Sprint 2: **Extend Audio Classification Use Cases**

Main Goal:

Broaden the current audio classification system beyond its initial bioacoustics-focused design. Extend its applicability to other significant environmental events, such as bushfires or weather anomalies. This extension requires adaptation and generalization of existing classification algorithms and the integration of diverse audio event categories.

Deliverables:

- An extended and generalized audio classification model supporting a broader range of environmental event detection.
- Comprehensive documentation outlining expanded use cases, performance evaluation, and integration guidelines.

Team Members and Task Segregation:

Riley Beckett: Build a high-performance model for detecting endangered species and environmental threats in the Otway's.

Irfan Boenardi: Data Collection & Preparation (Lead)

Venesh Kanagasingam : Documentation (Lead) & Data Collection and Preparation.

Sound Link:

https://drive.google.com/drive/folders/1hF-x9Mxoj_lWh-j2NQQwythWR_12Hd0F?usp=sharing

Code:

```
import os
import sys
import torch
import torch.nn as nn
```

```
import torch.optim as optim
import torch.nn.functional as F
from torch.utils.data import Dataset, DataLoader, Subset
from pathlib import Path
import random
import torchaudio.transforms as T
from tqdm import tqdm
from sklearn.metrics import classification_report, confusion_matrix
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt



# Load Pretrained EfficientAT Model with base frozen)
def load_mn40_as_ext_model(device):
project_root = r"C:\Users\riley\Documents\Project-Echo\src\Prototypes"
efficientat_root = os.path.join(project_root, "EfficientAT")
#Add EfficientAT repo to Python path if needed
if efficientat_root not in sys.path:
sys.path.append(efficientat_root)
from models.mn.model import get_model as get_mn
model = get_mn(pretrained_name="mn40_as_ext", width_mult=4.0)
model.to(device)
# Freeze all the layers except classifier for fine-tuning
for name, param in model.named_parameters():
if "classifier" not in name:
param.requires_grad = False
return model



# Data Augmentation for Training
class Augmentation(nn.Module):
def __init__(self, time_mask_param=30, freq_mask_param=15, noise_std=0.05,
max_time_shift=5, max_pitch_shift=2, time_stretch_range=(0.8, 1.2)):
super().__init__()
self.time_mask = T.TimeMasking(time_mask_param)
self.freq_mask = T.FrequencyMasking(freq_mask_param)
self.noise_std = noise_std #Standard deviation of Gaussian noise
self.noise_std = noise_std # Standard deviation of Gaussian noise
self.max_time_shift = max_time_shift # Max frame shift for time rolling
self.max_pitch_shift = max_pitch_shift # Max bin shift for pitch rolling
self.time_stretch_range = time_stretch_range # Stretch factor range (e.g., 0.8x to 1.2x)


def forward(self, spec):
"""
Applies a random subset of the augmentations to the input spectrogram.
"""
# Apply time and frequency masking
spec = self.time_mask(self.freq_mask(spec))


# Add Gaussian noise
if random.random() < 0.5:
spec += torch.randn_like(spec) * self.noise_std


# Random roll in time
if random.random() < 0.5:
```

```
spec = torch.roll(spec, random.randint(-self.max_time_shift, self.max_time_shift), dims=2)

# Random roll in frequency
if random.random() < 0.5:
spec = torch.roll(spec, random.randint(-self.max_pitch_shift, self.max_pitch_shift), dims=1)

# Random time stretching
if random.random() < 0.5:
orig_time = spec.shape[2]
factor = random.uniform(*self.time_stretch_range)
new_time = int(orig_time * factor)

# Resize spectrogram in time dimension using interpolation
spec = F.interpolate(spec.unsqueeze(0), size=(spec.shape[1], new_time),
mode='bilinear', align_corners=False).squeeze(0)

# Ensure the output length matches input by cropping or padding
if new_time > orig_time:
spec = spec[:, :, :orig_time]
else:
spec = F.pad(spec, (0, orig_time - new_time))

return spec

#Custom dataset to load mel spectrograms for animal and environmental sounds.
class CombinedEchoDataset(Dataset):
# Initialize dataset, assign labels, and load file paths.
def __init__(self, domain_dirs, transform=None, p_overlap=0.3):
self.samples = []
self.class_to_idx = {}
self.transform = transform
self.p_overlap = p_overlap

idx = 0
for domain, root_path in domain_dirs.items():
root = Path(root_path)
if domain == "env":
for subfolder in sorted(d.name for d in root.iterdir() if d.is_dir()):
class_name = f"{domain}_{subfolder}"
self.class_to_idx[class_name] = idx
idx += 1
