BitePulse AI - Modeling: Pose TCN vs Hyperband TCN

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Introduction

In this notebook we:

1. Build windowed pose data for BitePulse (EatSense).
2. Train a **baseline PyTorch Temporal ConvNet (PoseTCNPro)** on pose sequences.
3. Train a **Keras TCN with Hyperband** on the same windows.
4. Evaluate both models with the **same metrics and plots**:
   - Window-level confusion matrix, ROC, PR.
   - Event-level precision/recall based on window outputs.

The goal is to see how much Hyperband improves over the baseline TCN and to understand where each model succeeds or fails.

Data

Our input will be the artifacts we finalized at proveious Feature pipeline notebook:

- Manifest w/ splits: labels_v1/manifest_with_split.parquet (keys, paths, split).
- Per-frame labels: labels_v1/frames_idx.parquet (key, split, frame, time_sec, label).
- Event segments: labels_v1/segs_idx.parquet (key, split, start_sec, end_sec, label). These are the artifacts we finalized at the end of Week 2; the notebook will load them directly.

Imports and basic setup

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

```
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0:00:00
```

```
# Mount Google Drive:
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

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

```python
# Data / arrays
import numpy as np
import pandas as pd

# Plotting
import matplotlib.pyplot as plt

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

# Keras / Hyperband
import tensorflow as tf
import keras_tuner as kt

# Metrics
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
```

Paths setup

Here's let's define our exact folders on Drive.

```python
ROOT       = Path("/content/drive/MyDrive/eatsense")
DATA_DIR   = ROOT
LABELS_DIR = ROOT / "labels_v1"
POSE_DIR   = ROOT / "true2d_parquet"
FRAMES_DIR = ROOT / "frames"
CKPT_DIR   = ROOT / "checkpoints"
LOG_DIR    = ROOT / "logs"

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,
    # windowing
    "win_sec": 2.0,
    "stride_sec": 0.5,
    # training
    "epochs": 12,
    "batch_size": 32,
    "lr": 3e-4,
    "weight_decay": 1e-5,
    "pos_class_weight": 2.0,      # BCE pos_weight for TCN
    "amp": True,
    "amp_dtype": "bf16",
    # eval default threshold
    "pred_thresh": 0.5,
}

# Quick sanity checks:
need = [LABELS_DIR / "manifest_with_split.parquet",
        LABELS_DIR / "frames_idx.parquet",
        LABELS_DIR / "segs_idx.parquet",
        POSE_DIR]
missing = [str(p) for p in need if not Path(p).exists()]
if missing:
    print("Missing expected paths/files:\n - " + "\n -
".join(missing))
else:
    print("Paths OK")

print(f"ROOT={ROOT}\nLABELS_DIR={LABELS_DIR}\nPOSE_DIR={POSE_DIR}\
nFRAMES_DIR={FRAMES_DIR}\nCKPT_DIR={CKPT_DIR}\nLOG_DIR={LOG_DIR}")

Paths OK
ROOT=/content/drive/MyDrive/eatsense
LABELS_DIR=/content/drive/MyDrive/eatsense/labels_v1
POSE_DIR=/content/drive/MyDrive/eatsense/true2d_parquet
FRAMES_DIR=/content/drive/MyDrive/eatsense/frames
CKPT_DIR=/content/drive/MyDrive/eatsense/checkpoints
LOG_DIR=/content/drive/MyDrive/eatsense/logs
```

Helpers

```
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"])
```

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

```
Device: cuda | Torch: 2.9.0+cu126
```

```python
def get_logger(name="bitepulse", level=logging.INFO,
               log_file: Optional[Path] = LOG_DIR / "run_tcn.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()

class SmoothedValue:
    def __init__(self):
        self.n, self.total = 0, 0.0
    def update(self, val, cnt=1):
        self.total += float(val) * cnt
        self.n += cnt
    @property
    def avg(self):
        return self.total / max(self.n, 1)

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", "bf16") ==
"fp16")
           else None)
```

```
MANIFEST_PATH   = LABELS_DIR / "manifest_with_split.parquet"
FRAMES_IDX_PATH = LABELS_DIR / "frames_idx.parquet"
SEGS_IDX_PATH   = LABELS_DIR / "segs_idx.parquet"

for p in [MANIFEST_PATH, FRAMES_IDX_PATH, SEGS_IDX_PATH]:
    assert p.exists(), f"Missing: {p}"

manifest  = pd.read_parquet(MANIFEST_PATH)
frames_ix = pd.read_parquet(FRAMES_IDX_PATH)
segs_ix   = pd.read_parquet(SEGS_IDX_PATH)

_time_col = "time_sec" if "time_sec" in frames_ix.columns else None
if _time_col is None and {"frame","fps"}.issubset(frames_ix.columns):
    frames_ix = frames_ix.copy()
    frames_ix["time_sec"] = frames_ix["frame"] / frames_ix["fps"]
    _time_col = "time_sec"
assert _time_col is not None, "frames_idx must have time_sec or
(frame,fps)."

INTAKE_LABELS = {"Eat it"}
WINDOW_POS_OVERLAP = 0.25

WIN_SEC  = float(CONFIG["win_sec"])
STRIDE_S = float(CONFIG["stride_sec"])

def _dur(key: str) -> float:
    f = frames_ix[frames_ix["key"] == key]
    return float(f[_time_col].max()) if len(f) else 0.0

def _iou(a0, a1, b0, b1) -> float:
    inter = max(0.0, min(a1, b1) - max(a0, b0))
    if inter <= 0:
        return 0.0
    union = (a1 - a0) + (b1 - b0) - inter + 1e-9
    return inter / union

# keep only positive intake segments:
if "label" in segs_ix.columns:
    if segs_ix["label"].dtype.kind in "iu":
        segs_pos = segs_ix[segs_ix["label"].astype(int) == 1].copy()
    else:
        segs_pos =
segs_ix[segs_ix["label"].astype(str).isin(list(INTAKE_LABELS))].copy()
else:
    segs_pos = segs_ix.copy()

def _label_window(key: str, w0: float, w1: float) -> int:
    s = segs_pos[segs_pos["key"] == key]
    if s.empty:
        return 0
```

