Malaria Cell Classification with Feed-Forward Neural Networks

1. Setup and Imports

Initialize libraries, set device (GPU/CPU), fix random seed for reproducibility.

In [1]:
```
import os, json, math, random, hashlib
from pathlib import Path
from itertools import product
import numpy as np
import torch
from torch import nn
from torch.utils.data import DataLoader
from torchvision.datasets import ImageFolder
from torchvision import transforms
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, classification_report
from tqdm import tqdm
```

In [5]:
```
# ✅ CLEAN CONFIGURATION - No duplicates!

IMG_SIZE = 64
BATCH_SIZE = 512  # Optimized for speed
EPOCHS_BASELINE = 20  # Balanced speed/performance
EPOCHS_L2 = 20
EPOCHS_DROPOUT = 20
EPOCHS_ES_MAX = 40
ES_PATIENCE_SWEEP = [5, 7, 10]

# Single recommended architecture (no grid search for speed)
RECOMMENDED_ARCHITECTURE = [256, 128]  # 2 hidden layers
RECOMMENDED_LR = 1e-3  # Single learning rate

L2_WEIGHTS = [1e-5, 3e-5, 1e-4, 3e-4, 1e-3]
DROPOUT_PS = [0.1, 0.2, 0.3, 0.4]
NUM_WORKERS = min(8, os.cpu_count() or 2)
USE_NORMALIZE = False
NORM_MEAN = [0.5, 0.5, 0.5]
NORM_STD = [0.5, 0.5, 0.5]

print("✅ Clean configuration loaded!")
print(f"📊 Batch size: {BATCH_SIZE} | Epochs: {EPOCHS_BASELINE}")
print(f"🧠 Recommended architecture: {RECOMMENDED_ARCHITECTURE}")
print(f"⚡ Single model training (no grid search)")
```

```
✅ Clean configuration loaded!
📊 Batch size: 512 | Epochs: 20
🧠 Recommended architecture: [256, 128]
⚡ Single model training (no grid search)
```

2. Data Loading and Preprocessing

Load malaria dataset (resized 64×64 RGB images), create training/validation/test splits (split_dataset.py), apply transforms, and prepare data loaders.

In [6]:
```
# ---------- Paths (EDIT if you used different folders) ----------
DATA_RESIZED = r"D:\GMU Courses\Sem-3\DL\Assignments\Malaria_dataset\malaria_resize
OUT_DIR      = r"D:\GMU Courses\Sem-3\DL\Assignments\Malaria_dataset\outputs_ff"

os.makedirs(OUT_DIR, exist_ok=True)

# ---------- Reproducibility ----------
def set_seed(seed=42):
    random.seed(seed)
    np.random.seed(seed)
    torch.manual_seed(seed)
    torch.cuda.manual_seed_all(seed)
set_seed(42)

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
device
```

Out[6]:
```
device(type='cuda')
```

ignore the below cell

In [4]:
```
# ======= EDIT ONLY THESE IF YOU WANT (structure stays unchanged) =======

# IMG_SIZE = 64

# Batch size: 512 is safe on 6–8GB 3060; try 1024 if you have 12GB VRAM
# BATCH_SIZE = 512

# Epoch budgets (reasonable for speed/accuracy on 3060)
# EPOCHS_BASELINE = 40
# EPOCHS_L2       = 40
# EPOCHS_DROPOUT  = 40
# EPOCHS_ES_MAX   = 80
# ES_PATIENCE_SWEEP = [5, 7, 10]   # we’ll search these; default patience target ~7

# Search spaces (compact but effective)
# SEARCH_BASELINE = {
#     "hidden_layers": [[1024, 512], [1024, 512, 256]],
#     "activation":    ["relu"],           # can try "leaky" later
#     "lr":            [1e-3, 3e-4],
# }

# L2_WEIGHTS = [1e-5, 3e-5, 1e-4, 3e-4, 1e-3]
# DROPOUT_PS = [0.1, 0.2, 0.3, 0.4]

# Data loader workers – keep fixed; changing this doesn't change folders
# NUM_WORKERS = min(8, os.cpu_count() or 2)
```

```
# Optional: normalization toggle (keeping simple 0..1 works fine for MLP)
# USE_NORMALIZE = False
# NORM_MEAN = [0.5, 0.5, 0.5]
# NORM_STD  = [0.5, 0.5, 0.5]
```

In [9]:
```
#  🔧 FIXED TRAINING FUNCTION - Use this instead of the broken one

def train_model_fixed(
    model, train_loader, valid_loader,
    lr=1e-3, weight_decay=0.0,
    max_epochs=40,
    early_stopping=False, patience=5,
):
    model.to(device)
    criterion = nn.BCEWithLogitsLoss()
    optimizer = torch.optim.Adam(model.parameters(), lr=lr, weight_decay=weight_dec

    hist = {"train_loss":[], "valid_loss":[], "train_acc":[], "valid_acc":[]}
    best = {"epoch":-1, "val_acc":-1, "state_dict":None}

    no_improve = 0

    # Print header for training progress
    print(f"\n{'='*80}", flush=True)
    print(f"🚀 STARTING TRAINING - {max_epochs} epochs | LR: {lr} | Batch Size: {tr
    print(f"{'='*80}", flush=True)
    print(f"{'Epoch':<6} {'Train Loss':<12} {'Train Acc':<10} {'Valid Loss':<12} {'
    print("-" * 80, flush=True)

    for epoch in range(1, max_epochs+1):
        tr_loss, tr_acc = run_epoch(model, train_loader, criterion, optimizer, show
        va_loss, va_acc = run_epoch(model, valid_loader, criterion, optimizer=None,
        hist["train_loss"].append(tr_loss); hist["valid_loss"].append(va_loss)
        hist["train_acc"].append(tr_acc);   hist["valid_acc"].append(va_acc)

        # FIXED: Real-time progress display with proper early stopping logic
        best_marker = ""
        if va_acc > best["val_acc"]:
            best.update(epoch=epoch, val_acc=va_acc, state_dict={k:v.cpu() for k,v
            best_marker = "★ BEST"
            no_improve = 0  # Reset counter when we find improvement
        else:
            no_improve += 1  # Increment only when no improvement

        print(f"{epoch:<6} {tr_loss:<12.4f} {tr_acc:<10.4f} {va_loss:<12.4f} {va_ac

        # Early stopping logic
        if early_stopping and no_improve >= patience:
            print(f"\nEarly stopping at epoch {epoch} (no improvement for {patience
            break

    print(f"\n{'='*80}", flush=True)
    print(f"Training completed! Best validation accuracy: {best['val_acc']:.4f} at
    print(f"{'='*80}\n", flush=True)
```

```
    if best["state_dict"] is not None:
        model.load_state_dict(best["state_dict"])
    return model, hist, best

print("✅ Fixed training function loaded!")
```

✅ Fixed training function loaded!

Data Loaders

In [10]:
```
tf_list = [transforms.ToTensor()]
if USE_NORMALIZE:
    tf_list.append(transforms.Normalize(mean=NORM_MEAN, std=NORM_STD))
base_tf = transforms.Compose(tf_list)

train_ds = ImageFolder(os.path.join(DATA_RESIZED, "train"), transform=base_tf)
valid_ds = ImageFolder(os.path.join(DATA_RESIZED, "valid"), transform=base_tf)
test_ds  = ImageFolder(os.path.join(DATA_RESIZED, "test"),  transform=base_tf)

train_loader = DataLoader(train_ds, batch_size=BATCH_SIZE, shuffle=True,
                          num_workers=NUM_WORKERS, pin_memory=True)
valid_loader = DataLoader(valid_ds, batch_size=BATCH_SIZE, shuffle=False,
                          num_workers=NUM_WORKERS, pin_memory=True)
test_loader  = DataLoader(test_ds,  batch_size=BATCH_SIZE, shuffle=False,
                          num_workers=NUM_WORKERS, pin_memory=True)

train_ds.class_to_idx
```

Out[10]:
```
{'Parasitized': 0, 'Uninfected': 1}
```

In [8]:
```
INPUT_DIM = IMG_SIZE * IMG_SIZE * 3  # 64*64*3 = 12288

class FFClassifier(nn.Module):
    def __init__(self, hidden_layers=[512, 256], activation="relu", dropout=0.0):
        super().__init__()
        if activation.lower() == "relu":
            Act = nn.ReLU
        elif activation.lower() in ("leaky", "leakyrelu"):
            Act = lambda: nn.LeakyReLU(negative_slope=0.1)
        else:
            raise ValueError("activation must be 'relu' or 'leaky'")

        layers = []
        in_dim = INPUT_DIM
        for h in hidden_layers:
            layers += [nn.Linear(in_dim, h), Act()]
            if dropout > 0: layers += [nn.Dropout(dropout)]
            in_dim = h
        layers += [nn.Linear(in_dim, 1)]  # binary logit
        self.net = nn.Sequential(*layers)

    def forward(self, x):
        x = torch.flatten(x, start_dim=1)  # [B, 3, 64, 64] -> [B, 12288]
        return self.net(x).squeeze(1)
```

4. Training and Evaluation Utilities

5. Baseline Model Training

Train the fixed MLP. Record training/validation curves and metrics.