for f in (root / subfolder).glob("*.pt"):
self.samples.append((str(f), class_name))
else:
class_name = domain # just "animal"
if class_name not in self.class_to_idx:
self.class_to_idx[class_name] = idx
idx += 1
for f in root.glob("*.pt"):
self.samples.append((str(f), class_name))

self.num_classes = len(self.class_to_idx)

# Return total number of samples.
def __len__(self):
```

```
return len(self.samples)
# Load one spectrogram and one-hot label (with optional transform).

def get_sample(self, idx):
path, class_name = self.samples[idx]
mel = torch.load(path)
if self.transform:
mel = self.transform(mel)
label = torch.zeros(self.num_classes, dtype=torch.float32)
label[self.class_to_idx[class_name]] = 1.0
return mel, label

# Return sample, optionally mixed with another for multi-label overlap.
def __getitem__(self, idx):
mel, label = self.get_sample(idx)
if self.p_overlap > 0 and random.random() < self.p_overlap:
idx2 = random.choice([i for i in range(len(self.samples)) if i != idx])
mel2, label2 = self.get_sample(idx2)
min_T = min(mel.shape[2], mel2.shape[2])
mel = mel[:, :, :min_T]
mel2 = mel2[:, :, :min_T]
mel = (mel + mel2) / 2.0
label = torch.maximum(label, label2)
return mel, label




# Training and return average loss and accuracy
def train_epoch(model, loader, epoch, num_epochs, device, optimizer, criterion, threshold=0.5):
model.train()
total_loss, total_acc, total_samples = 0.0, 0.0, 0
for x, y in tqdm(loader, desc=f"Epoch {epoch}/{num_epochs} [Train]", leave=False):
if x.dim() == 3:
x = x.unsqueeze(1)
x, y = x.to(device), y.to(device)
output = model(x)
if isinstance(output, tuple): output = output[0]
loss = criterion(output, y)
optimizer.zero_grad()
loss.backward()
optimizer.step()
batch_size = x.size(0)
total_loss += loss.item() * batch_size
total_samples += batch_size
preds = (torch.sigmoid(output) > threshold).float()
total_acc += (preds == y).float().mean().item() * batch_size
return total_loss / total_samples, total_acc / total_samples



# Evaluate the model on validation data
def evaluate(model, loader, epoch, num_epochs, device, criterion, threshold=0.5):
model.eval()
total_loss, total_acc, total_samples = 0.0, 0.0, 0
with torch.no_grad():
for x, y in tqdm(loader, desc=f"Epoch {epoch}/{num_epochs} [Val]", leave=False):
if x.dim() == 3:
```

```
x = x.unsqueeze(1)
x, y = x.to(device), y.to(device)
output = model(x)
if isinstance(output, tuple): output = output[0]
loss = criterion(output, y)
batch_size = x.size(0)
total_loss += loss.item() * batch_size
total_samples += batch_size
preds = (torch.sigmoid(output) > threshold).float()
total_acc += (preds == y).float().mean().item() * batch_size
return total_loss / total_samples, total_acc / total_samples



# Get predictions and labels from the model for evaluation/reporting
def get_predictions(model, loader, device, threshold=0.5):
model.eval()
all_preds, all_labels = [], []
with torch.no_grad():
for x, y in loader:
if x.dim() == 3:
x = x.unsqueeze(1)
x = x.to(device)
output = model(x)
if isinstance(output, tuple): output = output[0]
probs = torch.sigmoid(output)
preds = (probs > threshold).float().cpu().numpy()
all_preds.append(preds)
all_labels.append(y.cpu().numpy())
return np.concatenate(all_labels, axis=0), np.concatenate(all_preds, axis=0)



# training parameters and paths
best_params = {
"lr": 0.0001,
"dropout": 0.3,
"weight_decay": 0.0001,
"p_overlap": 0.1,
"epochs": 5
}

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
project_root = r"C:\Users\riley\Documents\Project-Echo\src\Prototypes"
domain_dirs = {
"env": os.path.join(project_root, "data", "binary_dataset_16k_mp3_mel", "environment"),
"animal": os.path.join(project_root, "data", "binary_dataset_16k_mp3_mel", "animal")
}

# Load model and prepare datasets
train_transform = Augmentation()
base_model = load_mn40_as_ext_model(device)
full_dataset = CombinedEchoDataset(domain_dirs, transform=None, p_overlap=0.0)
NUM_CLASSES = len(full_dataset.class_to_idx)

#Split dataset into train/val subsets
indices = list(range(len(full_dataset)))
random.shuffle(indices)
```

```
split = int(0.8 * len(full_dataset))
train_dataset = Subset(CombinedEchoDataset(domain_dirs, transform=train_transform,
p_overlap=best_params["p_overlap"]), indices[:split])
val_dataset = Subset(CombinedEchoDataset(domain_dirs, transform=None, p_overlap=0.0), indices[split:])
train_loader = DataLoader(train_dataset, batch_size=8, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=8)

# Determine input feature size for classifier
sample, _ = full_dataset[0]