```
    ious = s.apply(
        lambda r: _iou(w0, w1, float(r["start_sec"]),
float(r["end_sec"])),
        axis=1
    ).to_numpy()
    return int((ious >= WINDOW_POS_OVERLAP).any())

rows = []
for key, g in manifest.groupby("key"):
    split = g["split"].iloc[0] if "split" in g.columns else "train"
    dur = _dur(key)
    if dur <= 0:
        continue
    t = 0.0
    while t + WIN_SEC <= dur + 1e-6:
        w0, w1 = t, t + WIN_SEC
        rows.append((key, split, w0, w1, _label_window(key, w0, w1)))
        t += STRIDE_S

windows_df = pd.DataFrame(
    rows, columns=["key","split","start_sec","end_sec","label"]
).astype({"key":"string","split":"string","start_sec":"float32","end_s
ec":"float32","label":"int8"})

out_path = LOG_DIR / "windows_idx.parquet"
windows_df.to_parquet(out_path)
cnt = windows_df.value_counts("split").to_dict()
pos_rate = float((windows_df["label"]==1).mean())
LOGGER.info(f"windows_idx saved: {out_path} | rows={len(windows_df)} |
by split={cnt} | pos_rate={pos_rate:.3f}")
```

```
2025-11-26 19:51:15,470 | INFO | windows_idx saved:
/content/drive/MyDrive/eatsense/logs/windows_idx.parquet | rows=98582
| by split={'train': 62568, 'val': 21184, 'test': 14830} |
pos_rate=0.006
```

```
INFO:bitepulse:windows_idx saved:
/content/drive/MyDrive/eatsense/logs/windows_idx.parquet | rows=98582
| by split={'train': 62568, 'val': 21184, 'test': 14830} |
pos_rate=0.006
```

Baseline PyTorch Temporal ConvNet (PoseTCNPro)

```
class PoseWindowDataset(Dataset):
    """
    Each item: (T, F) pose window tensor, label in {0,1}.
    Expects POSE_DIR / '{key}.parquet' with 'time_sec' and numeric
joint cols.
    """
    def __init__(self, windows: pd.DataFrame, fps: float = 30.0,
```

```
                 cols_regex: str = r"^(x_|y_|z_|j\d+)"):
        self.df = windows.reset_index(drop=True)
        self.fps = float(fps)
        self.T   = max(1, int(round(CONFIG["win_sec"] * self.fps)))
        self._re = re.compile(cols_regex)
        self._cache = {}

    def _pose_df(self, key: str) -> pd.DataFrame:
        if key in self._cache:
            return self._cache[key]
        p = POSE_DIR / f"{key}.parquet"
        df = pd.read_parquet(p)
        assert "time_sec" in df.columns, "pose parquet must include 
'time_sec'."
        cols = [c for c in df.columns
                if c!="time_sec" and 
pd.api.types.is_numeric_dtype(df[c])
                and self._re.search(str(c))]
        if not cols:
            cols = [c for c in df.columns
                    if c!="time_sec" and 
pd.api.types.is_numeric_dtype(df[c])]
        df = df[["time_sec"] + cols]
        self._cache[key] = df
        return df

    def _slice(self, key: str, w0: float, w1: float) -> torch.Tensor:
        df = self._pose_df(key)
        m  = (df["time_sec"] >= w0) & (df["time_sec"] < w1)
        clip = 
df.loc[m].drop(columns=["time_sec"]).to_numpy(dtype=np.float32)

        if clip.size == 0:
            F_ = len(df.columns) - 1
            arr = np.zeros((self.T, F_), dtype=np.float32)
        else:
            clip = np.nan_to_num(clip, nan=0.0, posinf=0.0, 
neginf=0.0)
            idx = np.linspace(0, max(len(clip)-1, 0), 
num=self.T).round().astype(int)
            arr = clip[idx]

        if arr.size:
            mu = arr.mean(0, keepdims=True)
            sd = arr.std(0, keepdims=True)
            sd = np.where(sd < 1e-6, 1e-6, sd)
            arr = (arr - mu) / sd

