

BitePulse AI - Modeling: RGB 3D CNN vs Hyperband 3D CNN

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Introduction

In this notebook we work with RGB clips instead of pose:

- Load window level labels and frame index for the EatSense videos.
- Build a **PyTorch 3D CNN baseline** that takes short RGB clips and predicts intake vs non intake.
- Build a **Keras 3D CNN** and use **Keras Tuner Hyperband** to search over architecture and training hyperparameters.
- Evaluate both models with exactly the same **window level metrics and plots** (confusion matrix, ROC, PR), so we can compare them and with the pose TCN.

```
# Mount Google Drive:
```

```
from google.colab import drive
drive.mount('/content/drive')
```

Mounted at /content/drive

```
!pip install -q keras-tuner
```

```
0.0/129.4 kB ? eta -:--:--
129.4/129.4 kB 4.2 MB/s eta
0:00:00
```

```
import os, sys, math, json, time, random, logging, re
from pathlib import Path
from typing import Dict, Any, Optional
```

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```
from PIL import Image
import subprocess, shutil
```

```
import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import Dataset, DataLoader,
WeightedRandomSampler
```

```
import tensorflow as tf
import keras_tuner as kt
```

```

from sklearn.metrics import (
    precision_recall_curve, roc_curve, roc_auc_score,
    average_precision_score,
    accuracy_score, precision_score, recall_score, f1_score,
    balanced_accuracy_score, matthews_corrcoef, confusion_matrix, auc,
    classification_report
)

from tqdm.auto import tqdm
from contextlib import nullcontext

plt.rcParams["figure.dpi"] = 120

POSE_FEATS_PATH =
Path("/content/drive/MyDrive/eatsense/windows/pose_feats.parquet")

pose_feats = pd.read_parquet(POSE_FEATS_PATH)
print("pose_feats shape:", pose_feats.shape)
pose_feats.head()

pose_feats shape: (98582, 18)

{"summary":{"\n  \"name\": \"pose_feats\",\n  \"rows\": 98582,\n  \"fields\": [\n    {\n      \"column\": \"key\",\n      \"properties\": {\n        \"dtype\": \"category\",\n        \"num_unique_values\": 135,\n        \"samples\": [\n          \"20230110_114618\",\n          \"20221013_131254\",\n          \"20230110_134822\",\n          ],\n        \"semantic_type\": \"\",\n        \"description\": \"\",\n        \"split\": \"train\",\n        \"properties\": {\n          \"dtype\": \"category\",\n          \"num_unique_values\": 3,\n          \"samples\": [\n            \"val\",\n            \"test\",\n            ],\n          \"semantic_type\": \"\",\n          \"description\": \"\",\n          },\n        {\n          \"column\": \"win_id\",\n          \"properties\": {\n            \"dtype\": \"number\",\n            \"std\": 388,\n            \"min\": 0,\n            \"max\": 2072,\n            \"num_unique_values\": 2073,\n            \"samples\": [\n              1498,\n              1333,\n              1808,\n            ],\n            \"semantic_type\": \"\",\n            \"description\": \"\",\n            \"start_sec\": \"\",\n            \"properties\": {\n              \"dtype\": \"number\",\n              \"std\": 194.03245452862419,\n              \"min\": 0.0,\n              \"max\": 1036.0,\n              \"num_unique_values\": 2073,\n              \"samples\": [\n                749.0,\n                666.5,\n                904.0,\n              ],\n              \"semantic_type\": \"\",\n              \"description\": \"\",\n            },\n            {\n          \"column\": \"end_sec\",\n          \"properties\": {\n            \"dtype\": \"number\",\n            \"std\": 194.03245452862419,\n            \"min\": 2.0,\n            \"max\": 1038.0,\n            \"num_unique_values\": 2073,\n            \"samples\": [\n              751.0,\n              668.5,\n              906.0,\n            ],\n          }

```

```

\"semantic_type\": \"\", \n      \"description\": \"\" \n    } \n  }, \n  { \n    \"column\": \"label\", \n    \"properties\": { \n      \"dtype\": \"number\", \n      \"std\": 0, \n      \"min\": 0, \n      \"max\": 1, \n      \"num_unique_values\": 2, \n      \"samples\": [ \n        1, \n        0 \n      ], \n      \"semantic_type\": \"\", \n      \"description\": \"\" \n    } \n  }, \n  { \n    \"column\": \"rw_speed_mean\", \n    \"properties\": { \n      \"dtype\": \"number\", \n      \"std\": 24.33982188285745, \n      \"min\": 0.00801266320426811, \n      \"max\": 1105.2935333031576, \n      \"num_unique_values\": 98582, \n      \"samples\": [ \n        30.13531184750308, \n        22.075381546873665 \n      ], \n      \"semantic_type\": \"\", \n      \"description\": \"\" \n    } \n  }, \n  { \n    \"column\": \"rw_speed_max\", \n    \"properties\": { \n      \"dtype\": \"number\", \n      \"std\": 110.32374073704662, \n      \"min\": 0.02220507721368822, \n      \"max\": 6614.9512166947, \n      \"num_unique_values\": 57853, \n      \"samples\": [ \n        9.455119186054414, \n        10.018440956556741 \n      ], \n      \"semantic_type\": \"\", \n      \"description\": \"\" \n    } \n  }, \n  { \n    \"column\": \"rw_head_min\", \n    \"properties\": { \n      \"dtype\": \"number\", \n      \"std\": 39.09028959178826, \n      \"min\": 0.5873013515401203, \n      \"max\": 271.81711304963875, \n      \"num_unique_values\": 57975, \n      \"samples\": [ \n        118.0655045994019, \n        52.37232298782691 \n      ], \n      \"semantic_type\": \"\", \n      \"description\": \"\" \n    } \n  }, \n  { \n    \"column\": \"rw_path\", \n    \"properties\": { \n      \"dtype\": \"number\", \n      \"std\": 51.25176255611852, \n      \"min\": 0.01940676395299922, \n      \"max\": 2127.9823211899215, \n      \"num_unique_values\": 98582, \n      \"samples\": [ \n        59.134021145496476, \n        48.0751711089649 \n      ], \n      \"semantic_type\": \"\", \n      \"description\": \"\" \n    } \n  }, \n  { \n    \"column\": \"lw_speed_mean\", \n    \"properties\": { \n      \"dtype\": \"number\", \n      \"std\": 24.452837158993937, \n      \"min\": 5.573618882666242e-13, \n      \"max\": 928.8229979693119, \n      \"num_unique_values\": 98582, \n      \"samples\": [ \n        18.55339536937793, \n        1.830677739083311 \n      ], \n      \"semantic_type\": \"\", \n      \"description\": \"\" \n    } \n  }, \n  { \n    \"column\": \"lw_speed_max\", \n    \"properties\": { \n      \"dtype\": \"number\", \n      \"std\": 122.74647351784876, \n      \"min\": 6.431098710768743e-13, \n      \"max\": 6604.368538089087, \n      \"num_unique_values\": 59144, \n      \"samples\": [ \n        63.792844095754475, \n        12.904262946985533 \n      ], \n      \"semantic_type\": \"\", \n      \"description\": \"\" \n    } \n  }, \n  { \n    \"column\": \"lw_head_min\", \n    \"properties\": { \n      \"dtype\": \"number\", \n      \"std\": 41.098975018434494, \n      \"min\": 0.0, \n      \"max\": 294.5214109513494, \n      \"num_unique_values\": 59372, \n

```

```

\"samples\": [\n          103.79806326896166,\n          169.5701838712913\n        ],\n        \"semantic_type\": \"\",\n        \"description\": \"\",\n        \"column\": \"lw_path\",\n        \"properties\": {\n          \"dtype\": \"number\",\n          \"std\": 58.380739269269306,\n          \"min\": 0.0,\n          \"max\": 2479.686875105099,\n          \"num_unique_values\": 98575,\n          \"samples\": [\n            18.687669860059938,\n            10.369406213105538\n          ],\n          \"semantic_type\": \"\",\n          \"description\": \"\",\n          \"column\": \"re_angle_mean\",\n          \"properties\": {\n            \"dtype\": \"number\",\n            \"std\": 41.810937801640385,\n            \"min\": 0.3569787476870709,\n            \"max\": 179.8201187446251,\n            \"num_unique_values\": 98582,\n            \"samples\": [\n              53.94185320087705,\n              63.571043576705115\n            ],\n            \"semantic_type\": \"\",\n            \"description\": \"\",\n            \"column\": \"re_angle_std\",\n            \"properties\": {\n              \"dtype\": \"number\",\n              \"std\": 15.313709858756834,\n              \"min\": 0.006132719445273099,\n              \"max\": 87.05938228479292,\n              \"num_unique_values\": 98582,\n              \"samples\": [\n                11.687669535127446,\n                16.99852090849505\n              ],\n              \"semantic_type\": \"\",\n              \"description\": \"\",\n              \"column\": \"le_angle_mean\",\n              \"properties\": {\n                \"dtype\": \"number\",\n                \"std\": 42.150906378037746,\n                \"min\": 0.13646436532583334,\n                \"max\": 179.90475920540828,\n                \"num_unique_values\": 98582,\n                \"samples\": [\n                  60.94813611973014,\n                  98.9314811702009\n                ],\n                \"semantic_type\": \"\",\n                \"description\": \"\",\n                \"column\": \"le_angle_std\",\n                \"properties\": {\n                  \"dtype\": \"number\",\n                  \"std\": 11.510725091381751,\n                  \"min\": 0.010677667435140608,\n                  \"max\": 84.96826767832528,\n                  \"num_unique_values\": 98582,\n                  \"samples\": [\n                    21.94339713867533,\n                    3.5710967735075645\n                  ],\n                  \"semantic_type\": \"\",\n                  \"description\": \"\"\n                }\n              }\n            }\n          }\n        },\n        \"type\": \"dataframe\", \"variable_name\": \"pose_feats\"}

```