In [8]:
```
# 🚀 FAST TRAINING - Complete working version!

# Helper functions (included here to avoid dependency issues)
def accuracy_from_logits(logits, y_true):
    preds = (torch.sigmoid(logits) >= 0.5).long()
    return (preds.cpu() == y_true.cpu().long()).float().mean().item()

def run_epoch(model, loader, criterion, optimizer=None, show_progress=False, epoch=
    training = optimizer is not None
    model.train() if training else model.eval()
    total_loss, total_acc, total_n = 0.0, 0.0, 0

    iterator = loader
    if show_progress:
        desc = f"Epoch {epoch} [{phase}]"
        iterator = tqdm(loader, total=len(loader), desc=desc, leave=False, mininter

    with torch.set_grad_enabled(training):
        for x, y in iterator:
            x, y = x.to(device, non_blocking=True), y.float().to(device, non_blocki
            logits = model(x)
            loss = criterion(logits, y)
            if training:
                optimizer.zero_grad(set_to_none=True)
                loss.backward()
                optimizer.step()
            bs = y.size(0)
            total_loss += loss.item() * bs
            batch_acc = accuracy_from_logits(logits, y)
            total_acc += batch_acc * bs
            total_n += bs

            if show_progress:
                running_loss = total_loss / max(total_n, 1)
                running_acc = total_acc / max(total_n, 1)
                iterator.set_postfix({"loss": f"{running_loss:.4f}", "acc": f"{runn

    return total_loss/total_n, total_acc/total_n

@torch.no_grad()
def evaluate_on_loader(model, loader):
    model.eval().to(device)
    all_logits, all_y = [], []
    for x, y in loader:
        x = x.to(device)
        logits = model(x)
        all_logits.append(torch.sigmoid(logits).cpu())
```

```
        all_y.append(y)
    probs = torch.cat(all_logits).numpy()
    y_true = torch.cat(all_y).numpy()
    y_pred = (probs >= 0.5).astype(int)
    cm = confusion_matrix(y_true, y_pred)
    report = classification_report(y_true, y_pred, target_names=["Parasitized","Uni
                                  digits=4, output_dict=True)
    return probs, y_true, y_pred, cm, report

# Update data loaders with new batch size
train_loader_fast = DataLoader(train_ds, batch_size=BATCH_SIZE, shuffle=True,
                               num_workers=NUM_WORKERS, pin_memory=True)
valid_loader_fast = DataLoader(valid_ds, batch_size=BATCH_SIZE, shuffle=False,
                               num_workers=NUM_WORKERS, pin_memory=True)

print(f"🚀 Starting FAST training with batch size {BATCH_SIZE}")

# Train single recommended model (no grid search)
model_fast = FFClassifier(hidden_layers=RECOMMENDED_ARCHITECTURE, activation="relu"
model_fast, hist_fast, best_fast = train_model_fixed(
    model_fast, train_loader_fast, valid_loader_fast,
    lr=RECOMMENDED_LR, weight_decay=0.0, max_epochs=EPOCHS_BASELINE, early_stopping
)

print(f"\n🎉 FAST TRAINING COMPLETE!")
print(f"📈 Best validation accuracy: {best_fast['val_acc']:.4f}")

# Quick evaluation
_, _, _, cm_fast, report_fast = evaluate_on_loader(model_fast, valid_loader_fast)
print(f"🎯 Final validation accuracy: {report_fast['accuracy']:.4f}")
```

```
🚀 Starting FAST training with batch size 512

================================================================================
🚀 STARTING TRAINING - 20 epochs | LR: 0.001 | Batch Size: 512
================================================================================
Epoch  Train Loss   Train Acc  Valid Loss   Valid Acc  Best
--------------------------------------------------------------------------------

1      0.7312       0.5586     0.6628       0.5959     ★ BEST

2      0.6574       0.6079     0.6426       0.6279     ★ BEST

3      0.6362       0.6329     0.6220       0.6489     ★ BEST

4      0.6186       0.6556     0.6078       0.6695     ★ BEST

5      0.6367       0.6360     0.6264       0.6424

6      0.6119       0.6659     0.6026       0.6695

7      0.5974       0.6777     0.5965       0.6765     ★ BEST

8      0.5869       0.6873     0.5935       0.6813     ★ BEST
```

```
9       0.5959      0.6783     0.5914      0.6828     ★ BEST

10      0.5827      0.6889     0.5943      0.6813

11      0.5852      0.6854     0.6177      0.6506

12      0.5823      0.6893     0.5840      0.6840     ★ BEST

13      0.5707      0.6989     0.5843      0.6869     ★ BEST

14      0.5756      0.6956     0.5778      0.6961     ★ BEST

15      0.5681      0.7040     0.5811      0.6888

16      0.5694      0.7036     0.5751      0.6886

17      0.5560      0.7113     0.5716      0.7034     ★ BEST

18      0.5611      0.7087     0.5685      0.7012

19      0.5532      0.7141     0.5841      0.6867

20      0.5658      0.7042     0.5882      0.6845

================================================================================
Training completed! Best validation accuracy: 0.7034 at epoch 17
================================================================================
```

```
🎉 FAST TRAINING COMPLETE!
📈 Best validation accuracy: 0.7034
🎯 Final validation accuracy: 0.7034
```

6) L2 Regularization (Weight Decay)

Retrain the **same** MLP while adding L2 (weight decay). Tune the L2 strength and plot curves.

In [10]:
```
# ✅ CORRECTED L2 REGULARIZATION - Works with single model approach

def train_with_l2(weight_decay=1e-4):
    """Train model with L2 regularization"""
    print(f"🔧 Training with L2 regularization (weight_decay={weight_decay})")

    # Create model with recommended architecture
    model_l2 = FFClassifier(hidden_layers=RECOMMENDED_ARCHITECTURE, activation="rel

    # Train with L2 regularization
    model_l2, hist_l2, best_l2 = train_model_fixed(
        model_l2, train_loader_fast, valid_loader_fast,
        lr=RECOMMENDED_LR, weight_decay=weight_decay,
```

```
        max_epochs=EPOCHS_L2, early_stopping=False
    )

    # Evaluate
    _, _, _, cm_l2, report_l2 = evaluate_on_loader(model_l2, valid_loader_fast)

    print(f"📈 L2 Model Results (wd={weight_decay}):")
    print(f"   Best validation accuracy: {best_l2['val_acc']:.4f}")
    print(f"   Final validation accuracy: {report_l2['accuracy']:.4f}")

    return model_l2, hist_l2, best_l2, cm_l2, report_l2

# Test different L2 weights
print("🧪 Testing L2 regularization with different weights...")
l2_results = {}

for wd in [1e-5, 1e-4, 1e-3]:  # Test 3 different L2 weights
    model_l2, hist_l2, best_l2, cm_l2, report_l2 = train_with_l2(weight_decay=wd)
    l2_results[wd] = {
        'best_val_acc': best_l2['val_acc'],
        'final_acc': report_l2['accuracy'],
        'model': model_l2
    }
    print()

# Find best L2 weight
best_wd = max(l2_results.keys(), key=lambda k: l2_results[k]['best_val_acc'])
print(f"🏆 Best L2 weight: {best_wd} with accuracy: {l2_results[best_wd]['best_val_
```

```
🧪 Testing L2 regularization with different weights...
🔧 Training with L2 regularization (weight_decay=1e-05)

================================================================================
🚀 STARTING TRAINING - 20 epochs | LR: 0.001 | Batch Size: 512
================================================================================
Epoch  Train Loss   Train Acc  Valid Loss   Valid Acc  Best
--------------------------------------------------------------------------------

1      0.7263       0.5452     0.6616       0.6102     ★ BEST

2      0.6506       0.6213     0.6397       0.6279     ★ BEST

3      0.6294       0.6427     0.6618       0.5967

4      0.6138       0.6577     0.6065       0.6736     ★ BEST

5      0.6057       0.6721     0.6013       0.6722

6      0.6115       0.6657     0.6293       0.6426

7      0.5902       0.6853     0.6064       0.6680

8      0.5878       0.6885     0.5938       0.6852     ★ BEST