        arr = np.nan_to_num(arr, nan=0.0, posinf=0.0, neginf=0.0)
        return torch.from_numpy(arr)
```

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

    def __getitem__(self, i):
        r = self.df.iloc[i]
        x = self._slice(r["key"], float(r["start_sec"]),
float(r["end_sec"]))
        y = torch.tensor(int(r["label"]), dtype=torch.long)
        return x, y

def collate_pose(batch):
    xs, ys = zip(*batch)
    return torch.stack(xs, dim=0), torch.tensor(ys, dtype=torch.long)

def make_pose_loader(windows_df, split, fps=15.0, balance=True):
    df_split = windows_df[windows_df["split"] ==
split].reset_index(drop=True)
    ds = PoseWindowDataset(df_split, fps=fps)

    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,
        collate_fn=collate_pose,
        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

train_pose_loader, train_pose_ds = make_pose_loader(windows_df,
"train", fps=15.0, balance=True)
val_pose_loader,   val_pose_ds   = make_pose_loader(windows_df, "val",
fps=15.0, balance=False)
```

```python
sample_x, _ = next(iter(train_pose_loader))
in_feats = sample_x.shape[-1]
print("Pose window shape:", sample_x.shape, " | in_feats:", in_feats)
```

```
Pose window shape: torch.Size([32, 30, 19])  | in_feats: 19
```

```python
class Chomp1d(nn.Module):
    def __init__(self, chomp):
        super().__init__()
        self.chomp = chomp
    def forward(self, x):
        return x[..., :-self.chomp] if self.chomp > 0 else x

class SE1D(nn.Module):
    def __init__(self, ch, r=8):
        super().__init__()
        self.fc = nn.Sequential(
            nn.AdaptiveAvgPool1d(1),
            nn.Conv1d(ch, ch // r, 1), nn.GELU(),
            nn.Conv1d(ch // r, ch, 1), nn.Sigmoid()
        )
    def forward(self, x):
        return x * self.fc(x)

class DSConv1D(nn.Module):
    """Depthwise-separable conv + LayerNorm + GELU."""
    def __init__(self, in_ch, out_ch, k=5, d=1, causal=True,
p_drop=0.2):
        super().__init__()
        pad = (k - 1) * d if causal else ((k - 1) * d) // 2
        self.depth = nn.Conv1d(in_ch, in_ch, k, dilation=d,
                               padding=pad, groups=in_ch, bias=False)
        self.chomp = Chomp1d(pad) if causal else nn.Identity()
        self.point = nn.Conv1d(in_ch, out_ch, 1, bias=False)
        self.norm  = nn.LayerNorm(out_ch)
        self.drop  = nn.Dropout(p_drop)

    def forward(self, x):              # (B, C, T)
        y = self.depth(x)
        y = self.chomp(y)
        y = self.point(y)              # (B, Cout, T)
        y = self.norm(y.transpose(1,2)).transpose(1,2)
        y = F.gelu(y)
        return self.drop(y)

class TemporalBlock(nn.Module):
    def __init__(self, in_ch, out_ch, k=5, d=1,
                 causal=True, p_drop=0.2, use_se=True):
        super().__init__()
```

```
        self.conv1 = DSConv1D(in_ch,  out_ch, k=k, d=d,
                              causal=causal, p_drop=p_drop)
        self.conv2 = DSConv1D(out_ch, out_ch, k=k, d=d,
                              causal=causal, p_drop=p_drop)
        self.se    = SE1D(out_ch) if use_se else nn.Identity()
        self.res   = nn.Conv1d(in_ch, out_ch, 1) if in_ch != out_ch
else nn.Identity()
        self.drop  = nn.Dropout(p_drop)

    def forward(self, x):
        y = self.conv2(self.conv1(x))
        y = self.se(y)
        y = y + self.res(x)
        return F.gelu(self.drop(y))

class AttnPool1D(nn.Module):
    """Additive attention pooling over time."""
    def __init__(self, ch, hidden=128):
        super().__init__()
        self.score = nn.Sequential(
            nn.Conv1d(ch, hidden, 1),
            nn.Tanh(),
            nn.Conv1d(hidden, 1, 1)
        )
    def forward(self, x):              # (B, C, T)
        w = torch.softmax(self.score(x), dim=-1)  # (B,1,T)
        return torch.sum(x * w, dim=-1)           # (B,C)

class PoseTCNPro(nn.Module):
    """Input: (B, T, F) -> logits (B,)"""
    def __init__(self, in_feats, base_ch=128, k=5,
                 dilations=(1,2,4,8,16), causal=True,
                 p_drop=0.2, use_se=True):
        super().__init__()
        self.in_proj = nn.Conv1d(in_feats, base_ch, 1)
        blocks, ch = [], base_ch
        for d in dilations:
            blocks.append(
                TemporalBlock(ch, ch, k=k, d=d,
                              causal=causal, p_drop=p_drop,
use_se=use_se)
            )
        self.tcn  = nn.Sequential(*blocks)
        self.pool = AttnPool1D(ch, hidden=ch//2)
        self.head = nn.Sequential(
            nn.LayerNorm(ch),
            nn.Linear(ch, ch//2),
            nn.GELU(),
            nn.Dropout(p_drop),
            nn.Linear(ch//2, 1),
```

```python
        )

    def forward(self, x):               # (B, T, F)
        x = x.transpose(1,2)            # (B, F, T)
        x = self.in_proj(x)
        x = self.tcn(x)                 # (B, C, T)
        x = self.pool(x)                # (B, C)
        return self.head(x).squeeze(-1)

def bin_metrics_from_logits_np(logits: np.ndarray,
                               targets: np.ndarray,
                               thr: float = 0.5) -> Dict[str, float]:
    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,
):
    """Scan PR curve, pick threshold with max F1 under
precision/recall floors."""
    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)  # (prec, rec, tp, fp, fn)

    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)
```

```python
            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 run_one_epoch(model, loader, optimizer=None):
    """
    One epoch over pose DataLoader.
    Returns: avg_loss, metrics_at_thr_0_5, 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 = x.to(DEVICE, non_blocking=True).float()   # (B, T, F)
        y = y.to(DEVICE, non_blocking=True).float()   # (B,)

        if train_mode:
            optimizer.zero_grad(set_to_none=True)

        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())

    logits_np  = torch.cat(all_logits, dim=0).numpy()
    targets_np = torch.cat(all_targets, dim=0).numpy().astype(int)
    m          = bin_metrics_from_logits_np(logits_np, targets_np,
thr=0.5)
```

```
    return total_loss / max(1, n_seen), m, logits_np, targets_np

def pick_best_threshold(logits_np, targets_np,
                        prec_floor=0.10, rec_floor=0.10):
    f1_star, thr_star, (prec, rec, tp, fp, fn) =
best_f1_threshold_with_floor(
        logits_np, targets_np,
        prec_floor=prec_floor,
        rec_floor=rec_floor,
    )

    m = bin_metrics_from_logits_np(logits_np, targets_np, thr_star)
    return dict(
        thr=float(thr_star),
        f1=float(f1_star),
        acc=m["acc"],
        prec=m["prec"],
        rec=m["rec"],
        tp=m["tp"],
        fp=m["fp"],
        fn=m["fn"],
        tn=m["tn"],
    )
```

Baseline TCN Model Training

```
def train_tcn(train_loader, val_loader, in_feats: int):
    model = PoseTCNPro(
        in_feats=in_feats,
        base_ch=128,
        k=5,
        dilations=(1,2,4,8,16),
        causal=True,
        p_drop=0.2,
        use_se=True,
    ).to(DEVICE)

    optimizer = torch.optim.AdamW(
        model.parameters(),
        lr=CONFIG["lr"],
        weight_decay=CONFIG["weight_decay"],
    )
    sched = torch.optim.lr_scheduler.OneCycleLR(
        optimizer, max_lr=8e-4,
        steps_per_epoch=len(train_loader),
        epochs=CONFIG["epochs"],
    )

    best_val_f1, best_state = -1.0, None
```