```
cols_needed = ["key", "start_sec", "end_sec", "label", "split"]
```

```

windows_df = (
    pose_feats[cols_needed]
    .drop_duplicates()
    .reset_index(drop=True)
)

```

```
print("windows_df shape:", windows_df.shape)
```

```
windows_df["split"].value_counts()
```

```
windows_df shape: (98582, 5)
```

```

split
train      62568
val        21184
test       14830
Name: count, dtype: int64

windows_df.head()

{"summary":{"\n  \"name\": \"windows_df\",\n  \"rows\": 98582,\n  \"fields\": [\n    {\n      \"column\": \"key\",\n      \"properties\": {\n        \"dtype\": \"category\",\n        \"num_unique_values\": 135,\n        \"samples\": [\n          \"20230110_114618\",\n          \"20221013_131254\",\n          \"20230110_134822\",\n          ],\n        \"semantic_type\": \"\",\n        \"description\": \"\",\n        \"start_sec\": 0.0,\n        \"properties\": {\n          \"dtype\": \"number\",\n          \"std\": 194.03245452862419,\n          \"min\": 0.0,\n          \"max\": 1036.0,\n          \"num_unique_values\": 2073,\n          \"samples\": [\n            749.0,\n            666.5,\n            904.0\n          ],\n          \"semantic_type\": \"\",\n          \"description\": \"\",\n          \"column\": \"end_sec\",\n          \"properties\": {\n            \"dtype\": \"number\",\n            \"std\": 194.03245452862419,\n            \"min\": 2.0,\n            \"max\": 1038.0,\n            \"num_unique_values\": 2073,\n            \"samples\": [\n              751.0,\n              668.5,\n              906.0\n            ],\n            \"semantic_type\": \"\",\n            \"description\": \"\",\n            \"column\": \"label\",\n            \"properties\": {\n              \"dtype\": \"number\",\n              \"std\": 0,\n              \"min\": 0,\n              \"max\": 1,\n              \"num_unique_values\": 2,\n              \"samples\": [\n                1,\n                0\n              ],\n              \"semantic_type\": \"\",\n              \"description\": \"\",\n              \"column\": \"split\",\n              \"properties\": {\n                \"dtype\": \"category\",\n                \"num_unique_values\": 3,\n                \"samples\": [\n                  \"train\",\n                  \"val\"\n                ],\n                \"semantic_type\": \"\",\n                \"description\": \"\"\n              }\n            }\n          ]\n        },\n        \"type\": \"dataframe\", \"variable_name\": \"windows_df\"}

```

Extract RGB Frames to Disk

Scan the EatSense RGB videos, match each labeled `key` to its source clip, and use `ffmpeg` to extract center-cropped 224x224 PNG frames at 15 FPS into `FRAMES_DIR` for the train/val/test splits.

```

# Path:
VIDEO_ROOTS = [
    Path("/content/drive/MyDrive/eatsense/rgb/deepfaked")
]

```

```

FRAMES_DIR = Path("/content/drive/MyDrive/eatsense/frames")
FRAMES_DIR.mkdir(parents=True, exist_ok=True)

# Splits to process:
SPLITS_TO_PROCESS = {"train", "val", "test"}

# Frame extraction settings:
FPS_TARGET = 15
TARGET_W, TARGET_H = 224, 224 # standard size for 3D-CNN inputs:
VIDEO_EXTS = {".mp4", ".mov", ".mkv", ".avi", ".m4v"}

split_col = windows_df["split"].astype(str).str.lower()
keys_needed = (
    windows_df.loc[split_col.isin(SPLITS_TO_PROCESS), "key"]
    .dropna().astype(str).unique().tolist()
)
print(f"Keys to process: {len(keys_needed)}")

# Index available videos once:
def all_videos_under(roots):
    out = []
    for r in roots:
        if not r.exists():
            continue
        for p in r.rglob("*"):
            if p.is_file() and p.suffix.lower() in VIDEO_EXTS:
                out.append(p)
    return out

videos = all_videos_under(VIDEO_ROOTS)
print(f"Found videos: {len(videos)}")
print("Sample:", [str(v) for v in videos[:3]])

# Heuristic matcher: map each key -> video path:
def match_video_for_key(k: str):
    k_low = k.lower()
    # exact stem match:
    for v in videos:
        if v.stem.lower() == k_low:
            return v
    # relaxed match (containment / prefix):
    for v in videos:
        stem = v.stem.lower()
        if (k_low in stem) or (stem in k_low) or
        stem.startswith(k_low) or k_low.startswith(stem):
            return v
    return None

key2vid = {k: match_video_for_key(k) for k in keys_needed}
missing = [k for k, v in key2vid.items() if v is None]

```

```

print(f"Matched: {sum(v is not None for v in key2vid.values())} |
Missing: {len(missing)}")
if missing:
    print("Missing examples (first 10):", missing[:10])

# Extract frames with ffmpeg (fps + center-crop square + resize to
TARGET_WxTARGET_H):
def extract_frames(video_path: Path, out_dir: Path, fps: int | None =
FPS_TARGET):
    out_dir.mkdir(parents=True, exist_ok=True)
    # Skip if already extracted (has at least one image)
    if any(out_dir.iterdir()):
        return "skip"

    vf = []
    if fps is not None:
        vf.append(f"fps={fps}")
    # center-crop shortest side to square, then high-quality resize:
    vf.append("crop='min(in_w,in_h)':'min(in_w,in_h)'")
    vf.append(f"scale={TARGET_W}:{TARGET_H}:flags=lanczos")

    cmd = [
        "ffmpeg", "-y",
        "-i", str(video_path),
        "-loglevel", "error",
        "-vf", ",".join(vf),
        str(out_dir / "%06d.png"),
    ]
    subprocess.run(cmd, check=True)
    return "ok"

ok, skipped, miss = 0, 0, 0
for k, vid in key2vid.items():
    if vid is None:
        miss += 1
        continue
    out = FRAMES_DIR / k
    try:
        status = extract_frames(vid, out, FPS_TARGET)
        ok += (status == "ok")
        skipped += (status == "skip")
        if status == "ok":
            cnt = sum(1 for _ in out.iterdir())
            print(f"[new] {k}: {cnt} frames -> {out}")
    except Exception as e:
        print(f"[error] {k} <- {vid} :: {e}")

print(f"\nSummary -> new: {ok}, skipped(already there): {skipped},
missing video: {miss}")
print("Frames root:", FRAMES_DIR)

```