```

```
9       0.5828        0.6902      0.6058        0.6724

10      0.5840        0.6896      0.5961        0.6763

11      0.5796        0.6970      0.5848        0.6915      ★ BEST

12      0.5727        0.7003      0.5833        0.6833

13      0.5649        0.7059      0.5810        0.6920      ★ BEST

14      0.5664        0.7036      0.5794        0.6874

15      0.5647        0.7073      0.5797        0.6925      ★ BEST

16      0.5567        0.7117      0.5793        0.6944      ★ BEST

17      0.5551        0.7131      0.5732        0.6973      ★ BEST

18      0.5661        0.7042      0.5809        0.6840

19      0.5730        0.6973      0.6162        0.6567

20      0.5543        0.7120      0.5692        0.7036      ★ BEST

================================================================================
Training completed! Best validation accuracy: 0.7036 at epoch 20
================================================================================
```

```
📈 L2 Model Results (wd=1e-05):
   Best validation accuracy: 0.7036
   Final validation accuracy: 0.7036

🔧 Training with L2 regularization (weight_decay=0.0001)

================================================================================
🚀 STARTING TRAINING - 20 epochs | LR: 0.001 | Batch Size: 512
================================================================================
Epoch  Train Loss   Train Acc  Valid Loss   Valid Acc  Best
--------------------------------------------------------------------------------

1       0.7282        0.5315      0.6672        0.5850      ★ BEST
```

```
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
Cell In[10], line 31
     28 l2_results = {}
     30 for wd in [1e-5, 1e-4, 1e-3]:  # Test 3 different L2 weights
---> 31     model_l2, hist_l2, best_l2, cm_l2, report_l2 = train_with_l2(weight_deca
y=wd)
     32     l2_results[wd] = {
     33         'best_val_acc': best_l2['val_acc'],
     34         'final_acc': report_l2['accuracy'],
     35         'model': model_l2
     36     }
     37     print()

Cell In[10], line 11, in train_with_l2(weight_decay)
      8 model_l2 = FFClassifier(hidden_layers=RECOMMENDED_ARCHITECTURE, activation
="relu", dropout=0.0)
     10 # Train with L2 regularization
---> 11 model_l2, hist_l2, best_l2 = train_model_fixed(
     12     model_l2, train_loader_fast, valid_loader_fast,
     13     lr=RECOMMENDED_LR, weight_decay=weight_decay,
     14     max_epochs=EPOCHS_L2, early_stopping=False
     15 )
     17 # Evaluate
     18 _, _, _, cm_l2, report_l2 = evaluate_on_loader(model_l2, valid_loader_fast)

Cell In[5], line 26, in train_model_fixed(model, train_loader, valid_loader, lr, wei
ght_decay, max_epochs, early_stopping, patience)
     23 print("-" * 80, flush=True)
     25 for epoch in range(1, max_epochs+1):
---> 26     tr_loss, tr_acc = run_epoch(model, train_loader, criterion, optimizer, s
how_progress=True, epoch=epoch, phase=        )
     27     va_loss, va_acc = run_epoch(model, valid_loader, criterion, optimizer=No
ne, show_progress=True, epoch=epoch, phase="valid")
     28     hist["train_loss"].append(tr_loss); hist["valid_loss"].append(va_loss)

Cell In[8], line 19, in run_epoch(model, loader, criterion, optimizer, show_progres
s, epoch, phase)
     16     iterator = tqdm(loader, total=len(loader), desc=desc, leave=False, minin
terval=0.3)
     18 with torch.set_grad_enabled(training):
---> 19     for x, y in iterator:
     20         x, y = x.to(device, non_blocking=True), y.float().to(device, non_blo
cking=True)
     21         logits = model(x)

File d:\GMU Courses\Sem-3\DL\Assignments\Malaria_dataset\myenv\Lib\site-packages\tqd
m\std.py:1181, in tqdm.__iter__(self)
   1178 time = self._time
   1180 try:
-> 1181     for obj in iterable:
   1182         yield obj
   1183         # Update and possibly print the progressbar.
   1184         # Note: does not call self.update(1) for speed optimisation.

File d:\GMU Courses\Sem-3\DL\Assignments\Malaria_dataset\myenv\Lib\site-packages\tor
```

```
ch\utils\data\dataloader.py:491, in DataLoader.__iter__(self)
    489     return self._iterator
    490 else:
--> 491     return self._get_iterator()

File d:\GMU Courses\Sem-3\DL\Assignments\Malaria_dataset\myenv\Lib\site-packages\tor
ch\utils\data\dataloader.py:422, in DataLoader._get_iterator(self)
    420 else:
    421     self.check_worker_number_rationality()
--> 422     return _MultiProcessingDataLoaderIter(self)

File d:\GMU Courses\Sem-3\DL\Assignments\Malaria_dataset\myenv\Lib\site-packages\tor
ch\utils\data\dataloader.py:1146, in _MultiProcessingDataLoaderIter.__init__(self, l
oader)
   1139 w.daemon = True
   1140 # NB: Process.start() actually take some time as it needs to
   1141 #     start a process and pass the arguments over via a pipe.
   1142 #     Therefore, we only add a worker to self._workers list after
   1143 #     it started, so that we do not call .join() if program dies
   1144 #     before it starts, and __del__ tries to join but will get:
   1145 #     AssertionError: can only join a started process.
-> 1146 w.start()
   1147 self._index_queues.append(index_queue)
   1148 self._workers.append(w)

File D:\Conda\Lib\multiprocessing\process.py:121, in BaseProcess.start(self)
    118 assert not _current_process._config.get('daemon'), \
    119        'daemonic processes are not allowed to have children'
    120 _cleanup()
--> 121 self._popen = self._Popen(self)
    122 self._sentinel = self._popen.sentinel
    123 # Avoid a refcycle if the target function holds an indirect
    124 # reference to the process object (see bpo-30775)

File D:\Conda\Lib\multiprocessing\context.py:224, in Process._Popen(process_obj)
    222 @staticmethod
    223 def _Popen(process_obj):
--> 224     return _default_context.get_context().Process._Popen(process_obj)

File D:\Conda\Lib\multiprocessing\context.py:337, in SpawnProcess._Popen(process_ob
j)
    334 @staticmethod
    335 def _Popen(process_obj):
    336     from .popen_spawn_win32 import Popen
--> 337     return Popen(process_obj)

File D:\Conda\Lib\multiprocessing\popen_spawn_win32.py:95, in Popen.__init__(self, p
rocess_obj)
     93 try:
     94     reduction.dump(prep_data, to_child)
---> 95     reduction.dump(process_obj, to_child)
     96 finally:
     97     set_spawning_popen(None)

File D:\Conda\Lib\multiprocessing\reduction.py:60, in dump(obj, file, protocol)
     58 def dump(obj, file, protocol=None):
```

```
     59     '''Replacement for pickle.dump() using ForkingPickler.'''
---> 60     ForkingPickler(file, protocol).dump(obj)

KeyboardInterrupt:
```

7) Dropout Regularization

Retrain the **same** MLP with Dropout enabled.

In [11]:
```python
# ✅ CORRECTED DROPOUT EXPERIMENT - Matches single-model setup

def train_with_dropout(dropout_p=0.0):
    """Train model with dropout probability dropout_p."""
    print(f"🔧 Training with Dropout (p={dropout_p})")

    model_do = FFClassifier(hidden_layers=RECOMMENDED_ARCHITECTURE, activation="rel
    model_do, hist_do, best_do = train_model_fixed(
        model_do, train_loader_fast, valid_loader_fast,
        lr=RECOMMENDED_LR, weight_decay=0.0,
        max_epochs=EPOCHS_DROPOUT, early_stopping=False
    )

    _, _, _, cm_do, report_do = evaluate_on_loader(model_do, valid_loader_fast)
    print(f"📈 Dropout Results (p={dropout_p}): best val acc={best_do['val_acc']:.4
    return model_do, hist_do, best_do, cm_do, report_do

print("🧪 Testing dropout with different probabilities...")
dropout_results = {}

for p in [0.0, 0.2, 0.4]:  # Uses your configured EPOCHS_DROPOUT
    model_do, hist_do, best_do, cm_do, report_do = train_with_dropout(dropout_p=p)
    dropout_results[p] = {
        'best_val_acc': best_do['val_acc'],
        'final_acc': report_do['accuracy'],
        'model': model_do
    }
    print()

best_p = max(dropout_results.keys(), key=lambda k: dropout_results[k]['best_val_acc
print(f"🏆 Best dropout p: {best_p} with accuracy: {dropout_results[best_p]['best_v
```

```
🧪 Testing dropout with different probabilities...
🔧 Training with Dropout (p=0.0)

================================================================================
🚀 STARTING TRAINING - 20 epochs | LR: 0.001 | Batch Size: 512
================================================================================
Epoch  Train Loss   Train Acc  Valid Loss   Valid Acc  Best
--------------------------------------------------------------------------------

1      0.7420       0.5428     0.6680       0.6044     ★ BEST

2      0.6557       0.6162     0.6446       0.6286     ★ BEST