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

        tr_loss, tr_m, _, _ = run_one_epoch(model, train_loader,
optimizer=optimizer)
        try:
            sched.step()
        except Exception:
            pass

        va_loss, va_m, va_logits_np, va_y_np = run_one_epoch(model,
val_loader, optimizer=None)
        best_val = pick_best_threshold(va_logits_np, va_y_np)

        LOGGER.info(
            f"train loss {tr_loss:.4f} | thr@0.5 acc {tr_m['acc']:.3f}
"
            f"prec {tr_m['prec']:.3f} rec {tr_m['rec']:.3f} f1
{tr_m['f1']:.3f}"
        )
        LOGGER.info(
            f" val  loss {va_loss:.4f} |
thr@best={best_val['thr']:.2f} "
            f"acc {best_val['acc']:.3f} prec {best_val['prec']:.3f} "
            f"rec {best_val['rec']:.3f} f1 {best_val['f1']:.3f}"
        )

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

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

# train baseline:
model_tcn = train_tcn(train_pose_loader, val_pose_loader,
in_feats=in_feats)
```

```
2025-11-26 19:53:00,253 | INFO | [TCN] epoch 1/12

INFO:bitepulse:[TCN] epoch 1/12
```

{"model_id":"05f4a618bfa748239f924a31ff033281","version_major":2,"version_minor":0}

{"model_id":"6858f1c1f15f4555834da34e3cd7a2bb","version_major":2,"version_minor":0}

```
2025-11-26 19:54:45,815 | INFO | train loss 0.5565 | thr@0.5 acc 0.776 prec 0.710 rec 0.936 f1 0.807

INFO:bitepulse:train loss 0.5565 | thr@0.5 acc 0.776 prec 0.710 rec 0.936 f1 0.807

2025-11-26 19:54:45,817 | INFO |  val  loss 0.5815 | thr@best=0.99 acc 0.996 prec 0.220 rec 0.158 f1 0.184

INFO:bitepulse: val  loss 0.5815 | thr@best=0.99 acc 0.996 prec 0.220 rec 0.158 f1 0.184

2025-11-26 19:54:46,747 | INFO | ✓ saved new best (f1=0.184 @ thr=0.99)

INFO:bitepulse:✓ saved new best (f1=0.184 @ thr=0.99)

2025-11-26 19:54:46,748 | INFO | [TCN] epoch 2/12

INFO:bitepulse:[TCN] epoch 2/12
```

{"model_id":"7599d4e50a364850ba2af407f48bd9bc","version_major":2,"version_minor":0}

{"model_id":"e7ba1fe9994f4c30a7881c87cfb4a7d6","version_major":2,"version_minor":0}

```
2025-11-26 19:55:40,873 | INFO | train loss 0.2481 | thr@0.5 acc 0.925 prec 0.893 rec 0.968 f1 0.929

INFO:bitepulse:train loss 0.2481 | thr@0.5 acc 0.925 prec 0.893 rec 0.968 f1 0.929

2025-11-26 19:55:40,874 | INFO |  val  loss 0.4421 | thr@best=1.00 acc 0.995 prec 0.175 rec 0.193 f1 0.198

INFO:bitepulse: val  loss 0.4421 | thr@best=1.00 acc 0.995 prec 0.175 rec 0.193 f1 0.198

2025-11-26 19:55:40,893 | INFO | ✓ saved new best (f1=0.198 @ thr=1.00)

INFO:bitepulse:✓ saved new best (f1=0.198 @ thr=1.00)

2025-11-26 19:55:40,895 | INFO | [TCN] epoch 3/12

INFO:bitepulse:[TCN] epoch 3/12
```

```
{"model_id":"1c61539438a8429d93df192f7cef2334","version_major":2,"version_minor":0}

{"model_id":"378635af6ec94636b35c519af0c21f93","version_major":2,"version_minor":0}

2025-11-26 19:56:34,613 | INFO | train loss 0.1618 | thr@0.5 acc 0.954 prec 0.928 rec 0.985 f1 0.956

INFO:bitepulse:train loss 0.1618 | thr@0.5 acc 0.954 prec 0.928 rec 0.985 f1 0.956

2025-11-26 19:56:34,614 | INFO |  val  loss 0.2524 | thr@best=1.00 acc 0.996 prec 0.212 rec 0.246 f1 0.228

INFO:bitepulse: val  loss 0.2524 | thr@best=1.00 acc 0.996 prec 0.212 rec 0.246 f1 0.228

2025-11-26 19:56:34,634 | INFO | ✓ saved new best (f1=0.228 @ thr=1.00)

INFO:bitepulse:✓ saved new best (f1=0.228 @ thr=1.00)

2025-11-26 19:56:34,635 | INFO | [TCN] epoch 4/12

INFO:bitepulse:[TCN] epoch 4/12

{"model_id":"e9b708e74dc24ac4b51419427a77be21","version_major":2,"version_minor":0}

{"model_id":"45345a29387f4c5ab25df4f637224f5b","version_major":2,"version_minor":0}

2025-11-26 19:57:28,812 | INFO | train loss 0.1237 | thr@0.5 acc 0.966 prec 0.945 rec 0.990 f1 0.967

INFO:bitepulse:train loss 0.1237 | thr@0.5 acc 0.966 prec 0.945 rec 0.990 f1 0.967

2025-11-26 19:57:28,814 | INFO |  val  loss 0.3408 | thr@best=1.00 acc 0.995 prec 0.189 rec 0.246 f1 0.214

INFO:bitepulse: val  loss 0.3408 | thr@best=1.00 acc 0.995 prec 0.189 rec 0.246 f1 0.214