sample = sample.unsqueeze(0).to(device) if sample.dim() == 3 else sample.to(device)
features = sample
for name, module in base_model.named_children():
if name == "classifier":
break
features = module(features)
channels = features.shape[1]

# Replace and initialize classifier head
base_model.classifier = nn.Sequential(
nn.AdaptiveAvgPool2d((1, 1)),
nn.Flatten(),
nn.Linear(channels, 256),
nn.ReLU(),
nn.Dropout(best_params["dropout"]),
nn.Linear(256, NUM_CLASSES)
)
for param in base_model.classifier.parameters():
param.requires_grad = True

# Loss and optimizer
criterion = nn.BCEWithLogitsLoss()
optimizer = optim.Adam(base_model.classifier.parameters(),
lr=best_params["lr"],
weight_decay=best_params["weight_decay"])



# Track loss and accuracy
train_losses, val_losses = [], []
train_accuracies, val_accuracies = [], []

# Training loop
for epoch in range(1, best_params["epochs"] + 1):
# Train
train_loss, train_acc = train_epoch(base_model, train_loader, epoch, best_params["epochs"], device, optimizer,
criterion)
# Validate
val_loss, val_acc = evaluate(base_model, val_loader, epoch, best_params["epochs"], device, criterion)
# Save metrics
train_losses.append(train_loss)
val_losses.append(val_loss)
train_accuracies.append(train_acc)
val_accuracies.append(val_acc)
# Print progress
print(f"Epoch {epoch}/{best_params['epochs']}:")
print(f" Train Loss: {train_loss:.4f} | Train Acc: {train_acc * 100:.2f}%")
print(f" Val Loss: {val_loss:.4f} | Val Acc: {val_acc * 100:.2f}%")
```

```
#Evaluation Report
true_labels, pred_labels = get_predictions(base_model, val_loader, device)
y_true = np.argmax(true_labels, axis=1)
y_pred = np.argmax(pred_labels, axis=1)

report = classification_report(y_true, y_pred, zero_division=0, output_dict=True)
print("\nSummary Classification Report:")
print(f"Accuracy: {report['accuracy']:.4f}")
print("Macro Avg - Precision: {:.4f}, Recall: {:.4f}, F1: {:.4f}".format(
report['macro avg']['precision'], report['macro avg']['recall'], report['macro avg']['f1-score']))
print("Weighted Avg - Precision: {:.4f}, Recall: {:.4f}, F1: {:.4f}".format(
report['weighted avg']['precision'], report['weighted avg']['recall'], report['weighted avg']['f1-score']))

# Confusion Matrix
plt.figure(figsize=(8, 6))
sns.heatmap(confusion_matrix(y_true, y_pred), annot=True, fmt="d", cmap="Blues",
xticklabels=full_dataset.class_to_idx.keys(),
yticklabels=full_dataset.class_to_idx.keys())
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.tight_layout()
plt.show()
```

```
C:\Users\riley\AppData\Local\Temp\ipykernel_35344\3632443034.py:126: FutureWarning: You are using `torch.load` with `weights_only=False` (the current default value), which uses the default pickle module implicitly. It is possible to construct malicious pickle data which will execute arbitrary code during unpickling (See https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for more details). In a future release, the default value for `weights_only` will be flipped to `True`. This limits the functions that could be executed during unpickling. Arbitrary objects will no longer be allowed to be loaded via this mode unless they are explicitly allowlisted by the user via `torch.serialization.add_safe_globals`. We recommend you start setting `weights_only=True` for any use case where you don't have full control of the loaded file. Please open an issue on GitHub for any issues related to this experimental feature. mel = torch.load(path)
MN( (features): Sequential( (0): ConvNormActivation( (0): Conv2d(1, 64, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False) (1): BatchNorm2d(64, eps=0.001, momentum=0.01, affine=True, track_running_stats=True) (2): Hardswish() ) (1): InvertedResidual( (block): Sequential( (0): ConvNormActivation( (0): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), groups=64, bias=False) (1): BatchNorm2d(64, eps=0.001, momentum=0.01, affine=True, track_running_stats=True) (2): ReLU(inplace=True) ) (1): ConvNormActivation( (0): Conv2d(64, 64, kernel_size=(1, 1), stride=(1, 1), bias=False) (1): BatchNorm2d(64, eps=0.001, momentum=0.01, affine=True, track_running_stats=True) ) ) ) (2): InvertedResidual( (block): Sequential( (0): ConvNormActivation( (0): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False) (1): BatchNorm2d(256, eps=0.001, momentum=0.01, affine=True, track_running_stats=True)
...
(4): Dropout(p=0.2, inplace=True) (5): Linear(in_features=5120, out_features=527, bias=True) ) )
```