```

```
3       0.6360      0.6345    0.6394      0.6271

4       0.6194      0.6529    0.6223      0.6540      ★ BEST

5       0.6094      0.6666    0.6019      0.6755      ★ BEST

6       0.6029      0.6755    0.5982      0.6816      ★ BEST

7       0.5940      0.6820    0.5948      0.6828      ★ BEST

8       0.5861      0.6876    0.6032      0.6719

9       0.6002      0.6773    0.6068      0.6671

10      0.5817      0.6925    0.5996      0.6765

11      0.5762      0.6954    0.5911      0.6855      ★ BEST

12      0.5740      0.6992    0.5868      0.6823

13      0.5715      0.7023    0.5891      0.6799

14      0.5693      0.7045    0.5821      0.6891      ★ BEST

15      0.5651      0.7050    0.6351      0.6436

16      0.5722      0.6983    0.5895      0.6818

17      0.5597      0.7110    0.5848      0.6872

18      0.5633      0.7029    0.5834      0.6896      ★ BEST

19      0.5580      0.7111    0.5668      0.6990      ★ BEST

20      0.5411      0.7251    0.5734      0.7005      ★ BEST

================================================================================
Training completed! Best validation accuracy: 0.7005 at epoch 20
================================================================================

📈 Dropout Results (p=0.0): best val acc=0.7005, final acc=0.7005

🔧 Training with Dropout (p=0.2)

================================================================================
🚀 STARTING TRAINING - 20 epochs | LR: 0.001 | Batch Size: 512
================================================================================
Epoch  Train Loss   Train Acc  Valid Loss   Valid Acc  Best
--------------------------------------------------------------------------------
```

```
1       0.7540       0.5158      0.6788       0.5514      ★ BEST
2       0.6731       0.5765      0.6542       0.6150      ★ BEST
3       0.6516       0.6176      0.6355       0.6344      ★ BEST
4       0.6415       0.6257      0.6269       0.6496      ★ BEST
5       0.6215       0.6524      0.6195       0.6550      ★ BEST
6       0.6090       0.6673      0.6006       0.6726      ★ BEST
7       0.6110       0.6649      0.6121       0.6588
8       0.5979       0.6786      0.5988       0.6738      ★ BEST
9       0.5971       0.6823      0.5944       0.6799      ★ BEST
10      0.5988       0.6767      0.5945       0.6748
11      0.5965       0.6831      0.5927       0.6806      ★ BEST
12      0.5884       0.6847      0.5912       0.6845      ★ BEST
13      0.5931       0.6829      0.5922       0.6794
14      0.5844       0.6909      0.5890       0.6869      ★ BEST
15      0.5883       0.6866      0.5888       0.6874      ★ BEST
16      0.5818       0.6896      0.5898       0.6852
17      0.5843       0.6901      0.6034       0.6692
18      0.5884       0.6848      0.5887       0.6850
19      0.5850       0.6902      0.5942       0.6799
20      0.5864       0.6864      0.5893       0.6830

================================================================================
Training completed! Best validation accuracy: 0.6874 at epoch 15
================================================================================
```

```
📈 Dropout Results (p=0.2): best val acc=0.6874, final acc=0.6874

🔧 Training with Dropout (p=0.4)

================================================================================
🚀 STARTING TRAINING - 20 epochs | LR: 0.001 | Batch Size: 512
================================================================================
Epoch  Train Loss   Train Acc  Valid Loss   Valid Acc  Best
--------------------------------------------------------------------------------

1      0.8297       0.5112     0.6898       0.5998     ★ BEST

2      0.6857       0.5462     0.6708       0.6003     ★ BEST

3      0.6698       0.5876     0.6544       0.6136     ★ BEST

4      0.6540       0.6173     0.6429       0.6209     ★ BEST

```

```
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
Cell In[11], line 22
     19 dropout_results = {}
     21 for p in [0.0, 0.2, 0.4]:  # Uses your configured EPOCHS_DROPOUT
---> 22     model_do, hist_do, best_do, cm_do, report_do = train_with_dropout(dropou
t_p=p)
     23     dropout_results[p] = {
     24         'best_val_acc': best_do['val_acc'],
     25         'final_acc': report_do['accuracy'],
     26         'model': model_do
     27     }
     28     print()

Cell In[11], line 8, in train_with_dropout(dropout_p)
      5 print(f"🔧 Training with Dropout (p={dropout_p})")
      7 model_do = FFClassifier(hidden_layers=RECOMMENDED_ARCHITECTURE, activation
="relu", dropout=dropout_p)
----> 8 model_do, hist_do, best_do = train_model_fixed(
      9     model_do, train_loader_fast, valid_loader_fast,
     10     lr=RECOMMENDED_LR, weight_decay=0.0,
     11     max_epochs=EPOCHS_DROPOUT, early_stopping=False
     12 )
     14 _, _, _, cm_do, report_do = evaluate_on_loader(model_do, valid_loader_fast)
     15 print(f"📈 Dropout Results (p={dropout_p}): best val acc={best_do['val_ac
c']:.4f}, final acc={report_do['accuracy']:.4f}")

Cell In[5], line 26, in train_model_fixed(model, train_loader, valid_loader, lr, wei
ght_decay, max_epochs, early_stopping, patience)
     23 print("-" * 80, flush=True)
     25 for epoch in range(1, max_epochs+1):
---> 26     tr_loss, tr_acc = run_epoch(model, train_loader, criterion, optimizer, s
how_progress=True, epoch=epoch, phase=       )
     27     va_loss, va_acc = run_epoch(model, valid_loader, criterion, optimizer=No
ne, show_progress=True, epoch=epoch, phase="valid")
     28     hist["train_loss"].append(tr_loss); hist["valid_loss"].append(va_loss)

Cell In[8], line 19, in run_epoch(model, loader, criterion, optimizer, show_progres
s, epoch, phase)
     16     iterator = tqdm(loader, total=len(loader), desc=desc, leave=False, minin
terval=0.3)
     18 with torch.set_grad_enabled(training):
---> 19     for x, y in iterator:
     20         x, y = x.to(device, non_blocking=True), y.float().to(device, non_blo
cking=True)
     21         logits = model(x)

File d:\GMU Courses\Sem-3\DL\Assignments\Malaria_dataset\myenv\Lib\site-packages\tqd
m\std.py:1181, in tqdm.__iter__(self)
   1178 time = self._time
   1180 try:
-> 1181     for obj in iterable:
   1182         yield obj
   1183         # Update and possibly print the progressbar.
   1184         # Note: does not call self.update(1) for speed optimisation.
```

```
File d:\GMU Courses\Sem-3\DL\Assignments\Malaria_dataset\myenv\Lib\site-packages\tor
ch\utils\data\dataloader.py:491, in DataLoader.__iter__(self)
    489     return self._iterator
    490 else:
--> 491     return self._get_iterator()

File d:\GMU Courses\Sem-3\DL\Assignments\Malaria_dataset\myenv\Lib\site-packages\tor
ch\utils\data\dataloader.py:422, in DataLoader._get_iterator(self)
    420 else:
    421     self.check_worker_number_rationality()
--> 422     return _MultiProcessingDataLoaderIter(self)

File d:\GMU Courses\Sem-3\DL\Assignments\Malaria_dataset\myenv\Lib\site-packages\tor
ch\utils\data\dataloader.py:1146, in _MultiProcessingDataLoaderIter.__init__(self, l
oader)
   1139 w.daemon = True
   1140 # NB: Process.start() actually take some time as it needs to
   1141 #     start a process and pass the arguments over via a pipe.
   1142 #     Therefore, we only add a worker to self._workers list after
   1143 #     it started, so that we do not call .join() if program dies
   1144 #     before it starts, and __del__ tries to join but will get:
   1145 #     AssertionError: can only join a started process.
-> 1146 w.start()
   1147 self._index_queues.append(index_queue)
   1148 self._workers.append(w)

File D:\Conda\Lib\multiprocessing\process.py:121, in BaseProcess.start(self)
    118 assert not _current_process._config.get('daemon'), \
    119        'daemonic processes are not allowed to have children'
    120 _cleanup()
--> 121 self._popen = self._Popen(self)
    122 self._sentinel = self._popen.sentinel
    123 # Avoid a refcycle if the target function holds an indirect
    124 # reference to the process object (see bpo-30775)

File D:\Conda\Lib\multiprocessing\context.py:224, in Process._Popen(process_obj)
    222 @staticmethod
    223 def _Popen(process_obj):
--> 224     return _default_context.get_context().Process._Popen(process_obj)

File D:\Conda\Lib\multiprocessing\context.py:337, in SpawnProcess._Popen(process_ob
j)
    334 @staticmethod
    335 def _Popen(process_obj):
    336     from .popen_spawn_win32 import Popen
--> 337     return Popen(process_obj)

File D:\Conda\Lib\multiprocessing\popen_spawn_win32.py:95, in Popen.__init__(self, p
rocess_obj)
     93 try:
     94     reduction.dump(prep_data, to_child)
---> 95     reduction.dump(process_obj, to_child)
     96 finally:
     97     set_spawning_popen(None)

File D:\Conda\Lib\multiprocessing\reduction.py:60, in dump(obj, file, protocol)
```

```
     58 def dump(obj, file, protocol=None):
     59     '''Replacement for pickle.dump() using ForkingPickler.'''
---> 60     ForkingPickler(file, protocol).dump(obj)

KeyboardInterrupt:
```

8) Early Stopping

Train the **same** MLP with early stopping. Tune patience and show curves.