2025-11-26 19:57:28,815 | INFO | [TCN] epoch 5/12

INFO:bitepulse:[TCN] epoch 5/12

{"model_id":"569940ae3c3e46e38319cd1dc03ac50e","version_major":2,"version_minor":0}
```

{"model_id":"4953a1a62ece449b838e7bbae40989c2","version_major":2,"version_minor":0}

2025-11-26 19:58:22,897 | INFO | train loss 0.0997 | thr@0.5 acc 0.974 prec 0.957 rec 0.993 f1 0.975

INFO:bitepulse:train loss 0.0997 | thr@0.5 acc 0.974 prec 0.957 rec 0.993 f1 0.975

2025-11-26 19:58:22,898 | INFO | val loss 0.2224 | thr@best=1.00 acc 0.997 prec 0.270 rec 0.175 f1 0.232

INFO:bitepulse: val loss 0.2224 | thr@best=1.00 acc 0.997 prec 0.270 rec 0.175 f1 0.232

2025-11-26 19:58:22,918 | INFO | ✓ saved new best (f1=0.232 @ thr=1.00)

INFO:bitepulse:✓ saved new best (f1=0.232 @ thr=1.00)

2025-11-26 19:58:22,920 | INFO | [TCN] epoch 6/12

INFO:bitepulse:[TCN] epoch 6/12

{"model_id":"ae5d4a2238124cb0a518ed219295028c","version_major":2,"version_minor":0}

{"model_id":"6c175955288f4333bac090326bbd9408","version_major":2,"version_minor":0}

2025-11-26 19:59:17,203 | INFO | train loss 0.0852 | thr@0.5 acc 0.978 prec 0.963 rec 0.995 f1 0.979

INFO:bitepulse:train loss 0.0852 | thr@0.5 acc 0.978 prec 0.963 rec 0.995 f1 0.979

2025-11-26 19:59:17,204 | INFO | val loss 0.2132 | thr@best=1.00 acc 0.996 prec 0.214 rec 0.211 f1 0.212

INFO:bitepulse: val loss 0.2132 | thr@best=1.00 acc 0.996 prec 0.214 rec 0.211 f1 0.212

2025-11-26 19:59:17,206 | INFO | [TCN] epoch 7/12

INFO:bitepulse:[TCN] epoch 7/12

{"model_id":"bc903cb594404cefb756ff92044f6402","version_major":2,"version_minor":0}

{"model_id":"c84abd34f9a84a6aa5f0411a95d2fdcd","version_major":2,"version_minor":0}

```
2025-11-26 20:00:10,758 | INFO | train loss 0.0736 | thr@0.5 acc 0.981 prec 0.968 rec 0.995 f1 0.981

INFO:bitepulse:train loss 0.0736 | thr@0.5 acc 0.981 prec 0.968 rec 0.995 f1 0.981

2025-11-26 20:00:10,759 | INFO |  val  loss 0.1771 | thr@best=1.00 acc 0.996 prec 0.222 rec 0.211 f1 0.216

INFO:bitepulse: val  loss 0.1771 | thr@best=1.00 acc 0.996 prec 0.222 rec 0.211 f1 0.216

2025-11-26 20:00:10,761 | INFO | [TCN] epoch 8/12

INFO:bitepulse:[TCN] epoch 8/12
```

{"model_id":"6f6879d6364449e296008fc06065faf4","version_major":2,"version_minor":0}

{"model_id":"16aca7d8505449d09b8a8bef13f248de","version_major":2,"version_minor":0}

```
2025-11-26 20:01:05,031 | INFO | train loss 0.0643 | thr@0.5 acc 0.983 prec 0.972 rec 0.995 f1 0.984

INFO:bitepulse:train loss 0.0643 | thr@0.5 acc 0.983 prec 0.972 rec 0.995 f1 0.984

2025-11-26 20:01:05,032 | INFO |  val  loss 0.1693 | thr@best=1.00 acc 0.995 prec 0.197 rec 0.228 f1 0.226

INFO:bitepulse: val  loss 0.1693 | thr@best=1.00 acc 0.995 prec 0.197 rec 0.228 f1 0.226

2025-11-26 20:01:05,034 | INFO | [TCN] epoch 9/12

INFO:bitepulse:[TCN] epoch 9/12
```

{"model_id":"c402fafe5766443abb240b31e4623a9b","version_major":2,"version_minor":0}

{"model_id":"dc69b28a4551413cbef921dc8a187398","version_major":2,"version_minor":0}

```
2025-11-26 20:01:59,784 | INFO | train loss 0.0563 | thr@0.5 acc 0.987 prec 0.977 rec 0.997 f1 0.987

INFO:bitepulse:train loss 0.0563 | thr@0.5 acc 0.987 prec 0.977 rec 0.997 f1 0.987

2025-11-26 20:01:59,786 | INFO |  val  loss 0.1901 | thr@best=1.00 acc 0.996 prec 0.238 rec 0.175 f1 0.202
```

```
INFO:bitepulse: val  loss 0.1901 | thr@best=1.00 acc 0.996 prec 0.238
rec 0.175 f1 0.202

2025-11-26 20:01:59,787 | INFO | [TCN] epoch 10/12

INFO:bitepulse:[TCN] epoch 10/12
```

{"model_id":"67a0500a5d424d588aaee63c9bfbd97c","version_major":2,"version_minor":0}

{"model_id":"710c86325477459bba1d9c9a0742a767","version_major":2,"version_minor":0}

```
2025-11-26 20:02:53,376 | INFO | train loss 0.0528 | thr@0.5 acc 0.987
prec 0.978 rec 0.996 f1 0.987

INFO:bitepulse:train loss 0.0528 | thr@0.5 acc 0.987 prec 0.978 rec
0.996 f1 0.987

2025-11-26 20:02:53,378 | INFO |  val  loss 0.1148 | thr@best=1.00 acc
0.997 prec 0.310 rec 0.228 f1 0.263

INFO:bitepulse: val  loss 0.1148 | thr@best=1.00 acc 0.997 prec 0.310
rec 0.228 f1 0.263

2025-11-26 20:02:53,403 | INFO | ✓ saved new best (f1=0.263 @
thr=1.00)

INFO:bitepulse:✓ saved new best (f1=0.263 @ thr=1.00)