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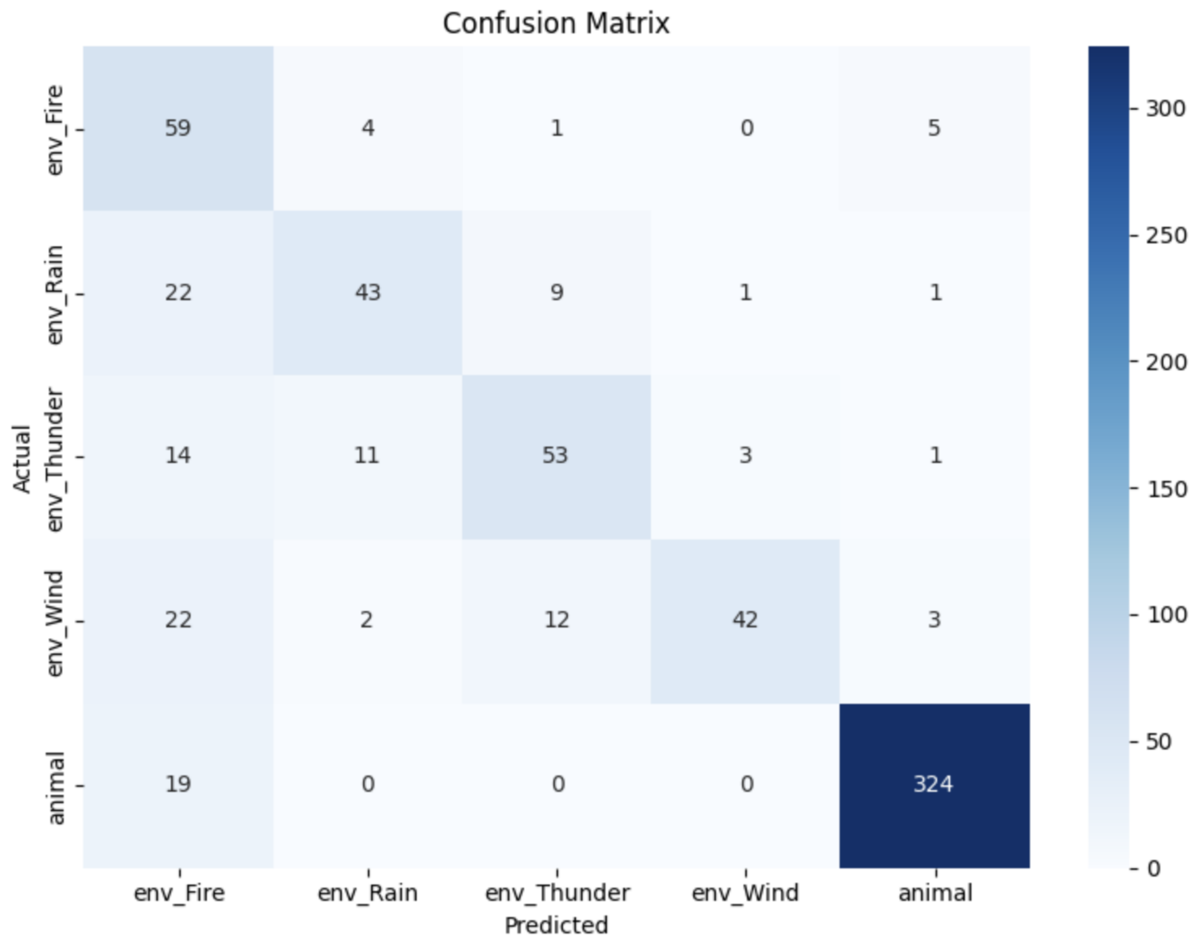
```
Epoch 1/5: Train Loss: 0.4081 | Train Acc: 85.35% Val Loss: 0.2473 | Val Acc: 90.14%
Epoch 2/5: Train Loss: 0.3053 | Train Acc: 87.46% Val Loss: 0.2043 | Val Acc: 92.50%
Epoch 3/5: Train Loss: 0.2867 | Train Acc: 88.45% Val Loss: 0.1886 | Val Acc: 93.00%
Epoch 4/5: Train Loss: 0.2695 | Train Acc: 88.83% Val Loss: 0.1779 | Val Acc: 93.09%
Epoch 5/5: Train Loss: 0.2641 | Train Acc: 88.95% Val Loss: 0.1724 | Val Acc: 93.46% Summary Classification Report: Accuracy: 0.8003 Macro Avg - Precision: 0.7481, Recall: 0.7061, F1: 0.7003 Weighted Avg - Precision: 0.8434, Recall: 0.8003, F1: 0.8065
```




```
from sklearn.metrics import confusion_matrix
from collections import defaultdict
import numpy as np

#Generate predictions
true_labels, pred_labels = get_predictions(base_model, val_loader, device=device)

# Convert multi-hot labels to single class predictions
true_single = np.argmax(true_labels, axis=1)
pred_single = np.argmax(pred_labels, axis=1)

# Confusion Matrix
cm = confusion_matrix(true_single, pred_single)

# Group-wise accuracy breakdown
classes = list(full_dataset.class_to_idx.keys())
idx_to_class = {i: c for c, i in full_dataset.class_to_idx.items()}

group_counts = defaultdict(lambda: {'correct': 0, 'total': 0})

for i in range(len(classes)):
class_name = idx_to_class[i]
group = class_name if class_name == "animal" else f"{class_name.split('_')[0]}_{class_name.split('_')[1]}"
correct = cm[i, i]
total = np.sum(cm[i])
group_counts[group]['correct'] += correct
```

```python
group_counts[group]['total'] += total

# Print results
print("\nClassification Summary by Class Group")
for group, stats in group_counts.items():
correct = stats['correct']
total = stats['total']
incorrect = total - correct
acc = correct / total if total > 0 else 0.0
print(f"{group:<12} | Total: {total:<4} | Correct: {correct:<4} | Misclassified: {incorrect:<4} | Acc: {acc:.2%}")
```