```
Keys to process: 135
Found videos: 135
Sample:
['/content/drive/MyDrive/eatsense/rgb/deepfaked/20210518_230219_anonym
ized.mp4',
'/content/drive/MyDrive/eatsense/rgb/deepfaked/20210523_202300_anonymi
zed.mp4',
'/content/drive/MyDrive/eatsense/rgb/deepfaked/20210529_150552_anonymi
zed.mp4']
Matched: 135 | Missing: 0
[new] 20210518_230219: 3668 frames ->
/content/drive/MyDrive/eatsense/frames/20210518_230219
[new] 20210523_202300: 5405 frames ->
/content/drive/MyDrive/eatsense/frames/20210523_202300
[new] 20210529_150552: 7502 frames ->
/content/drive/MyDrive/eatsense/frames/20210529_150552
[new] 20210529_153708: 1397 frames ->
/content/drive/MyDrive/eatsense/frames/20210529_153708
[new] 20210530_153343: 5084 frames ->
/content/drive/MyDrive/eatsense/frames/20210530_153343
[new] 20210531_150448: 5475 frames ->
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[new] 20210603_130948: 7740 frames ->
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[new] 20210605_155355: 3675 frames ->
/content/drive/MyDrive/eatsense/frames/20210605_155355
[new] 20210606_154234: 4892 frames ->
/content/drive/MyDrive/eatsense/frames/20210606_154234
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/content/drive/MyDrive/eatsense/frames/20210607_152559
[new] 20210607_154140: 2577 frames ->
/content/drive/MyDrive/eatsense/frames/20210607_154140
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/content/drive/MyDrive/eatsense/frames/20210609_215756
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/content/drive/MyDrive/eatsense/frames/20210610_144155
[new] 20210610_230110: 8582 frames ->
/content/drive/MyDrive/eatsense/frames/20210610_230110
[new] 20210616_163847: 4382 frames ->
/content/drive/MyDrive/eatsense/frames/20210616_163847
[new] 20210616_170258: 3221 frames ->
/content/drive/MyDrive/eatsense/frames/20210616_170258
```


[new] 20210617_165755: 6572 frames ->
/content/drive/MyDrive/eatsense/frames/20210617_165755
[new] 20210617_224119: 5445 frames ->
/content/drive/MyDrive/eatsense/frames/20210617_224119
[new] 20210620_150313: 8550 frames ->
/content/drive/MyDrive/eatsense/frames/20210620_150313
[new] 20210620_230306: 2222 frames ->
/content/drive/MyDrive/eatsense/frames/20210620_230306
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/content/drive/MyDrive/eatsense/frames/20220812_121833
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/content/drive/MyDrive/eatsense/frames/20220812_141747
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/content/drive/MyDrive/eatsense/frames/20221013_132443
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/content/drive/MyDrive/eatsense/frames/20221013_134216

[new] 20221013_135010: 5693 frames ->
/content/drive/MyDrive/eatsense/frames/20221013_135010
[new] 20221013_142709: 3020 frames ->
/content/drive/MyDrive/eatsense/frames/20221013_142709
[new] 20221013_143133: 1862 frames ->
/content/drive/MyDrive/eatsense/frames/20221013_143133
[new] 20221014_113751: 8606 frames ->
/content/drive/MyDrive/eatsense/frames/20221014_113751
[new] 20221014_114952: 5195 frames ->
/content/drive/MyDrive/eatsense/frames/20221014_114952
[new] 20221014_120757: 12842 frames ->
/content/drive/MyDrive/eatsense/frames/20221014_120757
[new] 20221014_122331: 12537 frames ->
/content/drive/MyDrive/eatsense/frames/20221014_122331
[new] 20221014_124303: 9081 frames ->
/content/drive/MyDrive/eatsense/frames/20221014_124303
[new] 20221014_125502: 14012 frames ->
/content/drive/MyDrive/eatsense/frames/20221014_125502
[new] 20221014_140942: 5082 frames ->
/content/drive/MyDrive/eatsense/frames/20221014_140942
[new] 20221014_141711: 9885 frames ->
/content/drive/MyDrive/eatsense/frames/20221014_141711
[new] 20221014_143649: 3719 frames ->
/content/drive/MyDrive/eatsense/frames/20221014_143649
[new] 20221014_144233: 9524 frames ->
/content/drive/MyDrive/eatsense/frames/20221014_144233
[new] 20230109_114530: 3807 frames ->
/content/drive/MyDrive/eatsense/frames/20230109_114530
[new] 20230109_115040: 4067 frames ->
/content/drive/MyDrive/eatsense/frames/20230109_115040
[new] 20230109_115716: 4010 frames ->
/content/drive/MyDrive/eatsense/frames/20230109_115716
[new] 20230109_120255: 2756 frames ->
/content/drive/MyDrive/eatsense/frames/20230109_120255
[new] 20230109_123622: 2634 frames ->
/content/drive/MyDrive/eatsense/frames/20230109_123622
[new] 20230109_124022: 4347 frames ->
/content/drive/MyDrive/eatsense/frames/20230109_124022
[new] 20230109_124729: 3015 frames ->
/content/drive/MyDrive/eatsense/frames/20230109_124729
[new] 20230109_125206: 1452 frames ->
/content/drive/MyDrive/eatsense/frames/20230109_125206
[new] 20230109_132632: 3518 frames ->
/content/drive/MyDrive/eatsense/frames/20230109_132632
[new] 20230109_133112: 3342 frames ->
/content/drive/MyDrive/eatsense/frames/20230109_133112
[new] 20230109_133609: 3630 frames ->
/content/drive/MyDrive/eatsense/frames/20230109_133609
[new] 20230109_134123: 3831 frames ->
/content/drive/MyDrive/eatsense/frames/20230109_134123

[new] 20230110_113650: 1547 frames ->
/content/drive/MyDrive/eatsense/frames/20230110_113650
[new] 20230110_113938: 1938 frames ->
/content/drive/MyDrive/eatsense/frames/20230110_113938
[new] 20230110_114318: 1748 frames ->
/content/drive/MyDrive/eatsense/frames/20230110_114318
[new] 20230110_114618: 2303 frames ->
/content/drive/MyDrive/eatsense/frames/20230110_114618
[new] 20230110_122933: 2673 frames ->
/content/drive/MyDrive/eatsense/frames/20230110_122933
[new] 20230110_123332: 2183 frames ->
/content/drive/MyDrive/eatsense/frames/20230110_123332
[new] 20230110_123733: 2720 frames ->
/content/drive/MyDrive/eatsense/frames/20230110_123733
[new] 20230110_124143: 2516 frames ->
/content/drive/MyDrive/eatsense/frames/20230110_124143
[new] 20230110_133309: 4886 frames ->
/content/drive/MyDrive/eatsense/frames/20230110_133309
[new] 20230110_133944: 6257 frames ->
/content/drive/MyDrive/eatsense/frames/20230110_133944
[new] 20230110_134822: 4220 frames ->
/content/drive/MyDrive/eatsense/frames/20230110_134822
[new] 20230110_135409: 5303 frames ->
/content/drive/MyDrive/eatsense/frames/20230110_135409
[new] 20230111_114057: 2486 frames ->
/content/drive/MyDrive/eatsense/frames/20230111_114057
[new] 20230111_114640: 2309 frames ->
/content/drive/MyDrive/eatsense/frames/20230111_114640
[new] 20230111_115239: 2817 frames ->
/content/drive/MyDrive/eatsense/frames/20230111_115239
[new] 20230111_115909: 2277 frames ->
/content/drive/MyDrive/eatsense/frames/20230111_115909
[new] 20230124_121223: 3137 frames ->
/content/drive/MyDrive/eatsense/frames/20230124_121223
[new] 20230124_121646: 2793 frames ->
/content/drive/MyDrive/eatsense/frames/20230124_121646
[new] 20230124_122123: 4197 frames ->
/content/drive/MyDrive/eatsense/frames/20230124_122123
[new] 20230124_122705: 2825 frames ->
/content/drive/MyDrive/eatsense/frames/20230124_122705
[new] 20230124_130607: 3989 frames ->
/content/drive/MyDrive/eatsense/frames/20230124_130607
[new] 20230124_131109: 4712 frames ->
/content/drive/MyDrive/eatsense/frames/20230124_131109
[new] 20230124_131740: 4110 frames ->
/content/drive/MyDrive/eatsense/frames/20230124_131740
[new] 20230124_132312: 3981 frames ->
/content/drive/MyDrive/eatsense/frames/20230124_132312
[new] 20230124_135539: 2862 frames ->
/content/drive/MyDrive/eatsense/frames/20230124_135539

```

[new] 20230124_135936: 3257 frames ->
/content/drive/MyDrive/eatsense/frames/20230124_135936
[new] 20230124_140432: 5501 frames ->
/content/drive/MyDrive/eatsense/frames/20230124_140432
[new] 20230124_141139: 3078 frames ->
/content/drive/MyDrive/eatsense/frames/20230124_141139
[new] 20230125_140902: 4277 frames ->
/content/drive/MyDrive/eatsense/frames/20230125_140902
[new] 20230125_141519: 3819 frames ->
/content/drive/MyDrive/eatsense/frames/20230125_141519
[new] 20230125_142103: 3722 frames ->
/content/drive/MyDrive/eatsense/frames/20230125_142103
[new] 20230125_142618: 2633 frames ->
/content/drive/MyDrive/eatsense/frames/20230125_142618
[new] 20230127_120259: 2582 frames ->
/content/drive/MyDrive/eatsense/frames/20230127_120259
[new] 20230127_120640: 3561 frames ->
/content/drive/MyDrive/eatsense/frames/20230127_120640
[new] 20230127_121212: 4748 frames ->
/content/drive/MyDrive/eatsense/frames/20230127_121212
[new] 20230127_121834: 3458 frames ->
/content/drive/MyDrive/eatsense/frames/20230127_121834
[new] 20230131_130800: 3626 frames ->
/content/drive/MyDrive/eatsense/frames/20230131_130800
[new] 20230131_131313: 4616 frames ->
/content/drive/MyDrive/eatsense/frames/20230131_131313
[new] 20230131_131949: 6122 frames ->
/content/drive/MyDrive/eatsense/frames/20230131_131949
[new] 20230131_132739: 7133 frames ->
/content/drive/MyDrive/eatsense/frames/20230131_132739

```

```

Summary -> new: 135, skipped(already there): 0, missing video: 0
Frames root: /content/drive/MyDrive/eatsense/frames

```

```

test_path =
Path("/content/drive/MyDrive/eatsense/frames/20210816_191136/005820.png")

```

```

print(test_path, "exists:", test_path.exists())

```

```

/content/drive/MyDrive/eatsense/frames/20210816_191136/005820.png
exists: True

```

```

FRAMES_DIR = Path("/content/drive/MyDrive/eatsense/frames")

```

```

dirs = [p for p in FRAMES_DIR.iterdir() if p.is_dir()]
print("Folders in FRAMES_DIR:", len(dirs))

```

```

keys_on_disk = {d.name for d in dirs}
keys_in_labels = set(keys_needed)

```

```

print("Missing on disk:", keys_in_labels - keys_on_disk)
print("Extra on disk:", keys_on_disk - keys_in_labels)

Folders in FRAMES_DIR: 135
Missing on disk: set()
Extra on disk: set()

rows = []
for d in sorted(dirs, key=lambda p: p.name):
    n_png = sum(1 for _ in d.glob("*.png"))
    rows.append({"key": d.name, "n_frames": n_png})

frames_summary = pd.DataFrame(rows)
frames_summary.head()

{"summary":{"\n  \"name\": \"frames_summary\",\n  \"rows\": 135,\n  \"fields\": [\n    {\n      \"column\": \"key\",\n      \"properties\": {\n        \"dtype\": \"string\",\n        \"num_unique_values\": 135,\n        \"samples\": [\n          \"20230110_114618\",\n          \"20221013_131254\",\n          \"20230110_134822\",\n          ],\n        \"semantic_type\": \"\",\n        \"description\": \"\",\n        \"n_frames\": 1,\n        \"properties\": {\n          \"dtype\": \"number\",\n          \"std\": 3090,\n          \"min\": 1142,\n          \"max\": 15578,\n          \"num_unique_values\": 133,\n          \"samples\": [\n            4532,\n            3020,\n            7802\n          ],\n          \"semantic_type\": \"\",\n          \"description\": \"\"\n        }\n      }\n    ]\n  }","type":"dataframe","variable_name":"frames_summary"}