2025-11-26 20:02:53,405 | INFO | [TCN] epoch 11/12

INFO:bitepulse:[TCN] epoch 11/12
```

{"model_id":"45d0e34a46444506bd2d8951c645af54","version_major":2,"version_minor":0}

{"model_id":"7547c5af44724687a7427b57d5a53518","version_major":2,"version_minor":0}

```
2025-11-26 20:03:47,020 | INFO | train loss 0.0496 | thr@0.5 acc 0.988
prec 0.979 rec 0.997 f1 0.988

INFO:bitepulse:train loss 0.0496 | thr@0.5 acc 0.988 prec 0.979 rec
0.997 f1 0.988

2025-11-26 20:03:47,022 | INFO |  val  loss 0.1573 | thr@best=1.00 acc
0.996 prec 0.245 rec 0.228 f1 0.236

INFO:bitepulse: val  loss 0.1573 | thr@best=1.00 acc 0.996 prec 0.245
rec 0.228 f1 0.236

2025-11-26 20:03:47,023 | INFO | [TCN] epoch 12/12
```

```
INFO:bitepulse:[TCN] epoch 12/12
```

{"model_id":"1213451c1a4f406d8b9dd595ef7c9b74","version_major":2,"version_minor":0}

{"model_id":"2355bdc332604c5d81518a2fb6cefdb9","version_major":2,"version_minor":0}

```
2025-11-26 20:04:40,631 | INFO | train loss 0.0425 | thr@0.5 acc 0.990 prec 0.983 rec 0.998 f1 0.990

INFO:bitepulse:train loss 0.0425 | thr@0.5 acc 0.990 prec 0.983 rec 0.998 f1 0.990

2025-11-26 20:04:40,632 | INFO |  val  loss 0.1499 | thr@best=1.00 acc 0.996 prec 0.217 rec 0.228 f1 0.222

INFO:bitepulse: val  loss 0.1499 | thr@best=1.00 acc 0.996 prec 0.217 rec 0.228 f1 0.222

2025-11-26 20:04:40,634 | INFO | [TCN] best val f1=0.263

INFO:bitepulse:[TCN] best val f1=0.263
```

Baseline TCN Model Performance Evaluation

```python
# Load best checkpoint:
ckpt = torch.load(CKPT_DIR / "tcn_best.pt", map_location=DEVICE)
best_thr_tcn = float(ckpt.get("best_thr", 0.5))
model_tcn.load_state_dict(ckpt["model"])
model_tcn.to(DEVICE).eval()

val_loss_tcn, val_m_tcn, val_logits_np_tcn, val_y_np = run_one_epoch(
    model_tcn, val_pose_loader, optimizer=None
)

LOGGER.info(f"[TCN] final val loss={val_loss_tcn:.4f},
f1@0.5={val_m_tcn['f1']:.3f}")
```

{"model_id":"534b4d1cc8434c239f175c7bcb6d9bbc","version_major":2,"version_minor":0}

```
2025-11-26 20:12:11,453 | INFO | [TCN] final val loss=0.1148, f1@0.5=0.095

INFO:bitepulse:[TCN] final val loss=0.1148, f1@0.5=0.095
```

```python
def evaluate_window_model(logits_np: np.ndarray,
                          targets_np: np.ndarray,
                          label: str = "model",
                          prec_floor: float = 0.10,
                          rec_floor: float = 0.10):
```

```
    """
    1) Find best F1 threshold with floors.
    2) Print scalar metrics & classification report.
    3) Plot confusion matrix + ROC + PR.
    """
    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)
    probs = 1.0 / (1.0 + np.exp(-logits_np.astype(np.float64)))
    y_pred = (probs >= thr).astype(int)

    tn, fp, fn, tp = confusion_matrix(y_true, y_pred).ravel()
    acc  = (tp + tn) / (tp + tn + fp + fn + 1e-12)
    prec = tp / (tp + fp + 1e-12)
    rec  = tp / (tp + fn + 1e-12)
    spec = tn / (tn + fp + 1e-12)
    f1   = 2 * prec * rec / (prec + rec + 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),
    }

    p_prob = probs
    roc_auc_overall = roc_auc_score(y_true, p_prob)
    pr_auc_overall  = average_precision_score(y_true, p_prob)
    metrics["roc_auc_overall"] = roc_auc_overall
    metrics["pr_auc_overall"]  = pr_auc_overall

    print(f"\n=== {label}: Validation 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))

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

    # Confusion matrix heatmap
    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)

    # ROC
    fpr, tpr, _ = roc_curve(y_true, p_prob)
    ax2 = plt.subplot(1,3,2)
    ax2.plot(fpr, tpr, label=f"AUC = {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")

    # PR
    P, R, _ = precision_recall_curve(y_true, p_prob)
    ax3 = plt.subplot(1,3,3)
    ax3.plot(R, P, label=f"AP = {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()
```

```python
    plt.show()

    return dict(metrics=metrics, thr=thr, probs=p_prob, y_true=y_true)

eval_tcn = evaluate_window_model(
    logits_np=val_logits_np_tcn,
    targets_np=val_y_np,
    label="PyTorch PoseTCNPro (baseline)"
)
best_thr_tcn = eval_tcn["thr"]
```

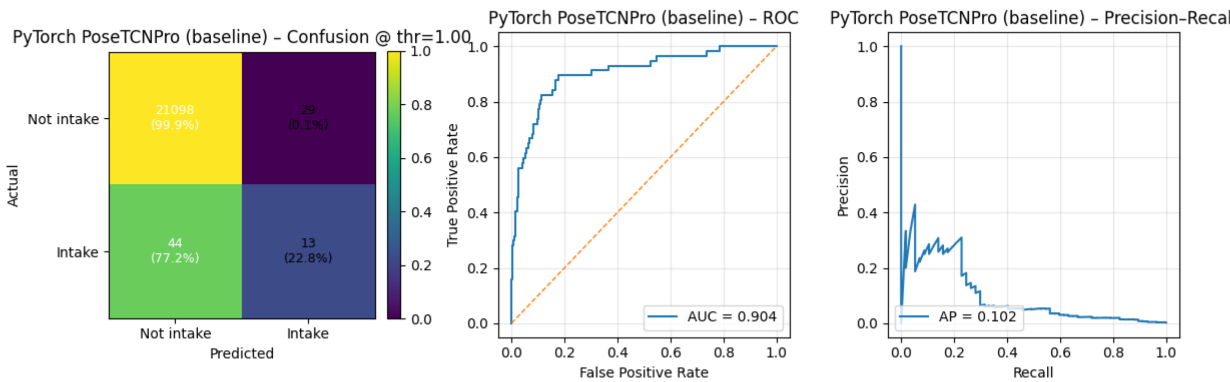
```
=== PyTorch PoseTCNPro (baseline): Validation metrics @ best F1
threshold ===
      threshold(F1*): 0.999
            accuracy: 0.997
           precision: 0.310
              recall: 0.228
                  f1: 0.263
         specificity: 0.999
        balanced_acc: 0.613
                 mcc: 0.264
     roc_auc_overall: 0.904
      pr_auc_overall: 0.102