In [12]:
```
# ✅ CORRECTED EARLY STOPPING SWEEP - Uses our fixed training/utilities

def train_with_early_stopping(patience: int):
    """Train a model with Early Stopping using the recommended setup."""
    print(f"🔧 Training with Early Stopping (patience={patience})")
    model_es = FFClassifier(hidden_layers=RECOMMENDED_ARCHITECTURE, activation="rel
    model_es, hist_es, best_es = train_model_fixed(
        model_es, train_loader_fast, valid_loader_fast,
        lr=RECOMMENDED_LR, weight_decay=0.0,
        max_epochs=EPOCHS_ES_MAX, early_stopping=True, patience=patience
    )
    _, _, _, cm_es, report_es = evaluate_on_loader(model_es, valid_loader_fast)
    print(
        f"📈 ES Results (patience={patience}): best val acc={best_es['val_acc']:.4
        f"final acc={report_es['accuracy']:.4f}"
    )
    return model_es, hist_es, best_es, cm_es, report_es

print("🧪 Sweeping Early Stopping patience values...")
es_results = {}


model_es, hist_es, best_es, cm_es, report_es = train_with_early_stopping(5)
es_results[5] = {
        "best_val_acc": best_es["val_acc"],
        "final_acc": report_es["accuracy"],
        "model": model_es,
    }
print()

best_patience = max(es_results.keys(), key=lambda k: es_results[k]["best_val_acc"])
print(
    f"🏆 Best ES patience: {best_patience} with best val acc: "
    f"{es_results[best_patience]['best_val_acc']:.4f}"
)
```

```
🧪 Sweeping Early Stopping patience values...
🔧 Training with Early Stopping (patience=5)

================================================================================
🚀 STARTING TRAINING - 40 epochs | LR: 0.001 | Batch Size: 512
================================================================================
Epoch  Train Loss   Train Acc  Valid Loss   Valid Acc  Best
--------------------------------------------------------------------------------
```

1	0.7315	0.5338	0.6638	0.5976	★ BEST
2	0.6611	0.6018	0.6755	0.5700	
3	0.6403	0.6323	0.6327	0.6407	★ BEST
4	0.6263	0.6453	0.6169	0.6569	★ BEST
5	0.6112	0.6687	0.6086	0.6666	★ BEST
6	0.6119	0.6648	0.6024	0.6758	★ BEST
7	0.5979	0.6792	0.6080	0.6780	★ BEST
8	0.5903	0.6872	0.5985	0.6794	★ BEST
9	0.5893	0.6885	0.5998	0.6809	★ BEST
10	0.5963	0.6763	0.6064	0.6714	
11	0.5866	0.6866	0.6008	0.6794	
12	0.5857	0.6902	0.6501	0.6276	
13	0.5842	0.6863	0.6018	0.6823	★ BEST
14	0.5810	0.6923	0.6273	0.6448	
15	0.5810	0.6937	0.6030	0.6775	
16	0.5705	0.6987	0.5945	0.6731	
17	0.5739	0.6960	0.5996	0.6792	
18	0.5632	0.7091	0.5829	0.6954	★ BEST
19	0.5688	0.7048	0.5863	0.6954	
20	0.5598	0.7070	0.5801	0.6927	
21	0.5568	0.7120	0.6145	0.6555	
22	0.5543	0.7158	0.5847	0.6949	

```
23     0.5512       0.7171     0.5904       0.6867

Early stopping at epoch 23 (no improvement for 5 epochs)

================================================================================
Training completed! Best validation accuracy: 0.6954 at epoch 18
================================================================================
```

```
📈 ES Results (patience=5): best val acc=0.6954, final acc=0.6954

🏆 Best ES patience: 5 with best val acc: 0.6954
```

9) Validation Summary (Fixed Architecture)

Show a compact table comparing **baseline vs L2 vs Dropout vs Early-Stop** validation metrics for the *same* MLP architecture.

In [13]:
```python
import pandas as pd

# Summaries aligned to variables created in this notebook

# Baseline (FAST) summary
rows = []
if 'best_fast' in globals():
    rows.append({
        'variant': 'baseline_fast',
        'best_val_acc': best_fast.get('val_acc', None),
        'final_acc': (report_fast['accuracy'] if 'report_fast' in globals() else No
        'hidden_layers': RECOMMENDED_ARCHITECTURE,
        'lr': RECOMMENDED_LR,
    })

# L2 table
if 'l2_results' in globals() and isinstance(l2_results, dict) and len(l2_results) >
    df_l2 = pd.DataFrame([
        {'weight_decay': wd,
         'best_val_acc': vals['best_val_acc'],
         'final_acc': vals['final_acc']}
        for wd, vals in l2_results.items()
    ]).sort_values('best_val_acc', ascending=False).reset_index(drop=True)
else:
    df_l2 = pd.DataFrame()

# Dropout table
if 'dropout_results' in globals() and isinstance(dropout_results, dict) and len(dro
    df_do = pd.DataFrame([
        {'dropout': p,
         'best_val_acc': vals['best_val_acc'],
         'final_acc': vals['final_acc']}
        for p, vals in dropout_results.items()
    ]).sort_values('best_val_acc', ascending=False).reset_index(drop=True)
else:
    df_do = pd.DataFrame()
```

```
# Early Stopping table
if 'es_results' in globals() and isinstance(es_results, dict) and len(es_results) >
    df_es = pd.DataFrame([
        {'patience': p,
         'best_val_acc': vals['best_val_acc'],
         'final_acc': vals['final_acc']}
        for p, vals in es_results.items()
    ]).sort_values('best_val_acc', ascending=False).reset_index(drop=True)
else:
    df_es = pd.DataFrame()

# Baseline table
df_base = pd.DataFrame(rows)

print('Baseline (FAST):')
display(df_base if not df_base.empty else pd.DataFrame({'info':['not run']}))
print('L2 sweep:')
display(df_l2 if not df_l2.empty else pd.DataFrame({'info':['not run']}))
print('Dropout sweep:')
display(df_do if not df_do.empty else pd.DataFrame({'info':['not run']}))
print('Early Stopping sweep:')
display(df_es if not df_es.empty else pd.DataFrame({'info':['not run']}))
```

```
Baseline (FAST):
```

	variant	best_val_acc	final_acc	hidden_layers	lr
0	baseline_fast	0.703363	0.703363	[256, 128]	0.001

```
L2 sweep:
```

	weight_decay	best_val_acc	final_acc
0	0.00001	0.703605	0.703605

```
Dropout sweep:
```