# Now let's look at few examples to confirm the extrctated frames:
CLIP_FPS = 15.0

# Find keys that have BOTH intake (1) and non-intake (0) windows:
keys_with_pos = set(windows_df.loc[windows_df["label"] == 1,
"key"].astype(str))
keys_with_neg = set(windows_df.loc[windows_df["label"] == 0,
"key"].astype(str))
candidate_keys = sorted(list(keys_with_pos & keys_with_neg))

print("Candidate keys with both classes:", len(candidate_keys))
if not candidate_keys:
    raise RuntimeError("No key has both intake and non-intake
windows.")

key = candidate_keys[0]
print("Using key:", key)

# Helper
def frame_path_for_time(key: str, t_sec: float, fps: float =
CLIP_FPS):
    kdir = FRAMES_DIR / str(key)

```

```

files = sorted(kdir.glob("*.png"))
if not files:
    raise RuntimeError(f"No PNG frames for key={key} in {kdir}")
n = len(files)
idx = int(round(t_sec * fps))
idx = max(0, min(n - 1, idx))
return files[idx]

# Filter windows for this key and select 5 intake + 5 non-intake:
df_key = windows_df[windows_df["key"].astype(str) == key].copy()

pos_rows = df_key[df_key["label"] == 1].head(5)
neg_rows = df_key[df_key["label"] == 0].head(5)

print(f"Found {len(pos_rows)} intake and {len(neg_rows)} non-intake
windows for key {key}")

if len(pos_rows) < 5 or len(neg_rows) < 5:
    raise RuntimeError("Not enough intake or non-intake windows (need
at least 5 of each).")

# Collect images:
img_infos = [] # list of (PIL.Image, title)

# First 5 intake:
for _, r in pos_rows.iterrows():
    t_mid = (float(r["start_sec"]) + float(r["end_sec"])) / 2.0
    p = frame_path_for_time(key, t_mid)
    img = Image.open(p).convert("RGB")
    img_infos.append((img, f"Intake @ {t_mid:.2f}s"))

# Then 5 non-intake:
for _, r in neg_rows.iterrows():
    t_mid = (float(r["start_sec"]) + float(r["end_sec"])) / 2.0
    p = frame_path_for_time(key, t_mid)
    img = Image.open(p).convert("RGB")
    img_infos.append((img, f"Non-intake @ {t_mid:.2f}s"))

# Plot as 2 rows x 5 columns:
rows, cols = 2, 5
n_imgs = len(img_infos)
assert n_imgs == rows * cols, f"Expected 10 images, got {n_imgs}"

fig, axes = plt.subplots(rows, cols, figsize=(cols * 3, rows * 3))

for idx, (img, title) in enumerate(img_infos):
    r = idx // cols
    c = idx % cols
    ax = axes[r, c]
    ax.imshow(img)

```

```
ax.set_title(title, fontsize=8)
ax.axis("off")
```

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

Candidate keys with both classes: 37

Using key: 20210523_202300

Found 5 intake and 5 non-intake windows for key 20210523_202300



Baseline RGB 3D-CNN Modeling

Ste up configuration:

```
ROOT      = Path("/content/drive/MyDrive/eatsense")
LABELS_DIR = ROOT / "labels_v1"
FRAMES_DIR = ROOT / "frames"
CKPT_DIR  = ROOT / "checkpoints_rgb"
LOG_DIR   = ROOT / "logs_rgb"

IMG_EXT   = ".png"
FRAME_PAD = 6
```

```
for d in [CKPT_DIR, LOG_DIR]:
    d.mkdir(parents=True, exist_ok=True)
```

```
CONFIG: Dict[str, Any] = {
    "seed": 1981,
    "num_workers": 2,
    "pin_memory": True,
    "persistent_workers": True,
    # training
    "epochs": 10,
```



```

    "batch_size": 8,
    "lr": 3e-4,
    "weight_decay": 1e-5,
    "pos_class_weight": 2.0,      # BCE pos_weight
    "amp": True,
    "amp_dtype": "bf16",         # "bf16" or "fp16"
    # RGB clip settings
    "clip_len": 16,              # frames per window
    "img_size": 112,             # 112x112 input to 3D CNN
}

def set_seed(seed: int = 1981):
    random.seed(seed)
    np.random.seed(seed)
    torch.manual_seed(seed)
    torch.cuda.manual_seed_all(seed)
    torch.backends.cudnn.deterministic = True
    torch.backends.cudnn.benchmark = False

set_seed(CONFIG["seed"])

DEVICE = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"Device: {DEVICE.type} | Torch: {torch.__version__}")

def get_logger(name="bitepulse_rgb",
               level=logging.INFO,
               log_file: Optional[Path] = LOG_DIR / "run_rgb3d.log"):
    logger = logging.getLogger(name)
    if logger.handlers:
        return logger
    logger.setLevel(level)
    fmt = logging.Formatter("%(asctime)s | %(levelname)s | %(message)s")
    sh = logging.StreamHandler(stream=sys.stdout)
    sh.setFormatter(fmt)
    logger.addHandler(sh)
    if log_file:
        fh = logging.FileHandler(log_file)
        fh.setFormatter(fmt)
        logger.addHandler(fh)
    return logger

LOGGER = get_logger()

def make_amp_ctx():
    if not CONFIG["amp"] or DEVICE.type != "cuda":
        return nullcontext
    if CONFIG.get("amp_dtype", "bf16") == "bf16":
        return lambda: torch.amp.autocast("cuda",
dtype=torch.bfloat16)

```

```

        else:
            return lambda: torch.amp.autocast("cuda", dtype=torch.float16)

AMP_CTX = make_amp_ctx()

SCALER = (
    torch.amp.GradScaler("cuda")
    if (CONFIG["amp"] and CONFIG.get("amp_dtype") == "fp16" and
        DEVICE.type == "cuda")
    else None
)

Device: cuda | Torch: 2.9.0+cu126

# Alright now let's load window table and frame index:

MANIFEST_PATH = LABELS_DIR / "manifest_with_split.parquet"
FRAMES_IDX_PATH = LABELS_DIR / "frames_idx.parquet"
WINDOWS_PATH = ROOT / "logs" / "windows_idx.parquet"

assert FRAMES_IDX_PATH.exists(), FRAMES_IDX_PATH
assert WINDOWS_PATH.exists(), WINDOWS_PATH

frames_ix = pd.read_parquet(FRAMES_IDX_PATH)
windows_df = pd.read_parquet(WINDOWS_PATH)

if "time_sec" not in frames_ix.columns and {"frame",
"fps"}.issubset(frames_ix.columns):
    frames_ix = frames_ix.copy()
    frames_ix["time_sec"] = frames_ix["frame"] / frames_ix["fps"]

assert "time_sec" in frames_ix.columns, "frames_idx needs 'time_sec'
column"

print("windows_df:", windows_df.shape)
print("frames_ix :", frames_ix.shape)

# class balance by split:
print("\nLabel distribution by split:")
print(
    windows_df.groupby("split")["label"]
    .value_counts(normalize=True)
    .unstack()
    .fillna(0.0)
)

windows_df: (98582, 5)
frames_ix : (742887, 5)

Label distribution by split:

```

label	0	1
split		
test	0.993999	0.006001
train	0.993255	0.006745
val	0.997309	0.002691

```

# Checking that keys in windows appear in frames_ix:
win_keys = set(windows_df["key"].astype(str))
frame_keys = set(frames_ix["key"].astype(str))
missing_keys = sorted(win_keys - frame_keys)
print(f"Unique keys in windows: {len(win_keys)}")
print(f"Unique keys in frames : {len(frame_keys)}")
print(f"Windows keys missing in frames_ix: {len(missing_keys)}")
if missing_keys:
    print("Example missing keys:", missing_keys[:10])

Unique keys in windows: 135
Unique keys in frames : 135
Windows keys missing in frames_ix: 0

# Now let's setup metric helpers and evaluation (similar to TCN)

def bin_metrics_from_logits_np(logits: np.ndarray,
                               targets: np.ndarray,
                               thr: float = 0.5):
    probs = 1.0 / (1.0 + np.exp(-logits))
    preds = (probs >= thr).astype(int)
    y = targets.astype(int)

    tp = int(((preds == 1) & (y == 1)).sum())
    fp = int(((preds == 1) & (y == 0)).sum())
    fn = int(((preds == 0) & (y == 1)).sum())
    tn = int(((preds == 0) & (y == 0)).sum())

    prec = tp / (tp + fp + 1e-9)
    rec = tp / (tp + fn + 1e-9)
    acc = (tp + tn) / (tp + tn + fp + fn + 1e-9)
    f1 = 2 * prec * rec / (prec + rec + 1e-9)

    return {"acc": acc, "prec": prec, "rec": rec, "f1": f1,
            "tp": tp, "fp": fp, "fn": fn, "tn": tn}

def best_f1_threshold_with_floor(
    logits: np.ndarray,
    targets: np.ndarray,
    prec_floor: float = 0.10,
    rec_floor: float = 0.10,
):
    y_true = targets.astype(int)
    probs = 1.0 / (1.0 + np.exp(-logits.astype(np.float64)))

```