C:\Users\riley\AppData\Local\Temp\ipykernel_35344\3632443034.py:126: FutureWarning: You are using `torch.load` with `weights_only=False` (the current default value), which uses the default pickle module implicitly. It is possible to construct malicious pickle data which will execute arbitrary code during unpickling (See https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for more details). In a future release, the default value for `weights_only` will be flipped to `True`. This limits the functions that could be executed during unpickling. Arbitrary objects will no longer be allowed to be loaded via this mode unless they are explicitly allowlisted by the user via `torch.serialization.add_safe_globals`. We recommend you start setting `weights_only=True` for any use case where you don't have full control of the loaded file. Please open an issue on GitHub for any issues related to this experimental feature. mel = torch.load(path)
Classification Summary by Class Group env_Fire | Total: 69 | Correct: 59 | Misclassified: 10 | Acc: 85.51% env_Rain | Total: 76 | Correct: 43 | Misclassified: 33 | Acc: 56.58% env_Thunder | Total: 82 | Correct: 53 | Misclassified: 29 | Acc: 64.63% env_Wind | Total: 81 | Correct: 42 | Misclassified: 39 | Acc: 51.85% animal | Total: 343 | Correct: 324 | Misclassified: 19 | Acc: 94.46%

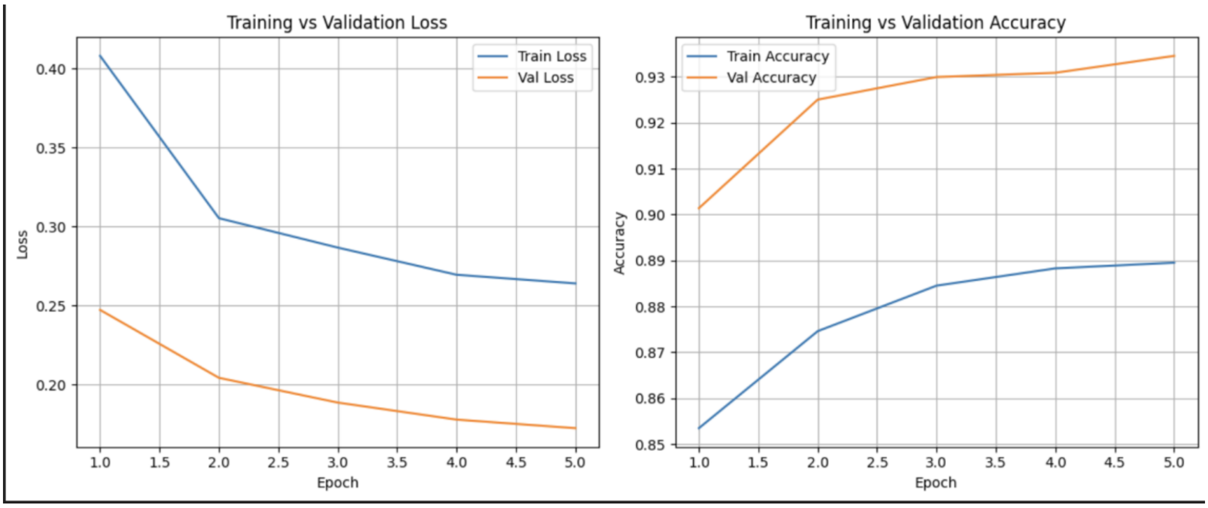
```python
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sns
import numpy as np

# Plot thr Loss and Accuracy Curves
epochs = list(range(1, best_params["epochs"] + 1))
plt.figure(figsize=(12, 5))

# Loss plot
plt.subplot(1, 2, 1)
plt.plot(epochs, train_losses, label="Train Loss")
plt.plot(epochs, val_losses, label="Val Loss")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.title("Training vs Validation Loss")
plt.legend()
plt.grid(True)

# Accuracy plot
plt.subplot(1, 2, 2)
plt.plot(epochs, train_accuracies, label="Train Accuracy")
plt.plot(epochs, val_accuracies, label="Val Accuracy")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.title("Training vs Validation Accuracy")
plt.legend()
plt.grid(True)
```

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



Performance Evaluation

The extended audio classification model was evaluated using validation datasets across both animal and environmental sound classes. The overall model achieved a validation accuracy of **93.46%** by the final epoch, with a weighted F1-score of **0.8065**.

When broken down by class groups:

- **Animal sounds** showed strong performance with an overall accuracy of **94.46%** (343 total samples, 324 correctly classified).
- Among environmental categories:
    - **Fire** events were classified accurately (**85.51%**).
    - **Thunder** showed moderate performance (**64.63%**).
    - **Rain** had a lower accuracy (**56.58%**).
    - **Wind** was the most challenging category, with an accuracy of only **51.85%**.

These results are visualized through both the classification report and the confusion matrix included in the evaluation.

Improvements and Observations

The model's performance on **animal sounds was excellent**, likely due to the more consistent acoustic patterns and cleaner datasets. In contrast, **environmental sounds**, especially rain and wind, had lower classification accuracy. This is potentially due to overlapping frequency characteristics or variability in the recordings.

To improve future performance:

- Collecting more diverse and higher-quality samples for rain and wind events could reduce noise and increase model generalization.
- Augmentation techniques could be refined specifically for environmental sounds.
- Consider fine-tuning the model further on underperforming classes or experimenting with class-specific thresholds.

Expanded Use Cases

In Sprint 2, the original animal-focused classification system was extended to include multiple environmental event categories, significantly broadening the model's utility. These new use cases include:

- Fire Event Detection: Identifying fire-related acoustic signals can assist in early warning systems for bushfire-prone regions.
- Rain and Thunderstorm Detection: Classifying rain and thunder sounds allows the system to monitor changing weather conditions, which can be useful for agriculture, flood warning systems, and infrastructure maintenance.
- Wind Detection: Capturing wind noise patterns enables environmental sensors to account for storm intensity or coastal weather fluctuations.

With the inclusion of these non-animal classes, the system now serves a dual purpose:

1. Wildlife Monitoring – continuing its role in biodiversity and conservation research.
2. Environmental Surveillance – enabling real-time acoustic monitoring for natural disaster management and climate-related events.

This expansion transforms the model into a more comprehensive solution for Eco acoustic sensing, enhancing its application potential in both scientific and operational environments.