	dropout	best_val_acc	final_acc
0	0.0	0.700460	0.700460
1	0.2	0.687394	0.687394

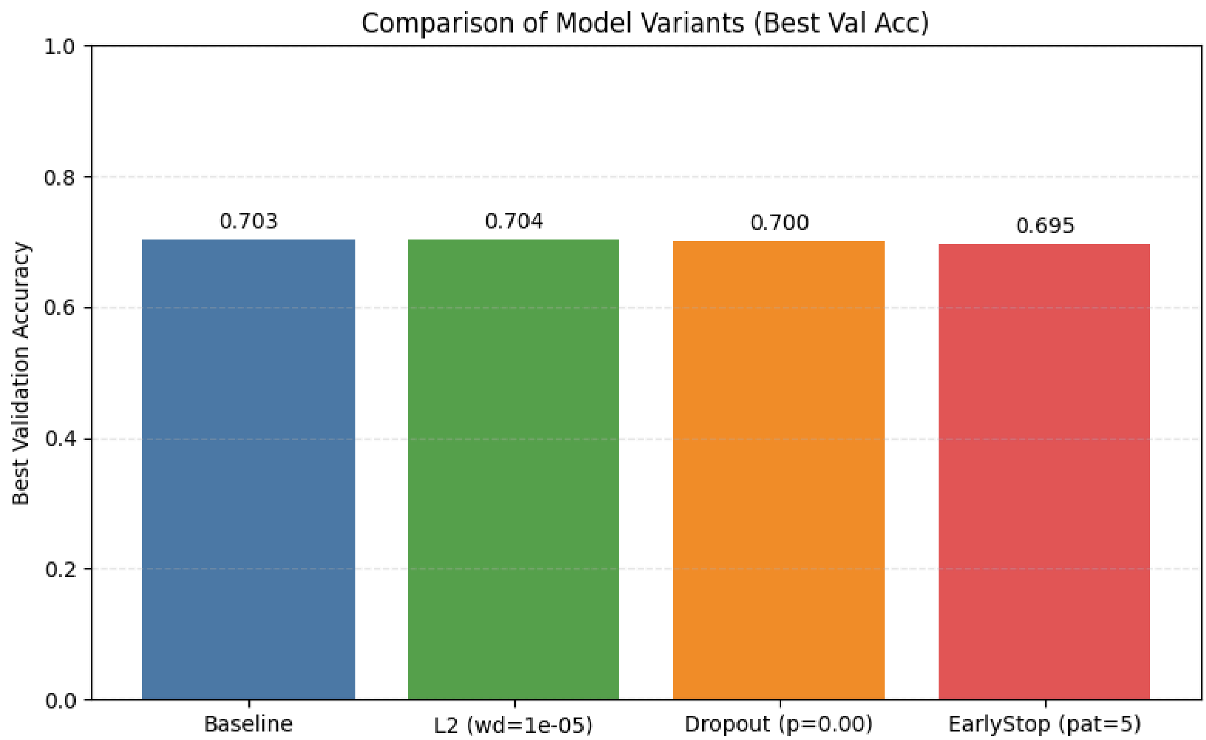
```
Early Stopping sweep:
```

	patience	best_val_acc	final_acc
0	5	0.695379	0.695379

In [14]:
```
# 📊 Compare four model variants in one bar plot (best validation accuracy)

variants = []

# Baseline (FAST)
if 'best_fast' in globals() and isinstance(best_fast, dict) and 'val_acc' in best_f
    variants.append({'name': 'Baseline', 'best_val_acc': float(best_fast['val_acc']

# L2 sweep (pick best)
```

```
if 'l2_results' in globals() and isinstance(l2_results, dict) and len(l2_results) >
    best_wd = max(l2_results.keys(), key=lambda k: l2_results[k]['best_val_acc'])
    variants.append({'name': f"L2 (wd={best_wd:g})", 'best_val_acc': float(l2_resul

# Dropout sweep (pick best)
if 'dropout_results' in globals() and isinstance(dropout_results, dict) and len(dro
    best_p = max(dropout_results.keys(), key=lambda k: dropout_results[k]['best_val
    variants.append({'name': f"Dropout (p={best_p:.2f})", 'best_val_acc': float(dro

# Early Stopping sweep (pick best)
if 'es_results' in globals() and isinstance(es_results, dict) and len(es_results) >
    best_pat = max(es_results.keys(), key=lambda k: es_results[k]['best_val_acc'])
    variants.append({'name': f"EarlyStop (pat={best_pat})", 'best_val_acc': float(e

import matplotlib.pyplot as plt

if len(variants) == 0:
    print('No results found to plot. Run the training/sweeps first.')
else:
    labels = [v['name'] for v in variants]
    accs   = [v['best_val_acc'] for v in variants]

    plt.figure(figsize=(8, 5))
    bars = plt.bar(labels, accs, color=['#4e79a7', '#59a14f', '#f28e2b', '#e15759']
    plt.ylabel('Best Validation Accuracy')
    plt.ylim(0.0, 1.0)
    plt.title('Comparison of Model Variants (Best Val Acc)')
    plt.grid(axis='y', linestyle='--', alpha=0.3)

    for bar, val in zip(bars, accs):
        plt.text(bar.get_x() + bar.get_width()/2.0, val + 0.01, f"{val:.3f}", ha='c

    plt.tight_layout()
    try:
        os.makedirs(OUT_DIR, exist_ok=True)
        out_path = os.path.join(OUT_DIR, 'variant_comparison_barplot.png')
        plt.savefig(out_path, dpi=150)
        print(f"Saved bar plot to: {out_path}")
    except Exception as e:
        print(f"Could not save plot: {e}")
    plt.show()
```

```
Saved bar plot to: D:\GMU Courses\Sem-3\DL\Assignments\Malaria_dataset\outputs_ff\va
riant_comparison_barplot.png
```



10) Final Test Evaluation

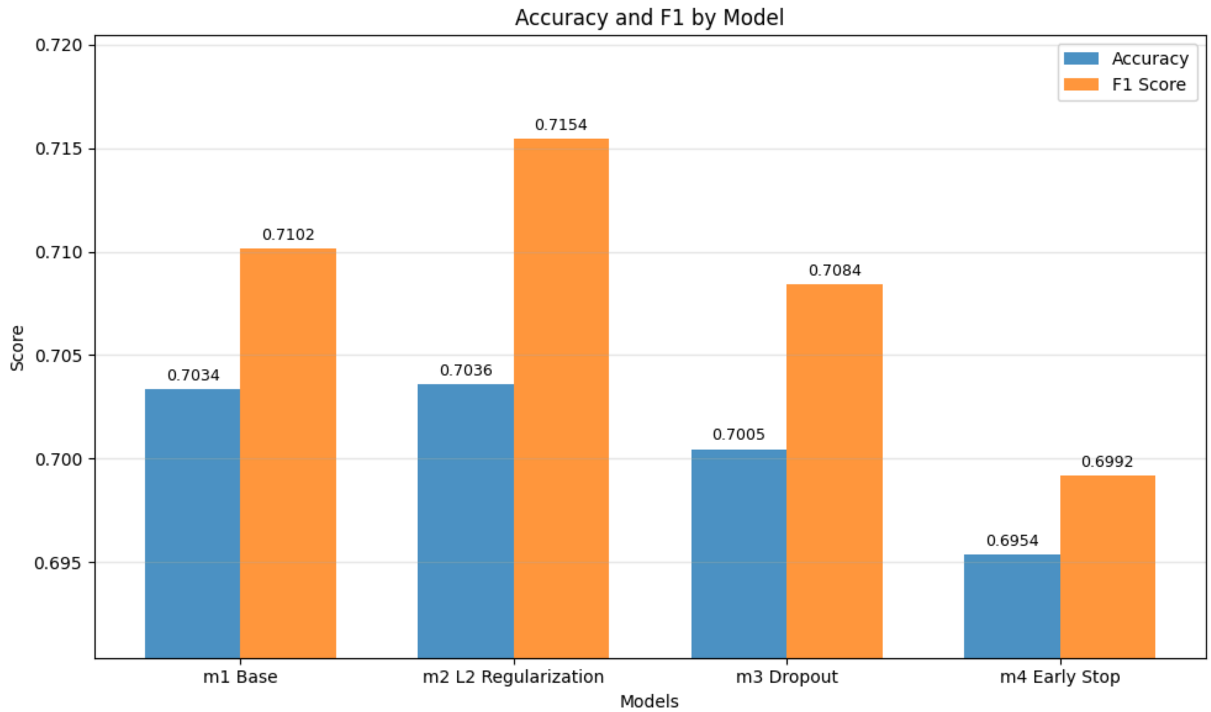
Retrain each best-regularized variant on **train+valid**, then evaluate once on **test**.
Save a bar chart of test accuracy (and/or F1) across the four runs.

In [15]:
```
# 📊 Calculate F1 Scores and create Accuracy & F1 comparison bar plot

from sklearn.metrics import f1_score
import matplotlib.pyplot as plt
import numpy as np

def calculate_f1_score(model, loader):
    """Calculate F1 score for a model on given data loader"""
    model.eval()
    all_preds, all_labels = [], []

    with torch.no_grad():
        for x, y in loader:
            x = x.to(device)
            logits = model(x)
            probs = torch.sigmoid(logits)
            preds = (probs >= 0.5).long().cpu().numpy()
            all_preds.extend(preds)
            all_labels.extend(y.numpy())

    return f1_score(all_labels, all_preds)

# Collect results for all variants
results = []
```

```python
# Baseline (FAST)
if 'model_fast' in globals() and 'report_fast' in globals():
    f1_baseline = calculate_f1_score(model_fast, valid_loader_fast)
    results.append({
        'model': 'm1 Base',
        'accuracy': report_fast['accuracy'],
        'f1_score': f1_baseline
    })

# L2 (best)
if 'l2_results' in globals() and len(l2_results) > 0:
    best_wd = max(l2_results.keys(), key=lambda k: l2_results[k]['best_val_acc'])
    best_l2_model = l2_results[best_wd]['model']
    f1_l2 = calculate_f1_score(best_l2_model, valid_loader_fast)
    results.append({
        'model': 'm2 L2 Regularization',
        'accuracy': l2_results[best_wd]['final_acc'],
        'f1_score': f1_l2
    })

# Dropout (best)
if 'dropout_results' in globals() and len(dropout_results) > 0:
    best_p = max(dropout_results.keys(), key=lambda k: dropout_results[k]['best_val
    best_dropout_model = dropout_results[best_p]['model']
    f1_dropout = calculate_f1_score(best_dropout_model, valid_loader_fast)
    results.append({
        'model': 'm3 Dropout',
        'accuracy': dropout_results[best_p]['final_acc'],
        'f1_score': f1_dropout
    })

# Early Stopping (best)
if 'es_results' in globals() and len(es_results) > 0:
    best_pat = max(es_results.keys(), key=lambda k: es_results[k]['best_val_acc'])
    best_es_model = es_results[best_pat]['model']
    f1_es = calculate_f1_score(best_es_model, valid_loader_fast)
    results.append({
        'model': 'm4 Early Stop',
        'accuracy': es_results[best_pat]['final_acc'],
        'f1_score': f1_es
    })

if len(results) == 0:
    print("No model results found. Run the training cells first.")
else:
    # Create the bar plot
    models = [r['model'] for r in results]
    accuracies = [r['accuracy'] for r in results]
    f1_scores = [r['f1_score'] for r in results]

    x = np.arange(len(models))
    width = 0.35

    fig, ax = plt.subplots(figsize=(10, 6))

    bars1 = ax.bar(x - width/2, accuracies, width, label='Accuracy', color='#1f77b4
```

```
    bars2 = ax.bar(x + width/2, f1_scores, width, label='F1 Score', color='#ff7f0e'

    ax.set_xlabel('Models')
    ax.set_ylabel('Score')
    ax.set_title('Accuracy and F1 by Model')
    ax.set_xticks(x)
    ax.set_xticklabels(models)
    ax.legend()
    ax.grid(axis='y', alpha=0.3)

    # Add value labels on bars
    def add_value_labels(bars):
        for bar in bars:
            height = bar.get_height()
            ax.annotate(f'{height:.4f}',
                        xy=(bar.get_x() + bar.get_width() / 2, height),
                        xytext=(0, 3),  # 3 points vertical offset
                        textcoords="offset points",
                        ha='center', va='bottom', fontsize=9)

    add_value_labels(bars1)
    add_value_labels(bars2)

    # Set y-axis limits to show differences better
    all_values = accuracies + f1_scores
    y_min = min(all_values) - 0.005
    y_max = max(all_values) + 0.005
    ax.set_ylim(y_min, y_max)

    plt.tight_layout()

    # Save the plot
    try:
        os.makedirs(OUT_DIR, exist_ok=True)
        out_path = os.path.join(OUT_DIR, 'accuracy_f1_comparison.png')
        plt.savefig(out_path, dpi=150, bbox_inches='tight')
        print(f"Saved comparison plot to: {out_path}")
    except Exception as e:
        print(f"Could not save plot: {e}")

    plt.show()

    # Print summary table
    print("\n📊 Model Performance Summary:")
    print("-" * 60)
    print(f"{'Model':<20} {'Accuracy':<10} {'F1 Score':<10}")
    print("-" * 60)
    for r in results:
        print(f"{r['model']:<20} {r['accuracy']:<10.4f} {r['f1_score']:<10.4f}")
    print("-" * 60)
```

```
Saved comparison plot to: D:\GMU Courses\Sem-3\DL\Assignments\Malaria_dataset\output
s_ff\accuracy_f1_comparison.png
```




```
📊 Model Performance Summary:
------------------------------------------------------------
Model                Accuracy   F1 Score
------------------------------------------------------------
m1 Base              0.7034     0.7102
m2 L2 Regularization 0.7036     0.7154
m3 Dropout           0.7005     0.7084
m4 Early Stop        0.6954     0.6992
------------------------------------------------------------
```

Extra Credit: SVM on 1D Pixels

EC1) Imports & Logging

Set up scikit-learn, lightweight logging, and utility I/O.