```

P, R, T = precision_recall_curve(y_true, probs)

best_f1, best_thr = 0.0, 0.5
best_tuple = (0.0, 0.0, 0, 0, 0)

for p, r, t in zip(P[:-1], R[:-1], T):
    if (p < prec_floor) or (r < rec_floor):
        continue
    f1 = 2 * p * r / (p + r + 1e-12)
    if f1 > best_f1:
        thr = float(t)
        preds = (probs >= thr).astype(int)
        tp = int(((preds==1) & (y_true==1)).sum())
        fp = int(((preds==1) & (y_true==0)).sum())
        fn = int(((preds==0) & (y_true==1)).sum())
        best_f1, best_thr = f1, thr
        best_tuple = (p, r, tp, fp, fn)

return best_f1, best_thr, best_tuple

def evaluate_window_model(logits_np: np.ndarray,
                          targets_np: np.ndarray,
                          label: str,
                          prec_floor: float = 0.10,
                          rec_floor: float = 0.10):
    y_true = targets_np.astype(int)
    f1_star, thr_star, _ = best_f1_threshold_with_floor(
        logits_np, y_true,
        prec_floor=prec_floor,
        rec_floor=rec_floor,
    )
    thr = float(thr_star)
    p_prob = 1.0 / (1.0 + np.exp(-logits_np.astype(np.float64)))
    y_pred = (p_prob >= thr).astype(int)

    tn, fp, fn, tp = confusion_matrix(y_true, y_pred).ravel()
    spec = tn / (tn + fp + 1e-12)

    metrics = {
        "threshold(F1*)": thr,
        "accuracy": accuracy_score(y_true, y_pred),
        "precision": precision_score(y_true, y_pred, zero_division=0),
        "recall": recall_score(y_true, y_pred, zero_division=0),
        "f1": f1_score(y_true, y_pred, zero_division=0),
        "specificity": spec,
        "balanced_acc": balanced_accuracy_score(y_true, y_pred),
        "mcc": matthews_corrcoef(y_true, y_pred),
        "roc_auc_overall": roc_auc_score(y_true, p_prob),
        "pr_auc_overall": average_precision_score(y_true, p_prob),
    }

```

```

}

print(f"\n=== {label}: metrics @ best F1 threshold ===")
for k, v in metrics.items():
    if isinstance(v, float):
        print(f"{k:>20s}: {v:0.3f}")
    else:
        print(f"{k:>20s}: {v}")

print("\nConfusion Matrix (rows=actual, cols=pred):")
print(np.array([[tn, fp], [fn, tp]]))
print("\nClassification report:\n",
      classification_report(y_true, y_pred, digits=3,
zero_division=0))

fig = plt.figure(figsize=(12, 4))

cm = np.array([[tn, fp], [fn, tp]], dtype=float)
cm_norm = cm / cm.sum(axis=1, keepdims=True).clip(1)

ax1 = plt.subplot(1, 3, 1)
im = ax1.imshow(cm_norm, vmin=0, vmax=1)
ax1.set_title(f"{label} - Confusion @ thr={thr:.2f}")
ax1.set_xlabel("Predicted")
ax1.set_ylabel("Actual")
ax1.set_xticks([0, 1]); ax1.set_xticklabels(["Not intake",
"Intake"])
ax1.set_yticks([0, 1]); ax1.set_yticklabels(["Not intake",
"Intake"])
for i in range(2):
    for j in range(2):
        ax1.text(j, i, f"{int(cm[i,j])}\n({cm_norm[i,j]*100:.1f}
%)",
                ha="center", va="center",
                color="white" if cm_norm[i,j] > 0.5 else "black",
                fontsize=9)
plt.colorbar(im, ax=ax1, fraction=0.046, pad=0.04)

fpr, tpr, _ = roc_curve(y_true, p_prob)
ax2 = plt.subplot(1, 3, 2)
ax2.plot(fpr, tpr, label=f"AUC =
{metrics['roc_auc_overall']:.3f}")
ax2.plot([0, 1], [0, 1], "--", linewidth=1)
ax2.set_title(f"{label} - ROC")
ax2.set_xlabel("False Positive Rate")
ax2.set_ylabel("True Positive Rate")
ax2.grid(True, alpha=0.3)
ax2.legend(loc="lower right")

P, R, _ = precision_recall_curve(y_true, p_prob)

```

```

ax3 = plt.subplot(1, 3, 3)
ax3.plot(R, P, label=f"AP = {metrics['pr_auc_overall']:.3f}")
ax3.set_title(f"{label} - Precision Recall")
ax3.set_xlabel("Recall")
ax3.set_ylabel("Precision")
ax3.grid(True, alpha=0.3)
ax3.legend(loc="lower left")

plt.tight_layout()
plt.show()

return {"metrics": metrics, "thr": thr, "probs": p_prob, "y_true":
y_true}

# Fixed RGB dataset + DataLoaders

IMG_EXT = ".png"
FRAME_PAD = 6
CLIP_FPS = float(FPS_TARGET) if "FPS_TARGET" in globals() else 15.0

class RGBWindowDataset(Dataset):
    """
    Each item is an RGB clip for a labeled window.
    x: (T, 3, H, W) in [0,1], y: scalar float32 (0 or 1).

    For each key we:
    1) List all PNG frames actually on disk.
    2) Map window times [w0, w1) to frame indices via CLIP_FPS.
    3) Clamp indices into [0, n_frames-1] so we never hit a missing
file.
    """
    def __init__(self,
                  windows: pd.DataFrame,
                  clip_len: int = 16,
                  img_size: int = 112,
                  fps: float = CLIP_FPS):
        self.df = windows.reset_index(drop=True)
        self.clip_len = int(clip_len)
        self.img_size = int(img_size)
        self.fps = float(fps)

    def _load_clip(self, key: str, w0: float, w1: float):
        key = str(key)
        kdir = FRAMES_DIR / key
        files = sorted(kdir.glob(f"*{IMG_EXT}"))

        if not files:
            raise RuntimeError(f"No frame files found for key={key} in
{kdir}")

```

```

n_frames = len(files)

#
times = np.linspace(w0, w1, num=self.clip_len, endpoint=False)

frames = []
for t in times:

    idx = int(round(t * self.fps))
    idx = max(0, min(n_frames - 1, idx))
    path = files[idx]

    img = Image.open(path).convert("RGB")
    img = img.resize((self.img_size, self.img_size))
    x = np.asarray(img, dtype=np.float32) / 255.0
    x = np.transpose(x, (2, 0, 1))
    frames.append(x)

arr = np.stack(frames, axis=0)
return arr.astype(np.float32)

def __len__(self):
    return len(self.df)

def __getitem__(self, i: int):
    r = self.df.iloc[i]
    key = r["key"]
    w0 = float(r["start_sec"])
    w1 = float(r["end_sec"])
    label = float(r["label"])

    clip = self._load_clip(key, w0, w1)
    x = torch.from_numpy(clip)
    y = torch.tensor(label, dtype=torch.float32)
    return x, y

def make_rgb_loader(windows_df, split: str, balance: bool = True):
    # take split:
    df_split = windows_df[windows_df["split"] ==
split].reset_index(drop=True)

    # PNGs location:
    keys_with_frames = []
    for p in FRAMES_DIR.iterdir():
        if p.is_dir() and any(p.glob(f"*{IMG_EXT}")):
            keys_with_frames.append(p.name)
    keys_with_frames = set(keys_with_frames)

    # filter windows:

```

```

mask = df_split["key"].astype(str).isin(keys_with_frames)
n_before = len(df_split)
df_split = df_split[mask].reset_index(drop=True)
n_after = len(df_split)
print(f"[{split}] windows with frames: {n_after}/{n_before} "
      f"(dropped {n_before - n_after})")

# dataset:
ds = RGBWindowDataset(
    df_split,
    clip_len=CONFIG["clip_len"],
    img_size=CONFIG["img_size"],
    fps=CLIP_FPS,
)

# class balancing:
if balance and split == "train":
    labels = ds.df["label"].astype(int).values
    counts = np.bincount(labels, minlength=2).astype(np.float32)
    weights = 1.0 / (counts[labels] + 1e-9)
    sampler = WeightedRandomSampler(
        weights.tolist(),
        num_samples=len(weights),
        replacement=True,
    )
    shuffle = False
else:
    sampler = None
    shuffle = (split == "train")

loader = DataLoader(
    ds,
    batch_size=CONFIG["batch_size"],
    shuffle=shuffle if sampler is None else False,
    sampler=sampler,
    num_workers=CONFIG["num_workers"],
    pin_memory=CONFIG["pin_memory"],
    persistent_workers=CONFIG["persistent_workers"] if
CONFIG["num_workers"] > 0 else False,
    drop_last=False,
)
return loader, ds

# Loaders:
train_rgb_loader, train_rgb_ds = make_rgb_loader(windows_df, "train",
balance=True)
val_rgb_loader, val_rgb_ds = make_rgb_loader(windows_df, "val",
balance=False)

```



```
# Sanity check:
clip, label = train_rgb_ds[0]
print("Single clip shape:", clip.shape, "label:", label)
print("clip stats: min", float(clip.min()),
      "max", float(clip.max()),
      "mean", float(clip.mean()),
      "std", float(clip.std()))

batch_x, batch_y = next(iter(train_rgb_loader))
print("Batch shape:", batch_x.shape)    # expect (B,T,3,112,112)
print("Batch stats:",
      float(batch_x.min()),
      float(batch_x.max()),
      float(batch_x.mean()),
      float(batch_x.std()))

[train] windows with frames: 7268/62568 (dropped 55300)
[val] windows with frames: 2565/21184 (dropped 18619)
Single clip shape: torch.Size([16, 3, 112, 112]) label: tensor(0.)
clip stats: min 0.0 max 1.0 mean 0.45068100094795227 std
0.24670635163784027
Batch shape: torch.Size([8, 16, 3, 112, 112])
Batch stats: 0.0 1.0 0.47496291995048523 0.25107431411743164
```

Baseline PyTorch 3D CNN - Training

```
class RGB3DNet(nn.Module):
    """
    3D CNN for RGB clips.
    Input: x (B, T, 3, H, W)
    Output: logits of shape (B,) for intake vs non-intake.
    """
    def __init__(self):
        super().__init__()
        # we'll permute to (B, 3, T, H, W) in forward
        self.features = nn.Sequential(
            nn.Conv3d(3, 32, kernel_size=(3, 7, 7),
                     stride=(1, 2, 2), padding=(1, 3, 3),
bias=False),
            nn.BatchNorm3d(32),
            nn.ReLU(inplace=True),
            nn.MaxPool3d(kernel_size=(1, 3, 3),
                        stride=(1, 2, 2), padding=(0, 1, 1)),

            nn.Conv3d(32, 64, kernel_size=3,
                     stride=1, padding=1, bias=False),
            nn.BatchNorm3d(64),
            nn.ReLU(inplace=True),
            nn.MaxPool3d(kernel_size=(2, 2, 2),
```

```

        stride=(2, 2, 2)),
        nn.Conv3d(64, 128, kernel_size=3,
                  stride=1, padding=1, bias=False),
        nn.BatchNorm3d(128),
        nn.ReLU(inplace=True),
        nn.MaxPool3d(kernel_size=(2, 2, 2),
                     stride=(2, 2, 2)),
    )

    self.pool = nn.AdaptiveAvgPool3d(1)  # (B, C, 1, 1, 1)
    self.fc = nn.Linear(128, 1)

def forward(self, x):
    # x: (B, T, 3, H, W) -> (B, 3, T, H, W)
    x = x.permute(0, 2, 1, 3, 4)
    x = self.features(x)
    x = self.pool(x).view(x.size(0), -1)
    x = self.fc(x)
    return x.squeeze(-1)  # (B,)

def run_rgb_epoch(model, loader, optimizer=None):
    """
    One pass over a DataLoader.
    If optimizer is None -> eval mode, no grads.
    Returns: avg_loss, metrics_dict, logits_np, targets_np
    """
    train_mode = optimizer is not None
    model.train(train_mode)

    pos_w = torch.tensor(
        [CONFIG.get("pos_class_weight", 1.0)],
        device=DEVICE, dtype=torch.float32,
    )
    criterion = nn.BCEWithLogitsLoss(pos_weight=pos_w)

    total_loss, n_seen = 0.0, 0
    all_logits, all_targets = [], []

    for x, y in tqdm(loader, desc="batches", leave=False):
        # x: (B,T,3,H,W), y: scalar {0,1}
        x = x.to(DEVICE, non_blocking=True).float()
        y = y.to(DEVICE, non_blocking=True).float()  # (B,)

        if train_mode:
            optimizer.zero_grad(set_to_none=True)

        with AMP_CTX():
            logits = model(x)  # (B,)

```

```

        loss = criterion(logits, y)

        if train_mode:
            loss.backward()
            optimizer.step()

        bs = x.size(0)
        total_loss += float(loss.item()) * bs
        n_seen += bs

        all_logits.append(logits.detach().cpu())
        all_targets.append(y.detach().cpu())

        # ---- FIX: cast bfloat16 -> float32 before converting to NumPy
        ----
        if len(all_logits) == 0:
            return 0.0, {"acc": 0, "prec": 0, "rec": 0, "f1": 0},
            np.array([]), np.array([])

        logits_cat = torch.cat(all_logits, dim=0).to(torch.float32)
        targets_cat = torch.cat(all_targets, dim=0).to(torch.float32)

        logits_np = logits_cat.numpy()
        targets_np = targets_cat.numpy().astype(int)

        metrics = bin_metrics_from_logits_np(logits_np, targets_np,
            thr=0.5)

        return total_loss / max(1, n_seen), metrics, logits_np, targets_np

def train_rgb3d(train_loader, val_loader):
    model = RGB3DNet().to(DEVICE)

    optimizer = torch.optim.AdamW(
        model.parameters(),
        lr=CONFIG["lr"],
        weight_decay=CONFIG["weight_decay"],
    )

    scheduler = torch.optim.lr_scheduler.OneCycleLR(
        optimizer,
        max_lr=8e-4,
        steps_per_epoch=len(train_loader),
        epochs=CONFIG["epochs"],
    )

    best_val_f1 = -1.0
    best_state = None

```

```

for epoch in range(CONFIG["epochs"]):
    LOGGER.info(f"[RGB3D] epoch {epoch+1}/{CONFIG['epochs']}")

    tr_loss, tr_m, _, _ = run_rgb_epoch(model, train_loader,
                                         optimizer=optimizer)

    try:
        scheduler.step()
    except Exception:
        pass

    va_loss, va_m, va_logits_np, va_y_np = run_rgb_epoch(
        model, val_loader, optimizer=None
    )

    f1_star, thr_star, _ = best_f1_threshold_with_floor(
        va_logits_np, va_y_np
    )

    LOGGER.info(
        f"train loss {tr_loss:.4f} | "
        f"acc {tr_m['acc']:.3f} prec {tr_m['prec']:.3f} "
        f"rec {tr_m['rec']:.3f} f1 {tr_m['f1']:.3f}"
    )
    LOGGER.info(
        f"val loss {va_loss:.4f} | best_f1 {f1_star:.3f} "
        f"thr {thr_star:.2f}"
    )

    if f1_star > best_val_f1:
        best_val_f1 = f1_star
        best_state = {
            "model": model.state_dict(),
            "val_f1": float(best_val_f1),
            "best_thr": float(thr_star),
        }
        torch.save(best_state, CKPT_DIR / "rgb3d_best.pt")
        LOGGER.info(
            f"✓ saved new best (f1={best_val_f1:.3f} @
thr={thr_star:.2f})"
        )

    LOGGER.info(f"[RGB3D] best val f1={best_val_f1:.3f}")
    return model

```

```
model_rgb3d = train_rgb3d(train_rgb_loader, val_rgb_loader)
```

```
2025-11-27 20:34:21,125 | INFO | [RGB3D] epoch 1/10
```

```
INFO:bitepulse_rgb:[RGB3D] epoch 1/10
```

```
{"model_id":"b770a33fafb413791b15d7dd8b706ec","version_major":2,"version_minor":0}
```

```
{"model_id":"551ced337ee44715bd6cccd703ce8ee8","version_major":2,"version_minor":0}
```

```
2025-11-27 21:54:39,647 | INFO | train loss 0.4772 | acc 0.816 prec 0.751 rec 0.952 f1 0.839
```

```
INFO:bitepulse_rgb:train loss 0.4772 | acc 0.816 prec 0.751 rec 0.952 f1 0.839
```

```
2025-11-27 21:54:39,649 | INFO | val loss 0.7800 | best_f1 0.134 thr 0.73
```

```
INFO:bitepulse_rgb: val loss 0.7800 | best_f1 0.134 thr 0.73
```

```
2025-11-27 21:54:40,498 | INFO | ✓ saved new best (f1=0.134 @ thr=0.73)
```

```
INFO:bitepulse_rgb:✓ saved new best (f1=0.134 @ thr=0.73)
```

```
2025-11-27 21:54:40,500 | INFO | [RGB3D] epoch 2/10
```

```
INFO:bitepulse_rgb:[RGB3D] epoch 2/10
```

```
{"model_id":"1850aec37d70459cb02d6381398ba5a1","version_major":2,"version_minor":0}
```

```
{"model_id":"69c8bf727534459b836760ade176c240","version_major":2,"version_minor":0}
```

```
2025-11-27 22:33:00,060 | INFO | train loss 0.3072 | acc 0.903 prec 0.855 rec 0.973 f1 0.910
```

```
INFO:bitepulse_rgb:train loss 0.3072 | acc 0.903 prec 0.855 rec 0.973 f1 0.910
```

```
2025-11-27 22:33:00,062 | INFO | val loss 0.3229 | best_f1 0.188 thr 0.56
```

```
INFO:bitepulse_rgb: val loss 0.3229 | best_f1 0.188 thr 0.56
```

```
2025-11-27 22:33:00,073 | INFO | ✓ saved new best (f1=0.188 @ thr=0.56)
```

```
INFO:bitepulse_rgb:✓ saved new best (f1=0.188 @ thr=0.56)
```

```
2025-11-27 22:33:00,074 | INFO | [RGB3D] epoch 3/10
```

```
INFO:bitepulse_rgb:[RGB3D] epoch 3/10
```

```
{"model_id":"4bdb3731fc674b4a9a022705f8f0c4f9","version_major":2,"version_minor":0}
```

```
{"model_id":"b4caf189f15840168d3fe0d366d6edcc","version_major":2,"version_minor":0}
```

```
2025-11-27 23:09:23,452 | INFO | train loss 0.2176 | acc 0.941 prec 0.902 rec 0.991 f1 0.944
```

```
INFO:bitepulse_rgb:train loss 0.2176 | acc 0.941 prec 0.902 rec 0.991 f1 0.944
```

```
2025-11-27 23:09:23,454 | INFO | val loss 0.1337 | best_f1 0.186 thr 0.03
```

```
INFO:bitepulse_rgb: val loss 0.1337 | best_f1 0.186 thr 0.03
```

```
2025-11-27 23:09:23,455 | INFO | [RGB3D] epoch 4/10
```

```
INFO:bitepulse_rgb:[RGB3D] epoch 4/10
```

```
{"model_id":"41d49a772acf45ddae254868e34b8512","version_major":2,"version_minor":0}
```