Confusion Matrix (rows=actual, cols=pred):
[[21098    29]
 [   44    13]]

Classification report:
               precision    recall  f1-score   support

           0      0.998     0.999     0.998     21127
           1      0.310     0.228     0.263        57

    accuracy                          0.997     21184
   macro avg      0.654     0.613     0.630     21184
weighted avg      0.996     0.997     0.996     21184
```



Keras TCN with Hyperband

```
def make_pose_numpy(windows_df, split, fps=15.0):
    df_split = windows_df[windows_df["split"] == split].reset_index(drop=True)
    ds = PoseWindowDataset(df_split, fps=fps)

    X_list, y_list = [], []
    for i in tqdm(range(len(ds)), desc=f"Building {split} pose numpy"):
        x, y = ds[i]             # x: (T, F); y: scalar
        X_list.append(x.numpy())
        y_list.append(int(y.item()))

    X = np.stack(X_list, axis=0).astype("float32")   # (N, T, F)
    y = np.array(y_list, dtype="int32")               # (N,)
    return X, y

X_train, y_train = make_pose_numpy(windows_df, "train", fps=15.0)
X_val,   y_val   = make_pose_numpy(windows_df, "val",   fps=15.0)

print("Train:", X_train.shape, y_train.shape)
print("Val:  ", X_val.shape,   y_val.shape)
```


{"model_id":"d47680a9d34d4087aa7e573f63aee518","version_major":2,"version_minor":0}

{"model_id":"b940b339798341f192c9336d09589da1","version_major":2,"version_minor":0}


```
Train: (62568, 30, 19) (62568,)
Val:   (21184, 30, 19) (21184,)
```

```
pos_rate = (y_train == 1).mean()
neg_rate = 1.0 - pos_rate
class_weight = {
    0: 1.0,
    1: float(neg_rate / max(pos_rate, 1e-6)),
```

```
}
print("class_weight:", class_weight)
```

```
class_weight: {0: 1.0, 1: 147.2654028436019}
```

```
T, F = X_train.shape[1], X_train.shape[2]

def build_tcn_model(hp: kt.HyperParameters):
    inputs = tf.keras.Input(shape=(T, F))
    x = inputs

    # Temporal blocks
    num_blocks = hp.Int("num_blocks", min_value=2, max_value=4,
step=1)
    for i in range(num_blocks):
        filters      = hp.Int(f"filters_{i}", min_value=32,
max_value=160, step=32)
        kernel_size  = hp.Choice("kernel_size", values=[3, 5, 7])
        dropout_rate = hp.Float("dropout", min_value=0.1,
max_value=0.5, step=0.1)
        dilation     = 2 ** i

        x = tf.keras.layers.Conv1D(
            filters=filters,
            kernel_size=kernel_size,
            padding="same",
            dilation_rate=dilation,
            use_bias=False,
        )(x)
        x = tf.keras.layers.BatchNormalization()(x)
        x = tf.keras.layers.ReLU()(x)
        x = tf.keras.layers.Dropout(dropout_rate)(x)

    # Global pooling over time
    x = tf.keras.layers.GlobalAveragePooling1D()(x)

    # Dense head
    dense_units   = hp.Int("dense_units", min_value=32, max_value=160,
step=32)
    dense_dropout = hp.Float("dense_dropout", min_value=0.0,
max_value=0.5, step=0.1)
    x = tf.keras.layers.Dense(dense_units, activation="relu")(x)
    x = tf.keras.layers.Dropout(dense_dropout)(x)

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

    lr = hp.Float("lr", min_value=1e-4, max_value=5e-3,
sampling="log")
    model.compile(
```

```
        optimizer=tf.keras.optimizers.Adam(learning_rate=lr),
        loss="binary_crossentropy",
        metrics=[
            tf.keras.metrics.Precision(name="precision"),
            tf.keras.metrics.Recall(name="recall"),
            tf.keras.metrics.AUC(name="auc"),
            tf.keras.metrics.AUC(curve="PR", name="prc"),
        ],
    )
    return model
```

Keras TCN - Hyperband Search

```
tuner = kt.Hyperband(
    build_tcn_model,
    objective=kt.Objective("val_prc", direction="max"),
    max_epochs=20,
    factor=3,
    directory="keras_tcn_tuning",
    project_name="bitepulse_tcn",
    overwrite=True,
)

early_stop = tf.keras.callbacks.EarlyStopping(
    monitor="val_prc",
    patience=4,
    mode="max",
    restore_best_weights=True,
)

tuner.search(
    X_train, y_train,
    validation_data=(X_val, y_val),
    epochs=20,
    batch_size=32,
    class_weight=class_weight,
    callbacks=[early_stop],
)
```

```
Trial 30 Complete [00h 01m 13s]
val_prc: 0.0968976616859436

Best val_prc So Far: 0.12982948124408722
Total elapsed time: 00h 31m 41s
```

```
best_hp     = tuner.get_best_hyperparameters(1)[0]
best_model  = tuner.get_best_models(1)[0]

print("Best hyperparameters:")
for k, v in best_hp.values.items():
```

```python
    print(f"{k}: {v}")

history = best_model.fit(
    X_train, y_train,
    validation_data=(X_val, y_val),
    epochs=10,
    batch_size=32,
    class_weight=class_weight,
    verbose=1,
)
```

```
Best hyperparameters:
num_blocks: 2
filters_0: 64
kernel_size: 7
dropout: 0.1
filters_1: 128
dense_units: 128
dense_dropout: 0.30000000000000004
lr: 0.0005320715464796309
filters_2: 64
filters_3: 96
tuner/epochs: 20
tuner/initial_epoch: 7
tuner/bracket: 1
tuner/round: 1
tuner/trial_id: 0019
Epoch 1/10
1956/1956 ━━━━━━━━━━━━━━━━━━━━ 20s 7ms/step - auc: 0.9789 - loss:
0.2990 - prc: 0.3860 - precision: 0.1107 - recall: 0.9175 - val_auc:
0.8877 - val_loss: 0.2365 - val_prc: 0.0863 - val_precision: 0.0168 -
val_recall: 0.6491
Epoch 2/10
1956/1956 ━━━━━━━━━━━━━━━━━━━━ 8s 4ms/step - auc: 0.9887 - loss:
0.2485 - prc: 0.4241 - precision: 0.0951 - recall: 0.9609 - val_auc:
0.9018 - val_loss: 0.2329 - val_prc: 0.0667 - val_precision: 0.0190 -
val_recall: 0.7368
Epoch 3/10
1956/1956 ━━━━━━━━━━━━━━━━━━━━ 8s 4ms/step - auc: 0.9893 - loss:
0.2333 - prc: 0.4711 - precision: 0.1119 - recall: 0.9771 - val_auc:
0.8837 - val_loss: 0.2038 - val_prc: 0.0834 - val_precision: 0.0225 -
val_recall: 0.7193
Epoch 4/10
1956/1956 ━━━━━━━━━━━━━━━━━━━━ 8s 4ms/step - auc: 0.9849 - loss:
0.1941 - prc: 0.4846 - precision: 0.1207 - recall: 0.9747 - val_auc:
0.8681 - val_loss: 0.1054 - val_prc: 0.0681 - val_precision: 0.0333 -
val_recall: 0.5263
Epoch 5/10
1956/1956 ━━━━━━━━━━━━━━━━━━━━ 8s 4ms/step - auc: 0.9844 - loss:
0.2413 - prc: 0.4063 - precision: 0.1076 - recall: 0.9669 - val_auc:
```

```
0.8977 - val_loss: 0.1839 - val_prc: 0.0964 - val_precision: 0.0289 -
val_recall: 0.7895
Epoch 6/10
1956/1956 ━━━━━━━━━━━━━━━━━━━━ 8s 4ms/step - auc: 0.9845 - loss:
0.2712 - prc: 0.3750 - precision: 0.0832 - recall: 0.9658 - val_auc:
0.9196 - val_loss: 0.1372 - val_prc: 0.0837 - val_precision: 0.0317 -
val_recall: 0.6842
Epoch 7/10
1956/1956 ━━━━━━━━━━━━━━━━━━━━ 8s 4ms/step - auc: 0.9915 - loss:
0.2126 - prc: 0.4705 - precision: 0.1094 - recall: 0.9698 - val_auc:
0.9329 - val_loss: 0.1659 - val_prc: 0.1045 - val_precision: 0.0316 -
val_recall: 0.7895
Epoch 8/10
1956/1956 ━━━━━━━━━━━━━━━━━━━━ 8s 4ms/step - auc: 0.9846 - loss:
0.1859 - prc: 0.5025 - precision: 0.1358 - recall: 0.9763 - val_auc:
0.9130 - val_loss: 0.1226 - val_prc: 0.0791 - val_precision: 0.0362 -
val_recall: 0.6667
Epoch 9/10
1956/1956 ━━━━━━━━━━━━━━━━━━━━ 8s 4ms/step - auc: 0.9825 - loss:
0.1874 - prc: 0.4458 - precision: 0.1173 - recall: 0.9611 - val_auc:
0.8662 - val_loss: 0.1257 - val_prc: 0.0503 - val_precision: 0.0301 -
val_recall: 0.5789
Epoch 10/10
1956/1956 ━━━━━━━━━━━━━━━━━━━━ 8s 4ms/step - auc: 0.9935 - loss:
0.1433 - prc: 0.5043 - precision: 0.1650 - recall: 0.9908 - val_auc:
0.9128 - val_loss: 0.1050 - val_prc: 0.1140 - val_precision: 0.0446 -
val_recall: 0.6842
```

Keras TCN - Hyperband Performance Evaluation

```
# Keras gives probabilities; convert to logits for fair comparison
val_probs_keras = best_model.predict(X_val, batch_size=256).reshape(-
1)
eps = 1e-7
val_probs_keras = np.clip(val_probs_keras, eps, 1 - eps)
val_logits_np_keras = np.log(val_probs_keras / (1 - val_probs_keras))

# Use same y_val as labels
eval_keras = evaluate_window_model(
    logits_np=val_logits_np_keras,
    targets_np=y_val,
    label="Keras TCN (Hyperband best)"
)
best_thr_keras = eval_keras["thr"]
```

```
83/83 ━━━━━━━━━━━━━━━━━━━━ 5s 29ms/step

=== Keras TCN (Hyperband best): Validation metrics @ best F1 threshold
===
      threshold(F1*): 0.996
```

```
           accuracy: 0.997
          precision: 0.300
             recall: 0.211
                 f1: 0.247
        specificity: 0.999
       balanced_acc: 0.605
                mcc: 0.250
    roc_auc_overall: 0.924
     pr_auc_overall: 0.134

Confusion Matrix (rows=actual, cols=pred):
[[21099    28]
 [   45    12]]

Classification report:
               precision    recall  f1-score   support

           0      0.998     0.999     0.998     21127
           1      0.300     0.211     0.247        57

    accuracy                          0.997     21184
   macro avg      0.649     0.605     0.623     21184
weighted avg      0.996     0.997     0.996     21184
```