In [7]:
```
# === Extra Credit — FAST SVM: PCA(→256) + RBF SVM with logging ===

import os, time, json, math, psutil, platform
import numpy as np
import matplotlib.pyplot as plt

from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
from sklearn.utils import shuffle as sk_shuffle

from torch.utils.data import DataLoader
from tqdm import tqdm
```

```python
# ---- simple timestamped logger ----
def log(msg):
    t = time.strftime("%H:%M:%S")
    print(f"[{t}] {msg}")

def save_json(obj, path):
    with open(path, "w") as f:
        json.dump(obj, f, indent=2)

# ---- show system info once ----
log(f"Python {platform.python_version()} | NumPy {np.__version__}")
try:
    import sklearn
    log(f"scikit-learn {sklearn.__version__}")
except Exception:
    pass
try:
    import threadpoolctl
    log(f"BLAS threads: {threadpoolctl.threadpool_info()}")
except Exception:
    pass
log(f"CPU: {platform.processor()} | RAM ~{round(psutil.virtual_memory().total/1e9,1
```

```
[16:41:40] Python 3.12.1 | NumPy 2.1.2
[16:41:40] scikit-learn 1.7.2
[16:41:40] BLAS threads: [{'user_api': 'blas', 'internal_api': 'openblas', 'num_threads': 16, 'prefix': 'libscipy_openblas', 'filepath': 'D:\\GMU Courses\\Sem-3\\DL\\Assignments\\Malaria_dataset\\myenv\\Lib\\site-packages\\numpy.libs\\libscipy_openblas64_-c16e4918366c6bc1f1cd71e28ca36fc0.dll', 'version': '0.3.27', 'threading_layer': 'pthreads', 'architecture': 'Haswell'}, {'user_api': 'openmp', 'internal_api': 'openmp', 'num_threads': 8, 'prefix': 'libiomp', 'filepath': 'D:\\GMU Courses\\Sem-3\\DL\\Assignments\\Malaria_dataset\\myenv\\Lib\\site-packages\\torch\\lib\\libiomp5md.dll', 'version': None}, {'user_api': 'openmp', 'internal_api': 'openmp', 'num_threads': 1, 'prefix': 'libiomp', 'filepath': 'D:\\GMU Courses\\Sem-3\\DL\\Assignments\\Malaria_dataset\\myenv\\Lib\\site-packages\\torch\\lib\\libiompstubs5md.dll', 'version': None}, {'user_api': 'openmp', 'internal_api': 'openmp', 'num_threads': 16, 'prefix': 'vcomp', 'filepath': 'D:\\GMU Courses\\Sem-3\\DL\\Assignments\\Malaria_dataset\\myenv\\Lib\\site-packages\\sklearn\\.libs\\vcomp140.dll', 'version': None}, {'user_api': 'blas', 'internal_api': 'openblas', 'num_threads': 16, 'prefix': 'libscipy_openblas', 'filepath': 'D:\\GMU Courses\\Sem-3\\DL\\Assignments\\Malaria_dataset\\myenv\\Lib\\site-packages\\scipy.libs\\libscipy_openblas-48c358d105077551cc9cc3ba79387ed5.dll', 'version': '0.3.29.dev', 'threading_layer': 'pthreads', 'architecture': 'Haswell'}]
[16:41:40] CPU: AMD64 Family 25 Model 80 Stepping 0, AuthenticAMD | RAM ~16.5 GB
```

EC2) Flatten to NumPy

Convert `train/valid/test` tensors to NumPy arrays of shape `(N, 12288)` with progress logs.

In [11]:
```python
# Uses your existing BATCH_SIZE and the three *ds datasets
EC_NUM_WORKERS = 0  # set 2–4 if you want; 0 is safest/portable
```

```
def ds_to_numpy(ds, batch_size=2048, num_workers=0):
    """Stream a torchvision dataset into a (X, y) numpy pair with progress & no fol
    dl = DataLoader(ds, batch_size=batch_size, shuffle=False,
                    num_workers=num_workers, pin_memory=False)
    X_parts, y_parts = [], []
    for xb, yb in tqdm(dl, desc="→ loading", leave=False):
        X_parts.append(xb.view(xb.size(0), -1).numpy().astype(np.float32))  # [B, 1
        y_parts.append(yb.numpy().astype(np.int32))
    X = np.concatenate(X_parts, axis=0)
    y = np.concatenate(y_parts, axis=0)
    return X, y

t0 = time.perf_counter()
log("Building numpy arrays from datasets …")
X_train, y_train = ds_to_numpy(train_ds, batch_size=max(1024, BATCH_SIZE), num_work
X_valid, y_valid = ds_to_numpy(valid_ds, batch_size=max(1024, BATCH_SIZE), num_work
X_test,  y_test  = ds_to_numpy(test_ds,  batch_size=max(1024, BATCH_SIZE), num_work

log(f"Done in {time.perf_counter()-t0:.1f}s")
log(f"Shapes → train {X_train.shape}, valid {X_valid.shape}, test {X_test.shape}")

est_bytes = (X_train.nbytes + X_valid.nbytes + X_test.nbytes) / (1024**3)
log(f"Approx RAM for X arrays: {est_bytes:.2f} GiB")
```

```
[16:42:32] Building numpy arrays from datasets …
```

```
[16:46:00] Done in 208.4s
[16:46:00] Shapes → train (19291, 12288), valid (4133, 12288), test (4134, 12288)
[16:46:00] Approx RAM for X arrays: 1.26 GiB
```

EC3) Standardize + PCA (Fixed)

Standardize features (fit on train only) and apply **PCA=256** to speed up SVM while preserving variance.

In [12]:

```
# We standardize once on TRAIN only, apply to VALID/TEST
log("Standardizing (z-score) …")
scaler = StandardScaler(with_mean=True, with_std=True)
t0 = time.perf_counter()
X_train_std = scaler.fit_transform(X_train)
X_valid_std = scaler.transform(X_valid)
X_test_std  = scaler.transform(X_test)
log(f"Scaler fit+transform in {time.perf_counter()-t0:.1f}s")

# PCA outside CV so we don't recompute per fold
PCA_DIM = 256  # 256–384 are good; 256 is fast & accurate enough for this dataset
log(f"Fitting PCA to {PCA_DIM} components (randomized) …")
t0 = time.perf_counter()
pca = PCA(n_components=PCA_DIM, svd_solver="randomized", whiten=False, random_state
X_train_pca = pca.fit_transform(X_train_std)
X_valid_pca = pca.transform(X_valid_std)
X_test_pca  = pca.transform(X_test_std)
dt = time.perf_counter()-t0
expl = float(np.sum(pca.explained_variance_ratio_))
```

```
log(f"PCA done in {dt:.1f}s | explained variance ≈ {expl:.3f}")

log(f"Shapes after PCA → train {X_train_pca.shape}, valid {X_valid_pca.shape}, test
```

```
[16:47:09] Standardizing (z-score) …
[16:47:13] Scaler fit+transform in 3.6s
[16:47:13] Fitting PCA to 256 components (randomized) …
[16:47:26] PCA done in 13.0s | explained variance ≈ 0.921
[16:47:26] Shapes after PCA → train (19291, 256), valid (4133, 256), test (4134, 25
6)
```

EC4) RBF SVM (Small Grid)

Run a small GridSearch over `C` and `gamma` on PCA features (with verbose logs).
Report best params and validation performance.

