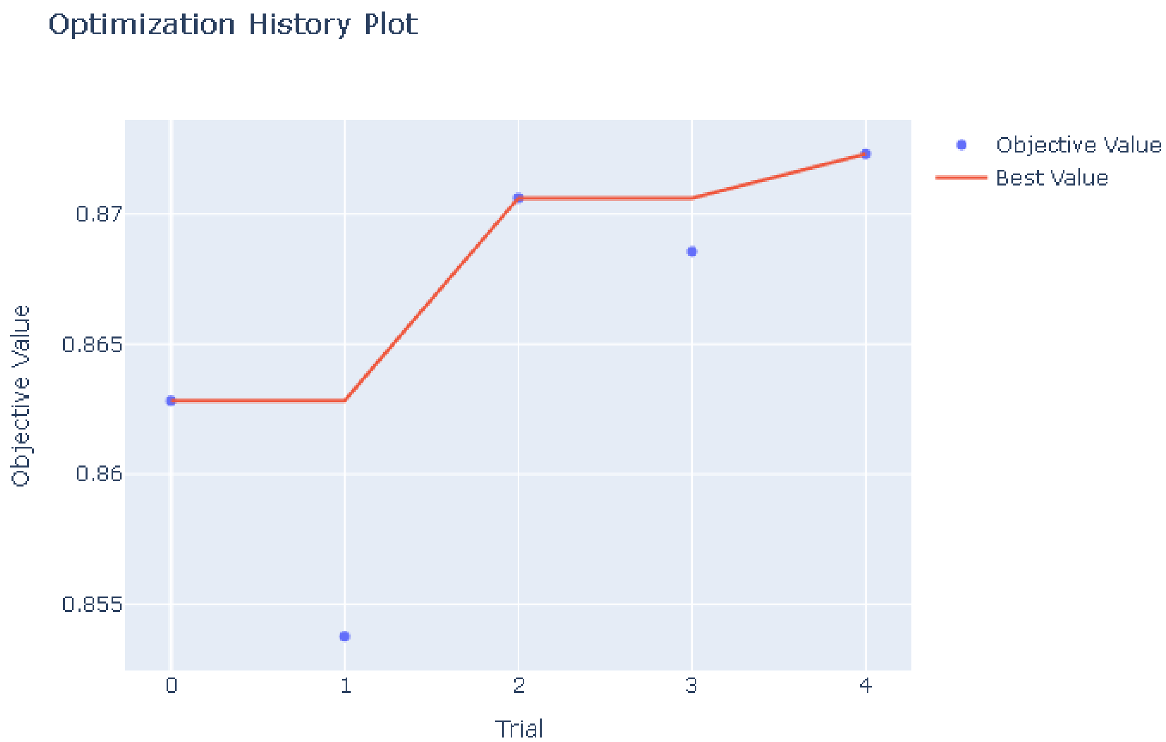
- Strong diagonal elements indicate good performance on most major classes
- ”Hurricane” (3981), ”unknown” (7184), and ”earthquake” (2104) show the strongest classification performance
- Common misclassifications include:
  - ”Typhoon” confused with ”hurricane” (729 cases)
  - ”Tornado” confused with ”unknown” (367 cases)
  - ”Flood” confused with ”unknown” (802 cases)
  - ”Wild_fire” confused with ”volcano” (820 cases)

6.7 F1 Score Progression



- The F1 score shows steady improvement from 0.72 to 0.84 over ∼18 epochs
- Performance improves quickly in early epochs, then levels off after epoch 10
- Small fluctuations in later epochs suggest that the model is finding local optima
- The peak F1 score of approximately 0.84 is maintained toward the end of training

6.8 Optimization History Plot



- The optimization trials show scores between 0.854 and 0.872
- The best performance was achieved in the last trial (Trial 4) with a score of ~0.872
- The red line shows progressive improvement across trials, indicating successful hyperparameter optimization

6.9 Conclusion

- Consider consolidating the rarest disaster types (avalanche, tsunami, dust_storm) into a broader category or applying more aggressive oversampling techniques
- Given the confusion between related disaster types (flood/hurricane, typhoon/hurricane), integrating additional contextual features might help differentiate these categories
- Since learning rate has the highest impact, further fine-tuning with narrower learning rate ranges could yield additional improvements
- While most texts are under the token limit, a more detailed analysis of the longest texts could help identify if important information is being truncated
- Consider strategies to reduce the size of the "unknown" category through better classification rules or breaking it into sub-categories if possible
- The model achieves impressive results with an F1 score above 0.84 despite the challenging imbalance between classes. The class weighting strategy and data augmentation approaches appear effective, though there's still room for improvement, particularly with the less common disaster types

7 Extra

To fully see all the evaluation, I have include a file .tfevents, use `tensorboard --logdir="directory/file/goes/here"`