```
{"model_id":"82fc9bec6a17417fadd456a055ef5e18","version_major":2,"version_minor":0}
```

```
2025-11-27 23:45:05,509 | INFO | train loss 0.1597 | acc 0.966 prec 0.943 rec 0.992 f1 0.967
```

```
INFO:bitepulse_rgb:train loss 0.1597 | acc 0.966 prec 0.943 rec 0.992 f1 0.967
```

```
2025-11-27 23:45:05,510 | INFO | val loss 3.3173 | best_f1 0.163 thr 1.00
```

```
INFO:bitepulse_rgb: val loss 3.3173 | best_f1 0.163 thr 1.00
```

```
2025-11-27 23:45:05,512 | INFO | [RGB3D] epoch 5/10
```

```
INFO:bitepulse_rgb:[RGB3D] epoch 5/10
```

```
{"model_id":"a751535ffea44d29ab45de000e861568","version_major":2,"version_minor":0}
```

```
{"model_id":"346034f0692244adbee9cf88a51d34ee","version_major":2,"version_minor":0}
```

```
2025-11-28 00:21:16,923 | INFO | train loss 0.1284 | acc 0.978 prec 0.960 rec 0.997 f1 0.978
```

```
INFO:bitepulse_rgb:train loss 0.1284 | acc 0.978 prec 0.960 rec 0.997 f1 0.978
```

```
2025-11-28 00:21:16,924 | INFO | val loss 0.2908 | best_f1 0.137 thr 0.65
```

```
INFO:bitepulse_rgb: val  loss 0.2908 | best_f1 0.137 thr 0.65
2025-11-28 00:21:16,926 | INFO | [RGB3D] epoch 6/10
INFO:bitepulse_rgb:[RGB3D] epoch 6/10
{"model_id":"7d106fb784334f35b78be771648dab9b","version_major":2,"version_minor":0}
{"model_id":"6fdc11a309974c28bcc58e83352475ca","version_major":2,"version_minor":0}
2025-11-28 00:56:34,979 | INFO | train loss 0.1022 | acc 0.984 prec
0.969 rec 0.999 f1 0.984
INFO:bitepulse_rgb:train loss 0.1022 | acc 0.984 prec 0.969 rec 0.999
f1 0.984
2025-11-28 00:56:34,980 | INFO | val  loss 0.1300 | best_f1 0.153 thr
0.15
INFO:bitepulse_rgb: val  loss 0.1300 | best_f1 0.153 thr 0.15
2025-11-28 00:56:34,981 | INFO | [RGB3D] epoch 7/10
INFO:bitepulse_rgb:[RGB3D] epoch 7/10
{"model_id":"0d9b5bd3d4e244d8945be0c39412bf41","version_major":2,"version_minor":0}
{"model_id":"c3c6f3f3dcb545649d78fbdf7b56f29a","version_major":2,"version_minor":0}
2025-11-28 01:31:01,353 | INFO | train loss 0.0903 | acc 0.984 prec
0.971 rec 0.998 f1 0.984
INFO:bitepulse_rgb:train loss 0.0903 | acc 0.984 prec 0.971 rec 0.998
f1 0.984
2025-11-28 01:31:01,354 | INFO | val  loss 0.1369 | best_f1 0.161 thr
0.17
INFO:bitepulse_rgb: val  loss 0.1369 | best_f1 0.161 thr 0.17
2025-11-28 01:31:01,355 | INFO | [RGB3D] epoch 8/10
INFO:bitepulse_rgb:[RGB3D] epoch 8/10
{"model_id":"dd9a9fedb9f8414d9cdeca71407f6d2a","version_major":2,"version_minor":0}
{"model_id":"21537472efb54629aa0f5c6b61dc938b","version_major":2,"version_minor":0}
```

```
2025-11-28 02:06:02,741 | INFO | train loss 0.0801 | acc 0.984 prec
0.970 rec 0.998 f1 0.984

INFO:bitepulse_rgb:train loss 0.0801 | acc 0.984 prec 0.970 rec 0.998
f1 0.984

2025-11-28 02:06:02,742 | INFO | val loss 1.4249 | best_f1 0.000 thr
0.50

INFO:bitepulse_rgb: val loss 1.4249 | best_f1 0.000 thr 0.50

2025-11-28 02:06:02,743 | INFO | [RGB3D] epoch 9/10

INFO:bitepulse_rgb:[RGB3D] epoch 9/10

{"model_id":"376845b9df28452f90026598589ca38b","version_major":2,"vers
ion_minor":0}

{"model_id":"f49d736915754191890553eec1bfd63c","version_major":2,"vers
ion_minor":0}

2025-11-28 02:41:38,777 | INFO | train loss 0.0639 | acc 0.989 prec
0.978 rec 1.000 f1 0.989

INFO:bitepulse_rgb:train loss 0.0639 | acc 0.989 prec 0.978 rec 1.000
f1 0.989

2025-11-28 02:41:38,778 | INFO | val loss 0.1281 | best_f1 0.175 thr
0.17

INFO:bitepulse_rgb: val loss 0.1281 | best_f1 0.175 thr 0.17

2025-11-28 02:41:38,779 | INFO | [RGB3D] epoch 10/10

INFO:bitepulse_rgb:[RGB3D] epoch 10/10

{"model_id":"333396442d4b472aadae0e9a1bfff368c","version_major":2,"vers
ion_minor":0}

{"model_id":"287c258b8d8c44ddb036e0db49d3e587","version_major":2,"vers
ion_minor":0}

2025-11-28 03:18:21,930 | INFO | train loss 0.0604 | acc 0.989 prec
0.979 rec 1.000 f1 0.989

INFO:bitepulse_rgb:train loss 0.0604 | acc 0.989 prec 0.979 rec 1.000
f1 0.989

2025-11-28 03:18:21,931 | INFO | val loss 0.1285 | best_f1 0.174 thr
0.12

INFO:bitepulse_rgb: val loss 0.1285 | best_f1 0.174 thr 0.12

2025-11-28 03:18:21,933 | INFO | [RGB3D] best val f1=0.188
```



```
INFO:bitepulse_rgb:[RGB3D] best val f1=0.188
```

Baseline PyTorch 3D CNN - Performance Evaluation

```
best_ckpt_path = CKPT_DIR / "rgb3d_best.pt"
print("Checkpoint:", best_ckpt_path, "| exists:",
best_ckpt_path.exists())

ckpt = torch.load(best_ckpt_path, map_location=DEVICE)

model_rgb3d_best = RGB3DNet().to(DEVICE)
model_rgb3d_best.load_state_dict(ckpt["model"])
model_rgb3d_best.eval()

print(f"Best val F1 (saved in ckpt): {ckpt.get('val_f1', None)} @
thr={ckpt.get('best_thr', None)}")

Checkpoint:
/content/drive/MyDrive/eatsense/checkpoints_rgb/rgb3d_best.pt |
exists: True
Best val F1 (saved in ckpt): 0.18803418803373279 @
thr=0.5640984800226174

# Best checkpoint model:
val_loss_rgb, val_m_rgb, val_logits_rgb, val_y_rgb = run_rgb_epoch(
    model_rgb3d_best,
    val_rgb_loader,
    optimizer=None,
)

print("=== RGB3D baseline: quick val metrics @ thr=0.5 ===")
for k, v in val_m_rgb.items():
    print(f"{k:>10s}: {v:.3f}")
print("val_loss:", val_loss_rgb)

{"model_id":"ed8b64fa7e6b4eadb4549c1c651cb5c4","version_major":2,"version_minor":0}

=== RGB3D baseline: quick val metrics @ thr=0.5 ===
    acc: 0.948
    prec: 0.122
    rec: 0.366
    f1: 0.183
    tp: 15.000
    fp: 108.000
    fn: 26.000
    tn: 2416.000
val_loss: 0.32293026334593405

rgb3d_eval = evaluate_window_model(
    logits_np = val_logits_rgb,
```

```

targets_np = val_y_rgb,
label       = "PyTorch RGB3D (baseline)",
prec_floor  = 0.10,
rec_floor   = 0.10,
)

=== PyTorch RGB3D (baseline): metrics @ best F1 threshold ===
    threshold(F1*): 0.564
    accuracy: 0.963
    precision: 0.145
    recall: 0.268
    f1: 0.188
    specificity: 0.974
    balanced_acc: 0.621
    mcc: 0.179
    roc_auc_overall: 0.733
    pr_auc_overall: 0.095

```

Confusion Matrix (rows=actual, cols=pred):

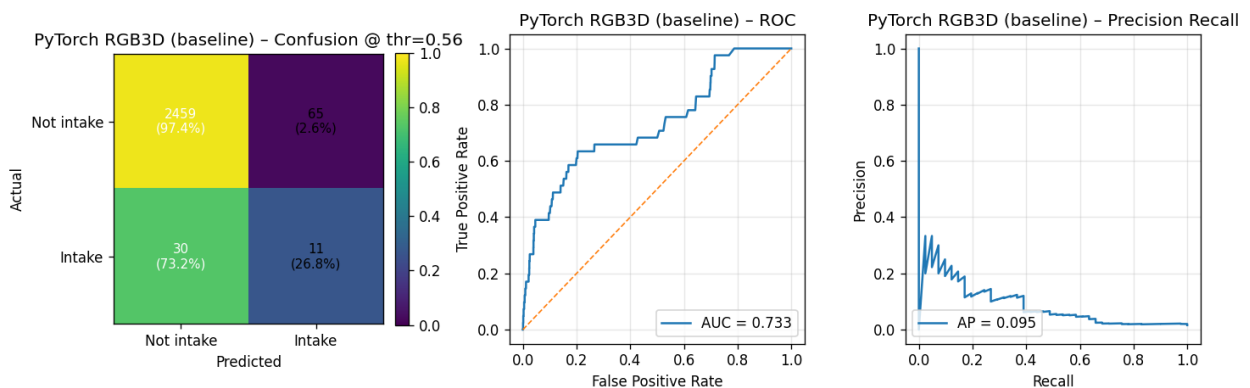
```

[[2459  65]
 [ 30  11]]

```

Classification report:

	precision	recall	f1-score	support
0	0.988	0.974	0.981	2524
1	0.145	0.268	0.188	41
accuracy			0.963	2565
macro avg	0.566	0.621	0.585	2565
weighted avg	0.974	0.963	0.968	2565



3D-CNN - hyperband Search

```

# TF GPU config:
import tensorflow as tf

```

```

gpus = tf.config.list_physical_devices("GPU")
for g in gpus:
    try:
        tf.config.experimental.set_memory_growth(g, True)
    except Exception:
        pass
print("TF GPUs:", gpus)

TF GPUs: [PhysicalDevice(name='/physical_device:GPU:0',
device_type='GPU')]

import math

class RGBWindowSequence(tf.keras.utils.Sequence):
    """
    Keras data generator: yields (X, y) batches for window-level RGB
    clips.

    X shape: (B, T, H, W, 3) in [0,1]
    y shape: (B, 1) float32 {0,1}
    """
    def __init__(self,
                 windows: pd.DataFrame,
                 batch_size: int = 4,
                 clip_len: int = 16,
                 img_size: int = 112,
                 fps: float = CLIP_FPS):
        self.df = windows.reset_index(drop=True)
        self.batch_size = int(batch_size)
        self.clip_len = int(clip_len)
        self.img_size = int(img_size)
        self.fps = float(fps)

    def __len__(self):
        return math.ceil(len(self.df) / self.batch_size)

    def _load_clip(self, key: str, w0: float, w1: float):
        key = str(key)
        kdir = FRAMES_DIR / key
        files = sorted(kdir.glob(f"*{IMG_EXT}"))

        if not files:
            raise RuntimeError(f"No frame files found for key={key} in
{kdir}")

        n_frames = len(files)
        times = np.linspace(w0, w1, num=self.clip_len, endpoint=False)

        frames = []

```

```

    for t in times:
        idx = int(round(t * self.fps))
        idx = max(0, min(n_frames - 1, idx))
        path = files[idx]

        img = Image.open(path).convert("RGB")
        img = img.resize((self.img_size, self.img_size))
        x = np.asarray(img, dtype=np.float32) / 255.0 # H,W,3
        frames.append(x)

    arr = np.stack(frames, axis=0) # T,H,W,3
    return arr.astype(np.float32)

def __getitem__(self, idx: int):
    b_start = idx * self.batch_size
    b_end = min(len(self.df), (idx + 1) * self.batch_size)
    batch_df = self.df.iloc[b_start:b_end]

    B = len(batch_df)
    X = np.zeros((B, self.clip_len, self.img_size, self.img_size,
3),
dtype=np.float32)
    y = np.zeros((B, 1), dtype=np.float32)

    for i, (_, r) in enumerate(batch_df.iterrows()):
        clip = self._load_clip(
            key = r["key"],
            w0 = float(r["start_sec"]),
            w1 = float(r["end_sec"]),
        ) # (T,H,W,3)
        X[i] = clip
        y[i, 0] = float(r["label"])

    return X, y

keys_with_frames = []
for p in FRAMES_DIR.iterdir():
    if p.is_dir() and any(p.glob(f"*{IMG_EXT}")):
        keys_with_frames.append(p.name)
keys_with_frames = set(keys_with_frames)
print("Keys with frames:", len(keys_with_frames))

# Filter windows for train / val:
train_df_keras = windows_df[
    (windows_df["split"] == "train") &
    (windows_df["key"].astype(str).isin(keys_with_frames))
].reset_index(drop=True)

val_df_keras = windows_df[
    (windows_df["split"] == "val") &

```

```

    (windows_df["key"].astype(str).isin(keys_with_frames))
].reset_index(drop=True)

print("Keras train windows:", train_df_keras.shape)
print("Keras val   windows:", val_df_keras.shape)

KERAS_BATCH = 4

train_seq = RGBWindowSequence(
    train_df_keras,
    batch_size=KERAS_BATCH,
    clip_len=CONFIG["clip_len"],
    img_size=CONFIG["img_size"],
    fps=CLIP_FPS,
)
val_seq = RGBWindowSequence(
    val_df_keras,
    batch_size=KERAS_BATCH,
    clip_len=CONFIG["clip_len"],
    img_size=CONFIG["img_size"],
    fps=CLIP_FPS,
)

# Class weights to handle imbalance:
train_labels_np = train_df_keras["label"].astype(int).values
counts = np.bincount(train_labels_np, minlength=2).astype(float)
total = counts.sum()
class_weight = {
    0: float(total / (2.0 * counts[0])),
    1: float(total / (2.0 * counts[1] + 1e-9)),
}
print("Class counts:", counts, "class_weight:", class_weight)

Keys with frames: 17
Keras train windows: (7268, 5)
Keras val   windows: (2565, 5)
Class counts: [7186.   82.] class_weight: {0: 0.505705538547175, 1:
44.317073170461484}

Xb, yb = train_seq[0]
print("Batch X shape:", Xb.shape) # (B,T,H,W,3)
print("Batch y shape:", yb.shape, "labels:", yb[:8].ravel())
print("Batch stats: min", Xb.min(), "max", Xb.max(), "mean",
Xb.mean(), "std", Xb.std())

Batch X shape: (4, 16, 112, 112, 3)
Batch y shape: (4, 1) labels: [0. 0. 0. 0.]
Batch stats: min 0.0 max 1.0 mean 0.45622057 std 0.24634425

def build_rgb3d_keras(hp):
    clip_len = CONFIG["clip_len"]

```

```

img_size = CONFIG["img_size"]

inputs = tf.keras.Input(
    shape=(clip_len, img_size, img_size, 3),
    name="rgb_clip",
)

# Hyperparameters
base_filters = hp.Choice("base_filters", [32, 48, 64])
num_blocks = hp.Int("num_blocks", min_value=2, max_value=4,
step=1)
dropout_rate = hp.Float("dropout", 0.0, 0.5, step=0.1)
lr = hp.Float("lr", 1e-4, 5e-3, sampling="log")

x = inputs
filters = base_filters
for b in range(num_blocks):
    x = tf.keras.layers.Conv3D(
        filters,
        kernel_size=(3, 3, 3),
        strides=(1, 2, 2) if b == 0 else (1, 1, 1),
        padding="same",
        use_bias=False,
    )(x)
    x = tf.keras.layers.BatchNormalization()(x)
    x = tf.keras.layers.Activation("relu")(x)
    x = tf.keras.layers.MaxPool3D(pool_size=(1, 2, 2))(x)
    filters *= 2 # double channels each block

x = tf.keras.layers.GlobalAveragePooling3D()(x)
if dropout_rate > 0.0:
    x = tf.keras.layers.Dropout(dropout_rate)(x)

outputs = tf.keras.layers.Dense(1, activation="sigmoid")(x)

model = tf.keras.Model(inputs, outputs, name="rgb3d_keras_hb")

model.compile(
    optimizer=tf.keras.optimizers.Adam(learning_rate=lr),
    loss=tf.keras.losses.BinaryCrossentropy(from_logits=False),
    metrics=[
        tf.keras.metrics.BinaryAccuracy(name="acc"),
        tf.keras.metrics.Precision(name="prec"),
        tf.keras.metrics.Recall(name="rec"),
        tf.keras.metrics.AUC(name="pr_auc", curve="PR"),
    ],
)
return model

```

```

import keras_tuner as kt

tuner_dir = ROOT / "keras_tuner_rgb"
tuner_dir.mkdir(parents=True, exist_ok=True)

tuner = kt.Hyperband(
    build_rgb3d_keras,
    objective=kt.Objective("val_pr_auc", direction="max"),
    max_epochs=6,
    factor=2,
    directory=str(tuner_dir),
    project_name="rgb3d_hyperband",
    overwrite=True,
)

early_stop = tf.keras.callbacks.EarlyStopping(
    monitor="val_pr_auc",
    mode="max",
    patience=2,
    restore_best_weights=True,
)

tuner.search(
    train_seq,
    validation_data=val_seq,
    epochs=6,
    callbacks=[early_stop],
    class_weight=class_weight,
)

```

Trial 1 Complete [04h 35m 19s]
val_pr_auc: 0.02312251180410385

Best val_pr_auc So Far: 0.02312251180410385
Total elapsed time: 04h 35m 19s

Search: Running Trial #2

Value	Best Value So Far	Hyperparameter
48	64	base_filters
2	2	num_blocks
0.2	0	dropout
0.00027996	0.0039115	lr
2	2	tuner/epochs
0	0	tuner/initial_epoch
2	2	tuner/bracket
0	0	tuner/round

Epoch 1/2

```
31/1817 _____ 1:56:40 4s/step - acc: 1.0000 - loss:
0.0703 - pr_auc: 0.0000e+00 - prec: 0.0000e+00 - rec: 0.0000e+00
```

3D-CNN - hyperband Result

Given the time and compute limits for the capstone, I stopped Hyperband after the first full trial as shown above and pivoted to the more efficient MS-TCN architecture with frame-level supervision instead of continuing the full RGB 3D-CNN search.