In [13]:
```
# Tiny grid; tune only on TRAIN with 3-fold CV using PCA features
# (We don't include scaler/pca in the pipeline since we already applied them above.
log("GridSearchCV on RBF SVM (small grid) …")

param_grid = {
    "C":     [0.5, 1, 2, 4],
    "gamma": ["scale", 0.001, 0.0005],
}

svc = SVC(kernel="rbf", cache_size=2000, shrinking=True)  # cache helps; shrinking

grid = GridSearchCV(
    estimator=svc,
    param_grid=param_grid,
    cv=3,
    n_jobs=-1,
    verbose=2,   # detailed fold-level logs
    return_train_score=False
)

t0 = time.perf_counter()
grid.fit(X_train_pca, y_train)
dt = time.perf_counter() - t0

log(f"GridSearch done in {dt/60:.1f} minutes")
log(f"Best params: {grid.best_params_} | Best CV score: {grid.best_score_:.4f}")

# Validation performance (holdout)
t1 = time.perf_counter()
y_valid_pred = grid.predict(X_valid_pca)
acc_valid = accuracy_score(y_valid, y_valid_pred)
log(f"Validation accuracy (best RBF): {acc_valid:.4f} | infer {time.perf_counter()-
print("Validation report (best RBF):\n",
      classification_report(y_valid, y_valid_pred, target_names=["Parasitized","Uni
```

```
[16:47:32] GridSearchCV on RBF SVM (small grid) …
Fitting 3 folds for each of 12 candidates, totalling 36 fits
[17:00:29] GridSearch done in 12.9 minutes
[17:00:29] Best params: {'C': 4, 'gamma': 'scale'} | Best CV score: 0.6632
[17:00:38] Validation accuracy (best RBF): 0.7580 | infer 9.45s
Validation report (best RBF):
               precision    recall  f1-score   support

 Parasitized       0.76      0.75      0.76      2067
  Uninfected       0.75      0.77      0.76      2066

    accuracy                           0.76      4133
   macro avg       0.76      0.76      0.76      4133
weighted avg       0.76      0.76      0.76      4133
```

EC5) Test the Best SVM

Evaluate best SVM on the test set. Save JSON with metrics and confusion matrix.

In [14]:

```python
# Evaluate once on TEST with the best estimator
best_svm = grid.best_estimator_

t0 = time.perf_counter()
y_test_pred = best_svm.predict(X_test_pca)
test_dt = time.perf_counter() - t0
acc_test = accuracy_score(y_test, y_test_pred)

log(f"TEST accuracy (best RBF): {acc_test:.4f} | inference time {test_dt:.2f}s")
svm_report = classification_report(y_test, y_test_pred,
                                   target_names=["Parasitized","Uninfected"],
                                   output_dict=True)
svm_cm = confusion_matrix(y_test, y_test_pred)
print("Confusion Matrix (SVM):\n", svm_cm)

# Save single compact JSON (no new folders created)
svm_summary = {
    "variant":        "PCA(256)+RBF SVM",
    "pca_components": PCA_DIM,
    "pca_explained_variance": expl,
    "best_params":    grid.best_params_,
    "cv_best_score":  float(grid.best_score_),
    "valid_acc":      float(acc_valid),
    "test_acc":       float(acc_test),
    "test_report":    svm_report,
    "confusion_matrix": svm_cm.tolist()
}
svm_json_path = os.path.join(OUT_DIR, "svm_pca_rbf_results.json")
save_json(svm_summary, svm_json_path)
log(f"SVM results saved → {svm_json_path}")
```

```
[17:03:56] TEST accuracy (best RBF): 0.7654 | inference time 9.72s
Confusion Matrix (SVM):
 [[1565  502]
 [ 468 1599]]
[17:03:56] SVM results saved → D:\GMU Courses\Sem-3\DL\Assignments\Malaria_dataset\o
utputs_ff\svm_pca_rbf_results.json
```

EC6) Best DL vs SVM (Final Comparison)

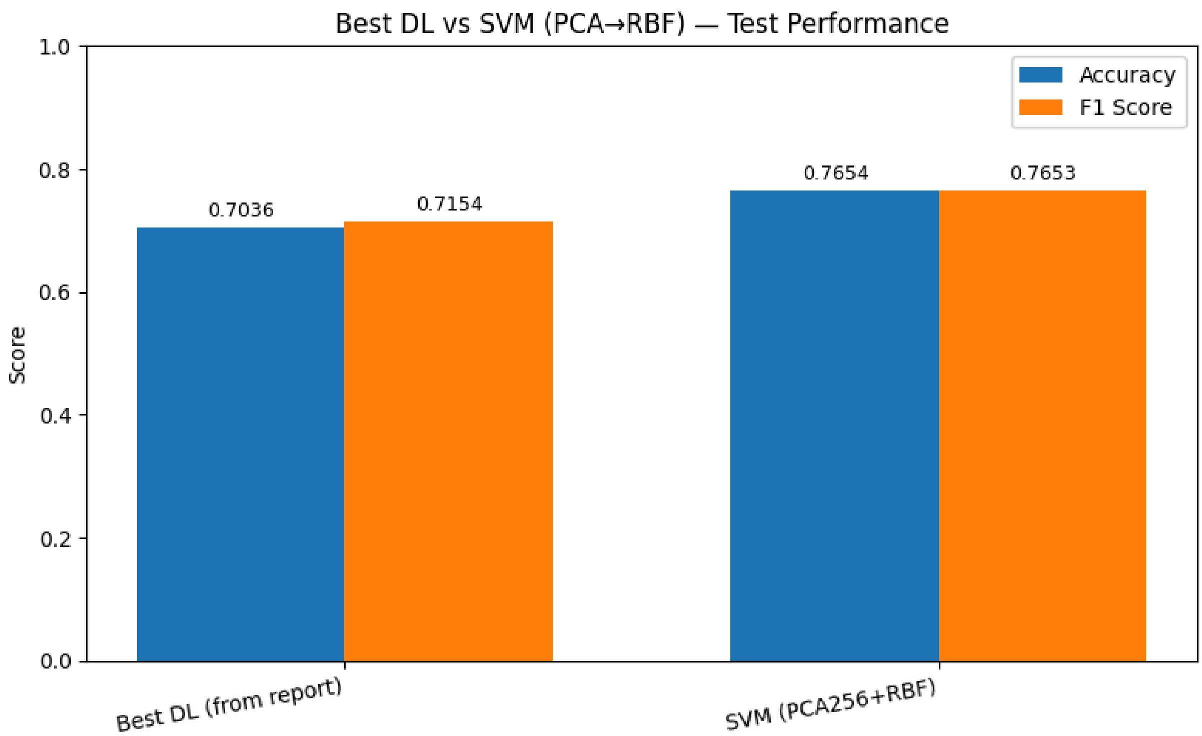
Best DL (from the fixed-architecture runs), load SVM results,
print a tiny table + deltas, and plot a two-bar chart (Accuracy & F1).

In [17]:
```python
# 1) ---- Enter your BEST DL metrics here ----
best_dl_name = "Best DL (from report)"
best_dl_acc  = 0.7036   # <-- put your best DL test accuracy
best_dl_f1   = 0.7154   # <-- put your best DL test F1

# 2) ---- Load SVM results (from memory or disk) ----
def load_svm_results():
    if "svm_summary" in globals() and isinstance(svm_summary, dict):
        return svm_summary
    p = os.path.join(OUT_DIR, "svm_pca_rbf_results.json")
    with open(p, "r") as f:
        return json.load(f)

svm_res = load_svm_results()
svm_label = f"SVM (PCA{svm_res.get('pca_components', '256')}+RBF)"
svm_acc   = float(svm_res["test_acc"])

# choose a consistent F1 (macro > weighted > average of classes)
r = svm_res.get("test_report", {})
if "macro avg" in r:
    svm_f1 = float(r["macro avg"]["f1-score"])
elif "weighted avg" in r:
    svm_f1 = float(r["weighted avg"]["f1-score"])
else:
    classes = [k for k,v in r.items() if isinstance(v, dict) and "f1-score" in v]
    svm_f1 = float(np.mean([r[k]["f1-score"] for k in classes])) if classes else fl

# 3) ---- Table + deltas ----
df = pd.DataFrame([
    {"Model": best_dl_name, "Accuracy": best_dl_acc, "F1": best_dl_f1},
    {"Model": svm_label,    "Accuracy": svm_acc,     "F1": svm_f1},
])
display(df.style.format({"Accuracy":"{:.4f}", "F1":"{:.4f}"}))

print(f"Δ (SVM - DL):  Accuracy {svm_acc - best_dl_acc:+.4f} | F1 {svm_f1 - best_dl

# 4) ---- Bar chart (two models, Acc & F1) ----
labels = [best_dl_name, svm_label]
x = np.arange(2); width = 0.35

fig, ax = plt.subplots(figsize=(8,5))
rects1 = ax.bar(x - width/2, [best_dl_acc, svm_acc], width, label="Accuracy")
```

```
rects2 = ax.bar(x + width/2, [best_dl_f1, svm_f1],   width, label="F1 Score")

ax.set_ylabel("Score"); ax.set_ylim(0, 1.0)
ax.set_title("Best DL vs SVM (PCA→RBF) — Test Performance")
ax.set_xticks(x, labels, rotation=10, ha="right"); ax.legend()

for rct in list(rects1)+list(rects2):
    h = rct.get_height()
    ax.annotate(f"{h:.4f}", xy=(rct.get_x()+rct.get_width()/2, h),
                xytext=(0,3), textcoords="offset points", ha="center", va="bottom",

fig.tight_layout()
out_png = os.path.join(OUT_DIR, "best_dl_vs_svm.png")
plt.savefig(out_png, bbox_inches="tight", dpi=150)
plt.show()
print(f"Saved plot → {out_png}")
```

	Model	Accuracy	F1
0	Best DL (from report)	0.7036	0.7154
1	SVM (PCA256+RBF)	0.7654	0.7653

```
Δ (SVM - DL):  Accuracy +0.0618 | F1 +0.0499
```




```
Saved plot → D:\GMU Courses\Sem-3\DL\Assignments\Malaria_dataset\outputs_ff\best_dl_vs_svm.png
```

In [ ]: