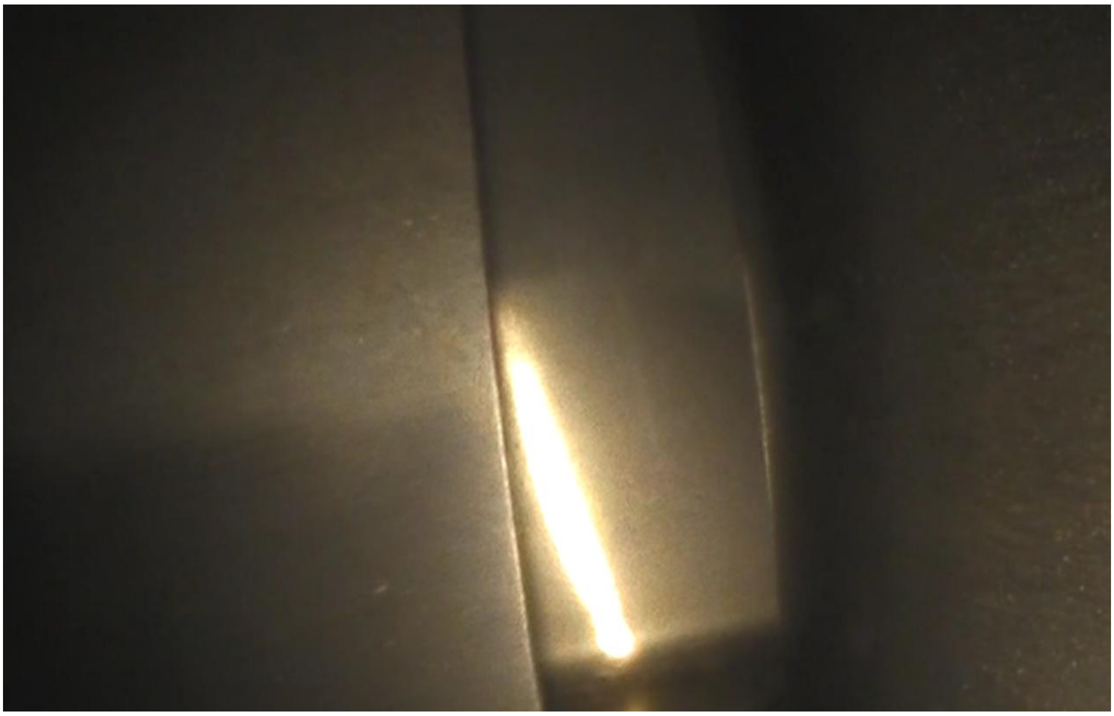
图片集数据增强和神经网络 train 模型

目标：飞机发动机在装机前及一定周期的飞行后需要对叶片表面是否发生损伤进行孔探检测，目前主要是靠检验人员人眼识别发动机叶片表面是否存在划痕、裂纹等异常，检测效率不高，同时受人主观判断影响较大。基于次工程问题提出通过神经网络和机器视觉的方法，对发动机叶片损伤进行智能化自动检测。

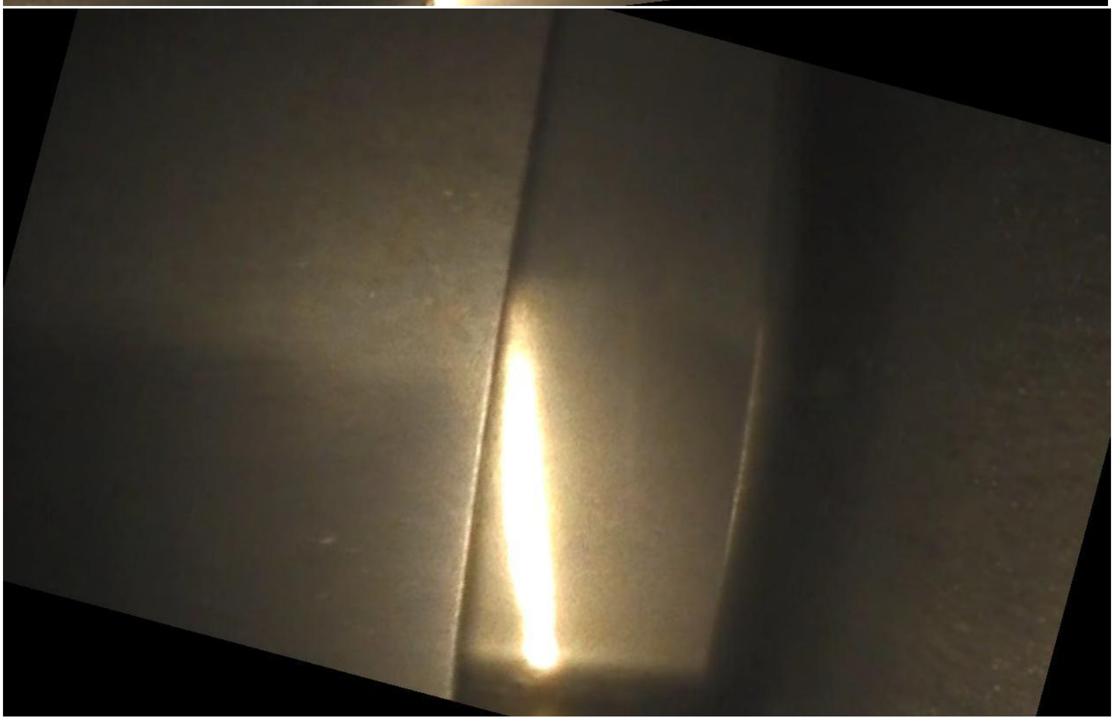
由于能获取到的各类发动机叶片损伤的数据有限，通过数据集增强来提高数据集中各类异常的样本数量，然后在神经网络训练模型中提高模型的检测精度。

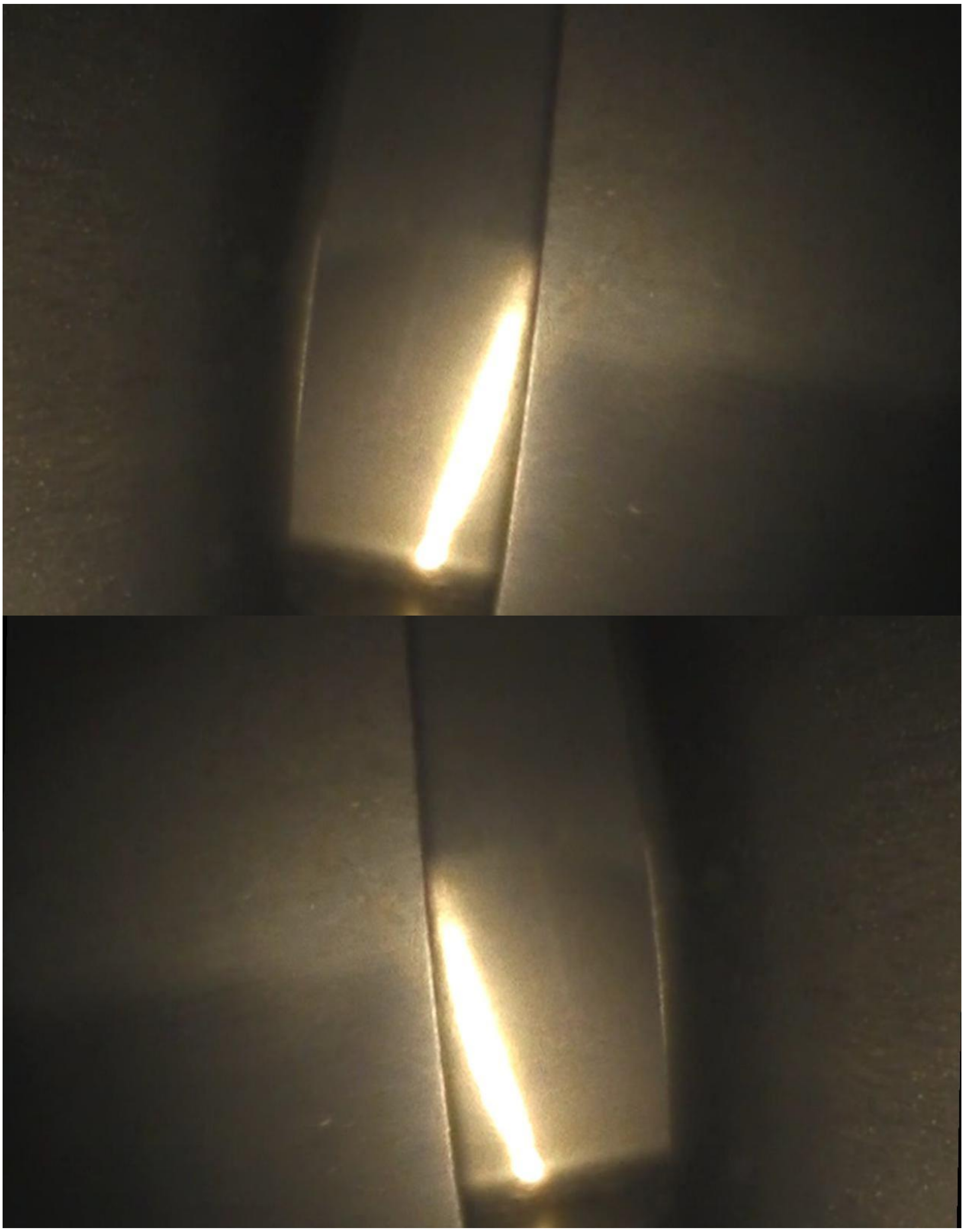
图片集数据增强算法：包括水平翻转，±20 度随机旋转，随机调整颜色和增加锐化效果四类增强算法。

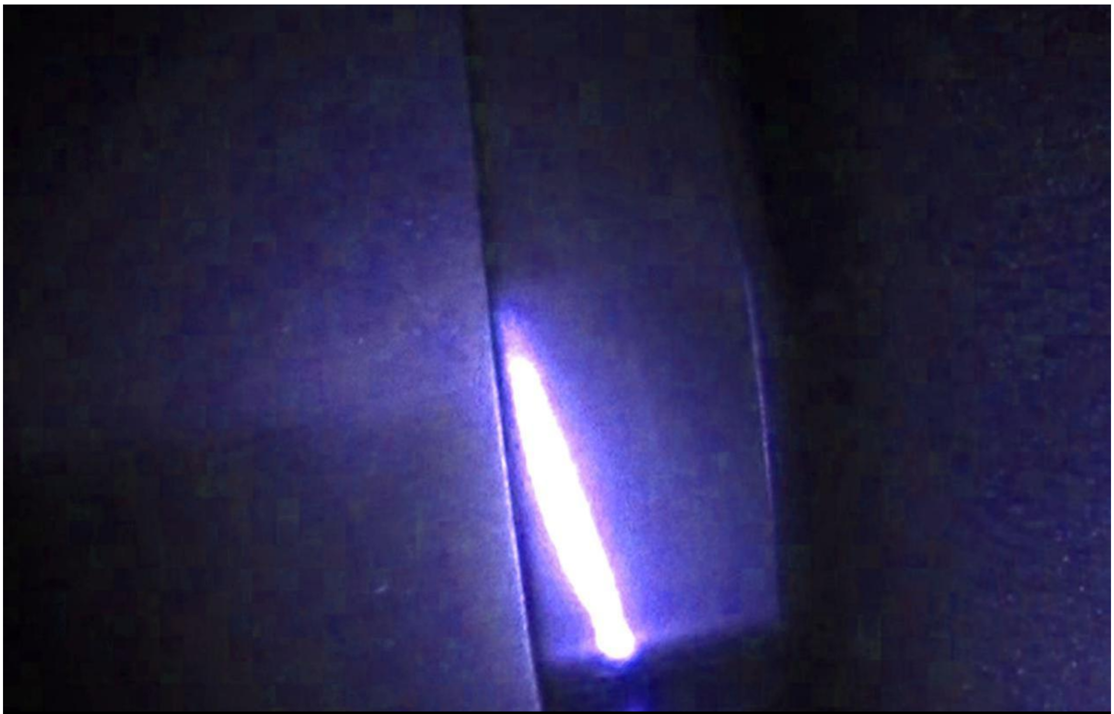
数据增强前：

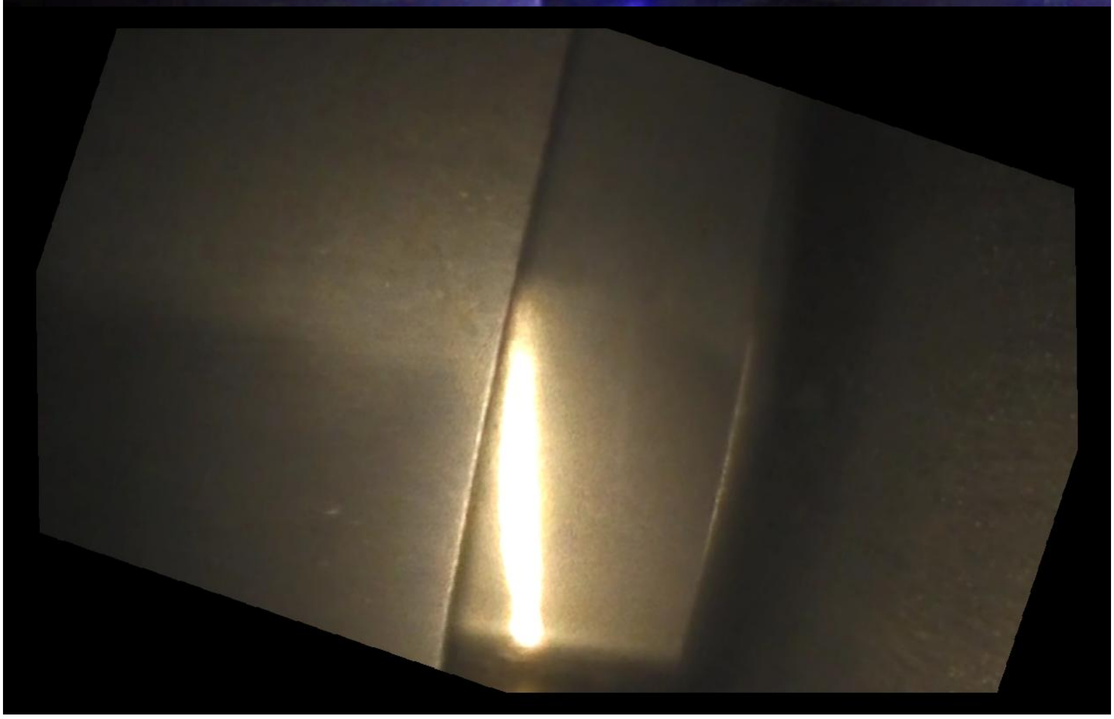


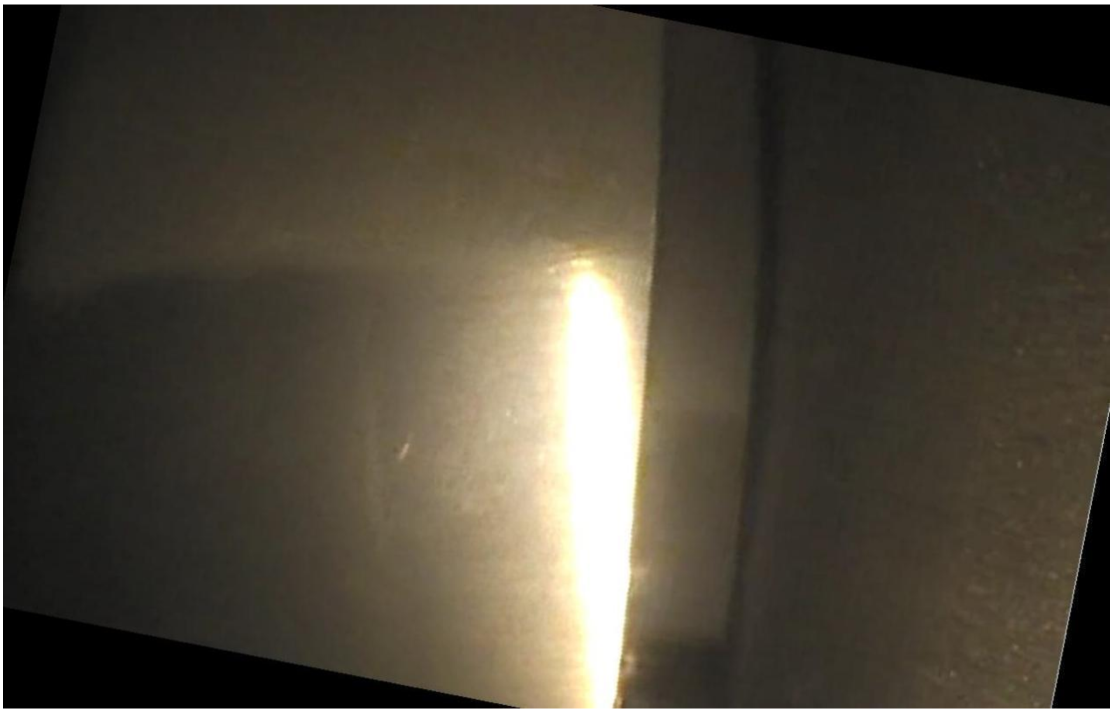
数据增强后：











数据增强代码：

```
import torch
from torchvision import transforms
from PIL import Image
import os

# 定义数据增强变换
transforms_list = [
    transforms.RandomHorizontalFlip(),   # 随机水平翻转
    transforms.RandomRotation(20),   # 随机旋转
    transforms.ColorJitter(brightness=0.5, contrast=0.5, saturation=0.5, hue=0.5),   # 随机调整
颜色
    transforms.RandomAffine(degrees=0, shear=10, scale=(0.9, 1.1), fillcolor=0),   # 锐化效果
    # 如果你还有其他变换，可以继续添加
]

# 图片所在的目录
input_dir = 'D:/bata5-5/windows/windows2/data1'   # 替换为你的图片目录
output_dir = 'D:/bata5-5/windows/windows2/data1out'   # 替换为保存增强图片的目录

# 确保输出目录存在
if not os.path.exists(output_dir):
    os.makedirs(output_dir)

# 遍历目录中的所有图片
for filename in os.listdir(input_dir):
    if filename.lower().endswith(('.png', '.jpg', '.jpeg', '.tiff', '.bmp', '.gif')):
```

```
        image_path = os.path.join(input_dir, filename)
        image = Image.open(image_path)

        # 应用每个变换并保存结果
        for transform in transforms_list:
            # 应用变换
            augmented_image = transform(image)
            # 保存增强后的图片
            output_path = os.path.join(output_dir, f'{filename}_{transform.__class__.__name__}.jpg')
            augmented_image.save(output_path)

print(f'All images have been augmented and saved to {output_dir}')
```

神经网络模型训练代码：

```
import argparse
import logging
import math
import os
import random
import time
from copy import deepcopy
from pathlib import Path
from threading import Thread
import os

os.environ['KMP_DUPLICATE_LIB_OK'] = 'True'

import numpy as np
import torch.distributed as dist
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import torch.optim.lr_scheduler as lr_scheduler
import torch.utils.data
import yaml
from torch.cuda import amp
from torch.nn.parallel import DistributedDataParallel as DDP
from torch.utils.tensorboard import SummaryWriter
from tqdm import tqdm

import test  # import test.py to get mAP after each epoch
from models.experimental import attempt_load
from models.yolo import Model
```

```
from utils.autoanchor import check_anchors
from utils.datasets import create_dataloader
from utils.general import labels_to_class_weights, increment_path, labels_to_image_weights, init_seeds, \
    fitness, strip_optimizer, get_latest_run, check_dataset, check_file, check_git_status, check_img_size, \
    check_requirements, print_mutation, set_logging, one_cycle, colorstr
from utils.google_utils import attempt_download
from utils.loss import ComputeLoss
from utils.plots import plot_images, plot_labels, plot_results, plot_evolution
from utils.torch_utils import ModelEMA, select_device, intersect_dicts, torch_distributed_zero_first, is_parallel
from utils.wandb_logging.wandb_utils import WandbLogger, check_wandb_resume

logger = logging.getLogger(__name__)


def train(hyp, opt, device, tb_writer=None):
    logger.info(colorstr('hyperparameters: ') + ', '.join(f'{k}={v}' for k, v in hyp.items()))
    save_dir, epochs, batch_size, total_batch_size, weights, rank = \
        Path(opt.save_dir), opt.epochs, opt.batch_size, opt.total_batch_size, opt.weights, opt.global_rank

    # Directories
    wdir = save_dir / 'weights'
    wdir.mkdir(parents=True, exist_ok=True)  # make dir
    last = wdir / 'last.pt'
    best = wdir / 'best.pt'
    results_file = save_dir / 'results.txt'

    # Save run settings
    with open(save_dir / 'hyp.yaml', 'w') as f:
        yaml.dump(hyp, f, sort_keys=False)
    with open(save_dir / 'opt.yaml', 'w') as f:
        yaml.dump(vars(opt), f, sort_keys=False)

    # Configure
    plots = not opt.evolve  # create plots
    cuda = device.type != 'cpu'
    init_seeds(2 + rank)
    with open(opt.data) as f:
        data_dict = yaml.load(f, Loader=yaml.SafeLoader)  # data dict
    is_coco = opt.data.endswith('coco.yaml')
```

```
    # Logging- Doing this before checking the dataset. Might update data_dict
    loggers = {'wandb': None}  # loggers dict
    if rank in [-1, 0]:
        opt.hyp = hyp  # add hyperparameters
        run_id = torch.load(weights).get('wandb_id') if weights.endswith('.pt') and os.path.isfile(weights) else None
        wandb_logger = WandbLogger(opt, Path(opt.save_dir).stem, run_id, data_dict)
        loggers['wandb'] = wandb_logger.wandb
        data_dict = wandb_logger.data_dict
        if wandb_logger.wandb:
            weights, epochs, hyp = opt.weights, opt.epochs, opt.hyp  # WandbLogger might update weights, epochs if resuming

    nc = 1 if opt.single_cls else int(data_dict['nc'])  # number of classes
    names = ['item'] if opt.single_cls and len(data_dict['names']) != 1 else data_dict['names']  # class names
    assert len(names) == nc, '%g names found for nc=%g dataset in %s' % (len(names), nc, opt.data)  # check

    # Model
    pretrained = weights.endswith('.pt')
    if pretrained:
        with torch_distributed_zero_first(rank):
            attempt_download(weights)  # download if not found locally
        ckpt = torch.load(weights, map_location=device)  # load checkpoint
        model = Model(opt.cfg or ckpt['model'].yaml, ch=3, nc=nc, anchors=hyp.get('anchors')).to(device)  # create
        exclude = ['anchor'] if (opt.cfg or hyp.get('anchors')) and not opt.resume else []  # exclude keys
        state_dict = ckpt['model'].float().state_dict()  # to FP32
        state_dict = intersect_dicts(state_dict, model.state_dict(), exclude=exclude)  # intersect
        model.load_state_dict(state_dict, strict=False)  # load
        logger.info('Transferred %g/%g items from %s' % (len(state_dict), len(model.state_dict()), weights))  # report
    else:
        model = Model(opt.cfg, ch=3, nc=nc, anchors=hyp.get('anchors')).to(device)  # create
    with torch_distributed_zero_first(rank):
        check_dataset(data_dict)  # check
    train_path = data_dict['train']
    test_path = data_dict['val']

    # Freeze
    freeze = []  # parameter names to freeze (full or partial)
    for k, v in model.named_parameters():
```

```
        v.requires_grad = True  # train all layers
        if any(x in k for x in freeze):
            print('freezing %s' % k)
            v.requires_grad = False

    # Optimizer
    nbs = 64  # nominal batch size
    accumulate = max(round(nbs / total_batch_size), 1)  # accumulate loss before optimizing
    hyp['weight_decay'] *= total_batch_size * accumulate / nbs  # scale weight_decay
    logger.info(f"Scaled weight_decay = {hyp['weight_decay']}")

    pg0, pg1, pg2 = [], [], []  # optimizer parameter groups
    for k, v in model.named_modules():
        if hasattr(v, 'bias') and isinstance(v.bias, nn.Parameter):
            pg2.append(v.bias)  # biases
        if isinstance(v, nn.BatchNorm2d):
            pg0.append(v.weight)  # no decay
        elif hasattr(v, 'weight') and isinstance(v.weight, nn.Parameter):
            pg1.append(v.weight)  # apply decay

    if opt.adam:
        optimizer = optim.Adam(pg0, lr=hyp['lr0'], betas=(hyp['momentum'], 0.999))  # adjust
beta1 to momentum
    else:
        optimizer = optim.SGD(pg0, lr=hyp['lr0'], momentum=hyp['momentum'],
nesterov=True)

    optimizer.add_param_group({'params': pg1, 'weight_decay': hyp['weight_decay']})  # add
pg1 with weight_decay
    optimizer.add_param_group({'params': pg2})  # add pg2 (biases)
    logger.info('Optimizer groups: %g .bias, %g conv.weight, %g other' % (len(pg2), len(pg1),
len(pg0)))
    del pg0, pg1, pg2

    # Scheduler https://arxiv.org/pdf/1812.01187.pdf
    # https://pytorch.org/docs/stable/_modules/torch/optim/lr_scheduler.html#OneCycleLR
    if opt.linear_lr:
        lf = lambda x: (1 - x / (epochs - 1)) * (1.0 - hyp['lrf']) + hyp['lrf']  # linear
    else:
        lf = one_cycle(1, hyp['lrf'], epochs)  # cosine 1->hyp['lrf']
    scheduler = lr_scheduler.LambdaLR(optimizer, lr_lambda=lf)
    # plot_lr_scheduler(optimizer, scheduler, epochs)

    # EMA
```

```
    ema = ModelEMA(model) if rank in [-1, 0] else None

    # Resume
    start_epoch, best_fitness = 0, 0.0
    if pretrained:
        # Optimizer
        if ckpt['optimizer'] is not None:
            optimizer.load_state_dict(ckpt['optimizer'])
            best_fitness = ckpt['best_fitness']

        # EMA
        if ema and ckpt.get('ema'):
            ema.ema.load_state_dict(ckpt['ema'].float().state_dict())
            ema.updates = ckpt['updates']

        # Results
        if ckpt.get('training_results') is not None:
            results_file.write_text(ckpt['training_results'])  # write results.txt

        # Epochs
        start_epoch = ckpt['epoch'] + 1
        if opt.resume:
            assert start_epoch > 0, '%s training to %g epochs is finished, nothing to resume.' % (weights, epochs)
        if epochs < start_epoch:
            logger.info('%s has been trained for %g epochs. Fine-tuning for %g additional epochs.' %
                        (weights, ckpt['epoch'], epochs))
            epochs += ckpt['epoch']  # finetune additional epochs

        del ckpt, state_dict

    # Image sizes
    gs = max(int(model.stride.max()), 32)  # grid size (max stride)
    nl = model.model[-1].nl  # number of detection layers (used for scaling hyp['obj'])
    imgsz, imgsz_test = [check_img_size(x, gs) for x in opt.img_size]  # verify imgsz are gs-multiples

    # DP mode
    if cuda and rank == -1 and torch.cuda.device_count() > 1:
        model = torch.nn.DataParallel(model)

    # SyncBatchNorm
    if opt.sync_bn and cuda and rank != -1:
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```
            model = torch.nn.SyncBatchNorm.convert_sync_batchnorm(model).to(device)
            logger.info('Using SyncBatchNorm()')

        # Trainloader
        dataloader, dataset = create_dataloader(train_path, imgsz, batch_size, gs, opt,
                                                hyp=hyp,                    augment=True,
cache=opt.cache_images, rect=opt.rect, rank=rank,
                                                world_size=opt.world_size,
workers=opt.workers,
                                                image_weights=opt.image_weights,
quad=opt.quad, prefix=colorstr('train: '))
        mlc = np.concatenate(dataset.labels, 0)[:, 0].max()  # max label class
        nb = len(dataloader)  # number of batches
        assert mlc < nc, 'Label class %g exceeds nc=%g in %s. Possible class labels are 0-%g' %
(mlc, nc, opt.data, nc - 1)

        # Process 0
        if rank in [-1, 0]:
            testloader = create_dataloader(test_path, imgsz_test, batch_size * 2, gs, opt,   #
testloader
                                           hyp=hyp,   cache=opt.cache_images   and   not
opt.notest, rect=True, rank=-1,
                                           world_size=opt.world_size,
workers=opt.workers,
                                           pad=0.5, prefix=colorstr('val: '))[0]

            if not opt.resume:
                labels = np.concatenate(dataset.labels, 0)
                c = torch.tensor(labels[:, 0])  # classes
                # cf = torch.bincount(c.long(), minlength=nc) + 1.  # frequency
                # model._initialize_biases(cf.to(device))
                if plots:
                    plot_labels(labels, names, save_dir, loggers)
                    if tb_writer:
                        tb_writer.add_histogram('classes', c, 0)

                # Anchors
                if not opt.noautoanchor:
                    check_anchors(dataset, model=model, thr=hyp['anchor_t'], imgsz=imgsz)
                model.half().float()  # pre-reduce anchor precision

        # DDP mode
        if cuda and rank != -1:
            model = DDP(model, device_ids=[opt.local_rank], output_device=opt.local_rank,
```

```
                    # nn.MultiheadAttention incompatibility with DDP https://github.com/pytorch/pytorch/issues/26698
                    find_unused_parameters=any(isinstance(layer, nn.MultiheadAttention) for layer in model.modules()))

    # Model parameters
    hyp['box'] *= 3. / nl  # scale to layers
    hyp['cls'] *= nc / 80. * 3. / nl  # scale to classes and layers
    hyp['obj'] *= (imgsz / 640) ** 2 * 3. / nl  # scale to image size and layers
    hyp['label_smoothing'] = opt.label_smoothing
    model.nc = nc  # attach number of classes to model
    model.hyp = hyp  # attach hyperparameters to model
    model.gr = 1.0  # iou loss ratio (obj_loss = 1.0 or iou)
    model.class_weights = labels_to_class_weights(dataset.labels, nc).to(device) * nc  # attach class weights
    model.names = names

    # Start training
    t0 = time.time()
    nw = max(round(hyp['warmup_epochs'] * nb), 1000)  # number of warmup iterations, max(3 epochs, 1k iterations)
    # nw = min(nw, (epochs - start_epoch) / 2 * nb)  # limit warmup to < 1/2 of training
    maps = np.zeros(nc)  # mAP per class
    results = (0, 0, 0, 0, 0, 0, 0)  # P, R, mAP@.5, mAP@.5-.95, val_loss(box, obj, cls)
    scheduler.last_epoch = start_epoch - 1  # do not move
    scaler = amp.GradScaler(enabled=cuda)
    compute_loss = ComputeLoss(model)  # init loss class
    logger.info(f'Image sizes {imgsz} train, {imgsz_test} test\n'
                f'Using {dataloader.num_workers} dataloader workers\n'
                f'Logging results to {save_dir}\n'
                f'Starting training for {epochs} epochs...')
    for epoch in range(start_epoch, epochs):  # epoch ------------------------------------------------------------------
        model.train()

        # Update image weights (optional)
        if opt.image_weights:
            # Generate indices
            if rank in [-1, 0]:
                cw = model.class_weights.cpu().numpy() * (1 - maps) ** 2 / nc  # class weights
                iw = labels_to_image_weights(dataset.labels, nc=nc, class_weights=cw)  # image weights
                dataset.indices = random.choices(range(dataset.n), weights=iw, k=dataset.n)
```

```
# rand weighted idx
                # Broadcast if DDP
                if rank != -1:
                    indices = (torch.tensor(dataset.indices) if rank == 0 else
torch.zeros(dataset.n)).int()
                    dist.broadcast(indices, 0)
                    if rank != 0:
                        dataset.indices = indices.cpu().numpy()

            # Update mosaic border
            # b = int(random.uniform(0.25 * imgsz, 0.75 * imgsz + gs) // gs * gs)
            # dataset.mosaic_border = [b - imgsz, -b]  # height, width borders

            mloss = torch.zeros(4, device=device)  # mean losses
            if rank != -1:
                dataloader.sampler.set_epoch(epoch)
            pbar = enumerate(dataloader)
            logger.info(('\n' + '%10s' * 8) % ('Epoch', 'gpu_mem', 'box', 'obj', 'cls', 'total', 'labels',
'img_size'))
            if rank in [-1, 0]:
                pbar = tqdm(pbar, total=nb)  # progress bar
            optimizer.zero_grad()
            for i, (imgs, targets, paths, _) in pbar:  # batch
-------------------------------------------------------------
                ni = i + nb * epoch  # number integrated batches (since train start)
                imgs = imgs.to(device, non_blocking=True).float() / 255.0  # uint8 to float32,
0-255 to 0.0-1.0

                # Warmup
                if ni <= nw:
                    xi = [0, nw]  # x interp
                    # model.gr = np.interp(ni, xi, [0.0, 1.0])  # iou loss ratio (obj_loss = 1.0 or
iou)
                    accumulate = max(1, np.interp(ni, xi, [1, nbs / total_batch_size]).round())
                    for j, x in enumerate(optimizer.param_groups):
                        # bias lr falls from 0.1 to lr0, all other lrs rise from 0.0 to lr0
                        x['lr'] = np.interp(ni, xi, [hyp['warmup_bias_lr'] if j == 2 else 0.0,
x['initial_lr'] * lf(epoch)])
                        if 'momentum' in x:
                            x['momentum'] = np.interp(ni, xi, [hyp['warmup_momentum'],
hyp['momentum']])

                # Multi-scale
                if opt.multi_scale:
```

```
            sz = random.randrange(imgsz * 0.5, imgsz * 1.5 + gs) // gs * gs  # size
            sf = sz / max(imgs.shape[2:])  # scale factor
            if sf != 1:
                ns = [math.ceil(x * sf / gs) * gs for x in imgs.shape[2:]]  # new shape (stretched to gs-multiple)
                imgs = F.interpolate(imgs, size=ns, mode='bilinear', align_corners=False)

        # Forward
        with amp.autocast(enabled=cuda):
            pred = model(imgs)  # forward
            loss, loss_items = compute_loss(pred, targets.to(device))  # loss scaled by batch_size
            if rank != -1:
                loss *= opt.world_size  # gradient averaged between devices in DDP mode
            if opt.quad:
                loss *= 4.

        # Backward
        scaler.scale(loss).backward()

        # Optimize
        if ni % accumulate == 0:
            scaler.step(optimizer)  # optimizer.step
            scaler.update()
            optimizer.zero_grad()
            if ema:
                ema.update(model)

        # Print
        if rank in [-1, 0]:
            mloss = (mloss * i + loss_items) / (i + 1)  # update mean losses
            mem = '%.3gG' % (torch.cuda.memory_reserved() / 1E9 if torch.cuda.is_available() else 0)  # (GB)
            s = ('%10s' * 2 + '%10.4g' * 6) % (
                '%g/%g' % (epoch, epochs - 1), mem, *mloss, targets.shape[0], imgs.shape[-1])
            pbar.set_description(s)

            # Plot
            if plots and ni < 3:
                f = save_dir / f'train_batch{ni}.jpg'  # filename
                Thread(target=plot_images, args=(imgs, targets, paths, f), daemon=True).start()
```

```
                    # if tb_writer:
                    #                    tb_writer.add_image(f,    result,    dataformats='HWC',
global_step=epoch)
                    #          tb_writer.add_graph(torch.jit.trace(model, imgs, strict=False), [])
# add model graph
                elif plots and ni == 10 and wandb_logger.wandb:
                    wandb_logger.log({"Mosaics":         [wandb_logger.wandb.Image(str(x),
caption=x.name) for x in
                                                  save_dir.glob('train*.jpg')            if
x.exists()]})

            #                                    end                                    batch
------------------------------------------------------------------------------------------------
        #                                    end                                    epoch
----------------------------------------------------------------------------------------------------

        # Scheduler
        lr = [x['lr'] for x in optimizer.param_groups]    # for tensorboard
        scheduler.step()

        # DDP process 0 or single-GPU
        if rank in [-1, 0]:
            # mAP
            ema.update_attr(model,   include=['yaml',   'nc',   'hyp',   'gr',   'names',   'stride',
'class_weights'])
            final_epoch = epoch + 1 == epochs
            if not opt.notest or final_epoch:    # Calculate mAP
                wandb_logger.current_epoch = epoch + 1
                results, maps, times = test.test(data_dict,
                                                 batch_size=batch_size * 2,
                                                 imgsz=imgsz_test,
                                                 model=ema.ema,
                                                 single_cls=opt.single_cls,
                                                 dataloader=testloader,
                                                 save_dir=save_dir,
                                                 verbose=nc < 50 and final_epoch,
                                                 plots=plots and final_epoch,
                                                 wandb_logger=wandb_logger,
                                                 compute_loss=compute_loss,
                                                 is_coco=is_coco)

            # Write
            with open(results_file, 'a') as f:
                f.write(s + '%10.4g' * 7 % results + '\n')    # append metrics, val_loss
```

```
        if len(opt.name) and opt.bucket:
            os.system('gsutil cp %s gs://%s/results/results%s.txt' % (results_file, opt.bucket, opt.name))

        # Log
        tags = ['train/box_loss', 'train/obj_loss', 'train/cls_loss',  # train loss
                'metrics/precision', 'metrics/recall', 'metrics/mAP_0.5', 'metrics/mAP_0.5:0.95',
                'val/box_loss', 'val/obj_loss', 'val/cls_loss',  # val loss
                'x/lr0', 'x/lr1', 'x/lr2']  # params
        for x, tag in zip(list(mloss[:-1]) + list(results) + lr, tags):
            if tb_writer:
                tb_writer.add_scalar(tag, x, epoch)  # tensorboard
            if wandb_logger.wandb:
                wandb_logger.log({tag: x})  # W&B

        # Update best mAP
        fi = fitness(np.array(results).reshape(1, -1))  # weighted combination of [P, R, mAP@.5, mAP@.5-.95]
        if fi > best_fitness:
            best_fitness = fi
        wandb_logger.end_epoch(best_result=best_fitness == fi)

        # Save model
        if (not opt.nosave) or (final_epoch and not opt.evolve):  # if save
            ckpt = {'epoch': epoch,
                    'best_fitness': best_fitness,
                    'training_results': results_file.read_text(),
                    'model': deepcopy(model.module if is_parallel(model) else model).half(),
                    'ema': deepcopy(ema.ema).half(),
                    'updates': ema.updates,
                    'optimizer': optimizer.state_dict(),
                    'wandb_id': wandb_logger.wandb_run.id if wandb_logger.wandb else None}

            # Save last, best and delete
            torch.save(ckpt, last)
            if best_fitness == fi:
                torch.save(ckpt, best)
            if wandb_logger.wandb:
                if ((epoch + 1) % opt.save_period == 0 and not final_epoch) and opt.save_period != -1:
                    wandb_logger.log_model(
```

```
                              last.parent, opt, epoch, fi, best_model=best_fitness == fi)
                    del ckpt

            #                                   end                                   epoch
------------------------------------------------------------------------------------------------
        # end training
        if rank in [-1, 0]:
            # Plots
            if plots:
                plot_results(save_dir=save_dir)  # save as results.png
                if wandb_logger.wandb:
                    files = ['results.png', 'confusion_matrix.png', *[f'{x}_curve.png' for x in ('F1',
'PR', 'P', 'R')]]
                    wandb_logger.log({"Results": [wandb_logger.wandb.Image(str(save_dir / f),
caption=f) for f in files
                                                  if (save_dir / f).exists()]})
            # Test best.pt
            logger.info('%g epochs completed in %.3f hours.\n' % (epoch - start_epoch + 1,
(time.time() - t0) / 3600))
            if opt.data.endswith('coco.yaml') and nc == 80:  # if COCO
                for m in (last, best) if best.exists() else (last):  # speed, mAP tests
                    results, _, _ = test.test(opt.data,
                                              batch_size=batch_size * 2,
                                              imgsz=imgsz_test,
                                              conf_thres=0.001,
                                              iou_thres=0.7,
                                              model=attempt_load(m, device).half(),
                                              single_cls=opt.single_cls,
                                              dataloader=testloader,
                                              save_dir=save_dir,
                                              save_json=True,
                                              plots=False,
                                              is_coco=is_coco)

            # Strip optimizers
            final = best if best.exists() else last  # final model
            for f in last, best:
                if f.exists():
                    strip_optimizer(f)  # strip optimizers
            if opt.bucket:
                os.system(f'gsutil cp {final} gs://{opt.bucket}/weights')  # upload
            if wandb_logger.wandb and not opt.evolve:  # Log the stripped model
                wandb_logger.wandb.log_artifact(str(final), type='model',
                                                name='run_' + wandb_logger.wandb_run.id
```

```
+ '_model',
                                                          aliases=['last', 'best', 'stripped'])
            wandb_logger.finish_run()
        else:
            dist.destroy_process_group()
        torch.cuda.empty_cache()
        return results


if __name__ == '__main__':
    parser = argparse.ArgumentParser()
    parser.add_argument('--weights', type=str, default='weights/yolov5s.pt', help='initial weights path')
    parser.add_argument('--cfg', type=str, default='models/blade.yaml', help='model.yaml path')
    parser.add_argument('--data', type=str, default='data/blade.yaml', help='data.yaml path')
    parser.add_argument('--hyp', type=str, default='data/hyp.scratch.yaml', help='hyperparameters path')
    parser.add_argument('--epochs', type=int, default=1000)
    parser.add_argument('--batch-size', type=int, default=16, help='total batch size for all GPUs')
    parser.add_argument('--img-size', nargs='+', type=int, default=[640, 640], help='[train, test] image sizes')
    parser.add_argument('--rect', action='store_true', help='rectangular training')
    parser.add_argument('--resume', nargs='?', const=True, default=False, help='resume most recent training')
    parser.add_argument('--nosave', action='store_true', help='only save final checkpoint')
    parser.add_argument('--notest', action='store_true', help='only test final epoch')
    parser.add_argument('--noautoanchor', action='store_true', help='disable autoanchor check')
    parser.add_argument('--evolve', action='store_true', help='evolve hyperparameters')
    parser.add_argument('--bucket', type=str, default='', help='gsutil bucket')
    parser.add_argument('--cache-images', action='store_true', help='cache images for faster training')
    parser.add_argument('--image-weights', action='store_true', help='use weighted image selection for training')
    parser.add_argument('--device', default='0', help='cuda device, i.e. 0 or 0,1,2,3 or cpu')
    parser.add_argument('--multi-scale', action='store_true', help='vary img-size +/- 50%%')
    parser.add_argument('--single-cls', action='store_true', help='train multi-class data as single-class')
    parser.add_argument('--adam', action='store_true', help='use torch.optim.Adam() optimizer')
    parser.add_argument('--sync-bn', action='store_true', help='use SyncBatchNorm, only available in DDP mode')
    parser.add_argument('--local_rank', type=int, default=-1, help='DDP parameter, do not modify')
    parser.add_argument('--workers', type=int, default=8, help='maximum number of dataloader workers')
```

```
    parser.add_argument('--project', default='runs/train', help='save to project/name')
    parser.add_argument('--entity', default=None, help='W&B entity')
    parser.add_argument('--name', default='exp', help='save to project/name')
    parser.add_argument('--exist-ok', action='store_true', help='existing project/name ok, do not increment')
    parser.add_argument('--quad', action='store_true', help='quad dataloader')
    parser.add_argument('--linear-lr', action='store_true', help='linear LR')
    parser.add_argument('--label-smoothing', type=float, default=0.0, help='Label smoothing epsilon')
    parser.add_argument('--upload_dataset', action='store_true', help='Upload dataset as W&B artifact table')
    parser.add_argument('--bbox_interval', type=int, default=-1, help='Set bounding-box image logging interval for W&B')
    parser.add_argument('--save_period', type=int, default=-1, help='Log model after every "save_period" epoch')
    parser.add_argument('--artifact_alias', type=str, default="latest", help='version of dataset artifact to be used')
    opt = parser.parse_args()

    # Set DDP variables
    opt.world_size = int(os.environ['WORLD_SIZE']) if 'WORLD_SIZE' in os.environ else 1
    opt.global_rank = int(os.environ['RANK']) if 'RANK' in os.environ else -1
    set_logging(opt.global_rank)
    if opt.global_rank in [-1, 0]:
        check_git_status()
        check_requirements()

    # Resume
    wandb_run = check_wandb_resume(opt)
    if opt.resume and not wandb_run:  # resume an interrupted run
        ckpt = opt.resume if isinstance(opt.resume, str) else get_latest_run()  # specified or most recent path
        assert os.path.isfile(ckpt), 'ERROR: --resume checkpoint does not exist'
        apriori = opt.global_rank, opt.local_rank
        with open(Path(ckpt).parent.parent / 'opt.yaml') as f:
            opt = argparse.Namespace(**yaml.load(f, Loader=yaml.SafeLoader))  # replace
        opt.cfg, opt.weights, opt.resume, opt.batch_size, opt.global_rank, opt.local_rank = '', ckpt, True, opt.total_batch_size, *apriori  # reinstate
        logger.info('Resuming training from %s' % ckpt)
    else:
        # opt.hyp = opt.hyp or ('hyp.finetune.yaml' if opt.weights else 'hyp.scratch.yaml')
        opt.data, opt.cfg, opt.hyp = check_file(opt.data), check_file(opt.cfg), check_file(opt.hyp)  # check files
        assert len(opt.cfg) or len(opt.weights), 'either --cfg or --weights must be specified'
```

```
        opt.img_size.extend([opt.img_size[-1]] * (2 - len(opt.img_size)))  # extend to 2 sizes (train, test)
        opt.name = 'evolve' if opt.evolve else opt.name
        opt.save_dir = increment_path(Path(opt.project) / opt.name, exist_ok=opt.exist_ok | opt.evolve)  # increment run

    # DDP mode
    opt.total_batch_size = opt.batch_size
    device = select_device(opt.device, batch_size=opt.batch_size)
    if opt.local_rank != -1:
        assert torch.cuda.device_count() > opt.local_rank
        torch.cuda.set_device(opt.local_rank)
        device = torch.device('cuda', opt.local_rank)
        dist.init_process_group(backend='nccl', init_method='env://')  # distributed backend
        assert opt.batch_size % opt.world_size == 0, '--batch-size must be multiple of CUDA device count'
        opt.batch_size = opt.total_batch_size // opt.world_size

    # Hyperparameters
    with open(opt.hyp) as f:
        hyp = yaml.load(f, Loader=yaml.SafeLoader)  # load hyps

    # Train
    logger.info(opt)
    if not opt.evolve:
        tb_writer = None  # init loggers
        if opt.global_rank in [-1, 0]:
            prefix = colorstr('tensorboard: ')
            logger.info(f"{prefix}Start with 'tensorboard --logdir {opt.project}', view at http://localhost:6006/")
            tb_writer = SummaryWriter(opt.save_dir)  # Tensorboard
        train(hyp, opt, device, tb_writer)

    # Evolve hyperparameters (optional)
    else:
        # Hyperparameter evolution metadata (mutation scale 0-1, lower_limit, upper_limit)
        meta = {'lr0': (1, 1e-5, 1e-1),  # initial learning rate (SGD=1E-2, Adam=1E-3)
                'lrf': (1, 0.01, 1.0),  # final OneCycleLR learning rate (lr0 * lrf)
                'momentum': (0.3, 0.6, 0.98),  # SGD momentum/Adam beta1
                'weight_decay': (1, 0.0, 0.001),  # optimizer weight decay
                'warmup_epochs': (1, 0.0, 5.0),  # warmup epochs (fractions ok)
                'warmup_momentum': (1, 0.0, 0.95),  # warmup initial momentum
                'warmup_bias_lr': (1, 0.0, 0.2),  # warmup initial bias lr
                'box': (1, 0.02, 0.2),  # box loss gain
```

```
            'cls': (1, 0.2, 4.0),  # cls loss gain
            'cls_pw': (1, 0.5, 2.0),  # cls BCELoss positive_weight
            'obj': (1, 0.2, 4.0),  # obj loss gain (scale with pixels)
            'obj_pw': (1, 0.5, 2.0),  # obj BCELoss positive_weight
            'iou_t': (0, 0.1, 0.7),  # IoU training threshold
            'anchor_t': (1, 2.0, 8.0),  # anchor-multiple threshold
            'anchors': (2, 2.0, 10.0),  # anchors per output grid (0 to ignore)
            'fl_gamma': (0, 0.0, 2.0),  # focal loss gamma (efficientDet default gamma=1.5)
            'hsv_h': (1, 0.0, 0.1),  # image HSV-Hue augmentation (fraction)
            'hsv_s': (1, 0.0, 0.9),  # image HSV-Saturation augmentation (fraction)
            'hsv_v': (1, 0.0, 0.9),  # image HSV-Value augmentation (fraction)
            'degrees': (1, 0.0, 45.0),  # image rotation (+/- deg)
            'translate': (1, 0.0, 0.9),  # image translation (+/- fraction)
            'scale': (1, 0.0, 0.9),  # image scale (+/- gain)
            'shear': (1, 0.0, 10.0),  # image shear (+/- deg)
            'perspective': (0, 0.0, 0.001),  # image perspective (+/- fraction), range 0-0.001
            'flipud': (1, 0.0, 1.0),  # image flip up-down (probability)
            'fliplr': (0, 0.0, 1.0),  # image flip left-right (probability)
            'mosaic': (1, 0.0, 1.0),  # image mixup (probability)
            'mixup': (1, 0.0, 1.0)}  # image mixup (probability)

    assert opt.local_rank == -1, 'DDP mode not implemented for --evolve'
    opt.notest, opt.nosave = True, True  # only test/save final epoch
    # ei = [isinstance(x, (int, float)) for x in hyp.values()]  # evolvable indices
    yaml_file = Path(opt.save_dir) / 'hyp_evolved.yaml'  # save best result here
    if opt.bucket:
        os.system('gsutil cp gs://%s/evolve.txt .' % opt.bucket)  # download evolve.txt if exists

    for _ in range(300):  # generations to evolve
        if Path('evolve.txt').exists():  # if evolve.txt exists: select best hyps and mutate
            # Select parent(s)
            parent = 'single'  # parent selection method: 'single' or 'weighted'
            x = np.loadtxt('evolve.txt', ndmin=2)
            n = min(5, len(x))  # number of previous results to consider
            x = x[np.argsort(-fitness(x))][:n]  # top n mutations
            w = fitness(x) - fitness(x).min()  # weights
            if parent == 'single' or len(x) == 1:
                # x = x[random.randint(0, n - 1)]  # random selection
                x = x[random.choices(range(n), weights=w)[0]]  # weighted selection
            elif parent == 'weighted':
                x = (x * w.reshape(n, 1)).sum(0) / w.sum()  # weighted combination
```

```
            # Mutate
            mp, s = 0.8, 0.2  # mutation probability, sigma
            npr = np.random
            npr.seed(int(time.time()))
            g = np.array([x[0] for x in meta.values()])  # gains 0-1
            ng = len(meta)
            v = np.ones(ng)
            while all(v == 1):  # mutate until a change occurs (prevent duplicates)
                v = (g * (npr.random(ng) < mp) * npr.randn(ng) * npr.random() * s + 1).clip(0.3, 3.0)
            for i, k in enumerate(hyp.keys()):  # plt.hist(v.ravel(), 300)
                hyp[k] = float(x[i + 7] * v[i])  # mutate

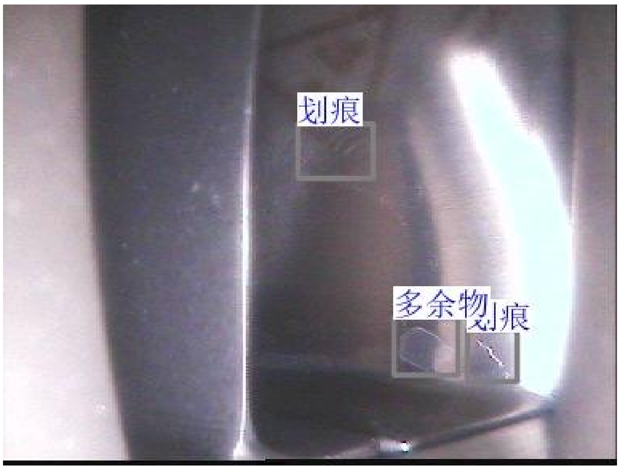
        # Constrain to limits
        for k, v in meta.items():
            hyp[k] = max(hyp[k], v[1])  # lower limit
            hyp[k] = min(hyp[k], v[2])  # upper limit
            hyp[k] = round(hyp[k], 5)  # significant digits

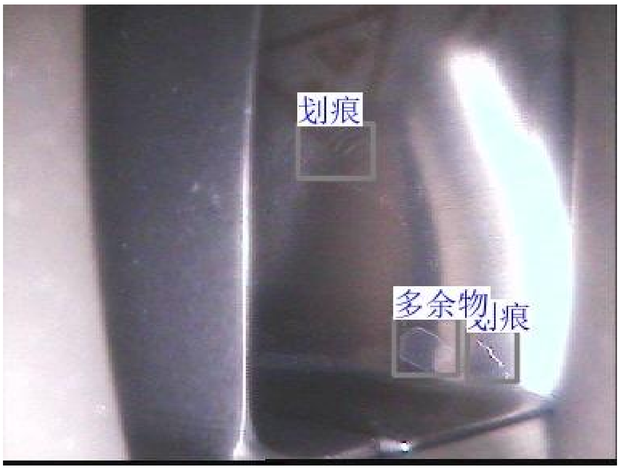
        # Train mutation
        results = train(hyp.copy(), opt, device)

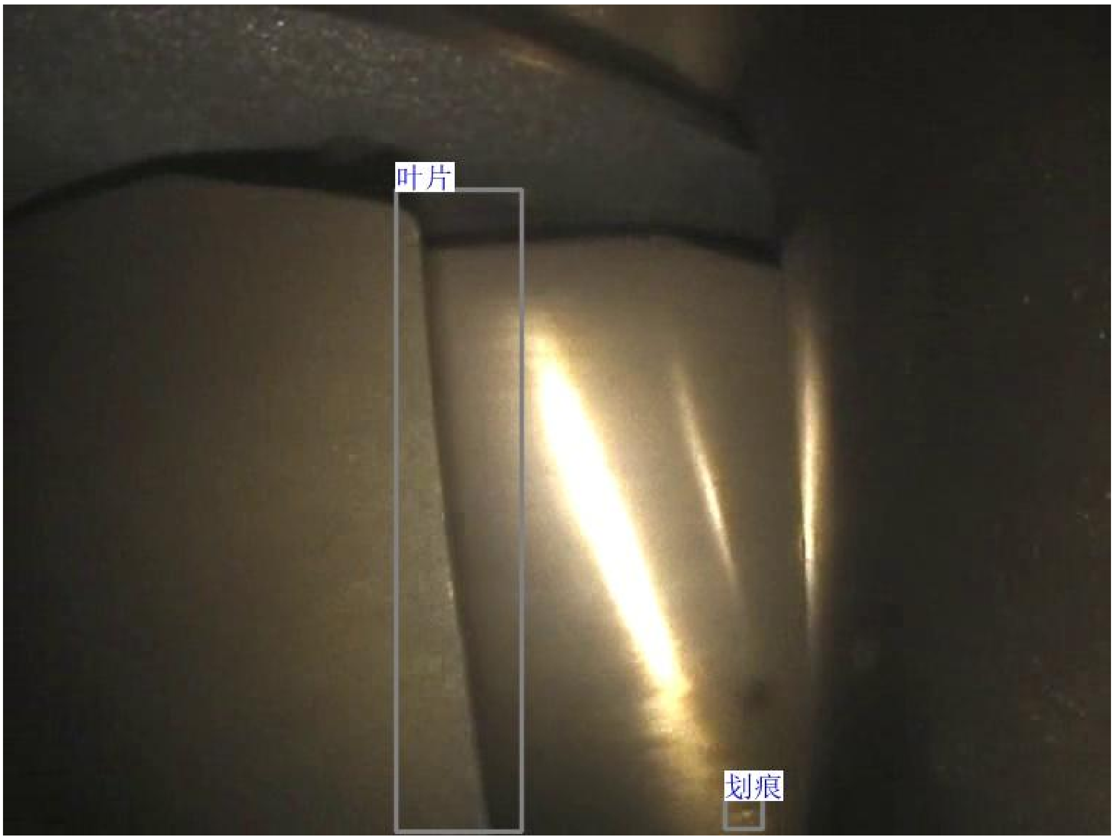
        # Write mutation results
        print_mutation(hyp.copy(), results, yaml_file, opt.bucket)

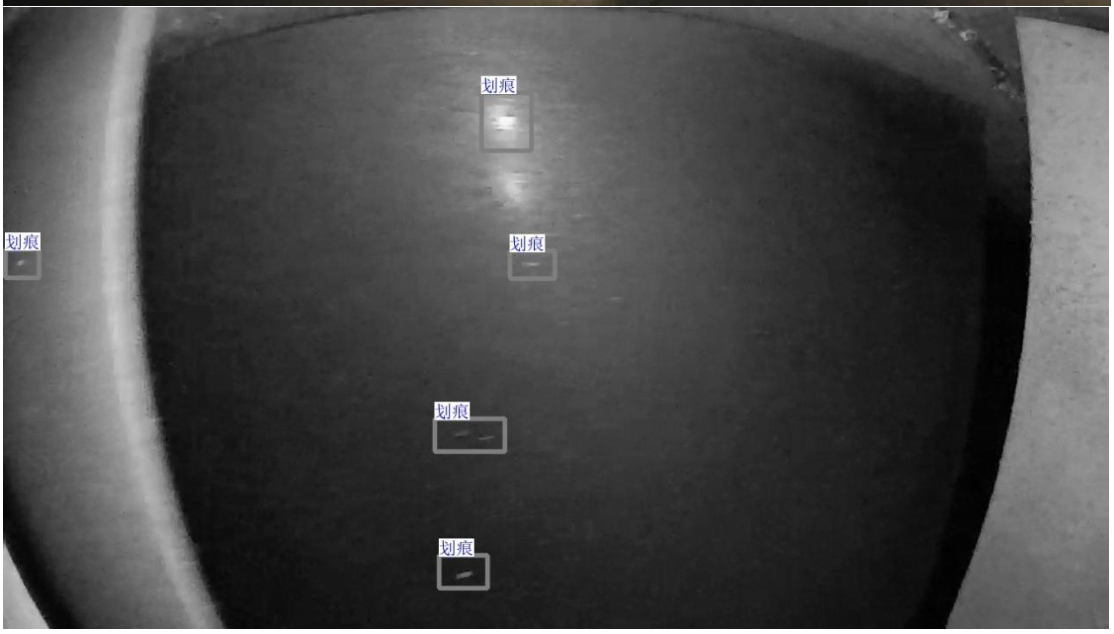
    # Plot results
    plot_evolution(yaml_file)
    print(f'Hyperparameter evolution complete. Best results saved as: {yaml_file}\n'
          f'Command to train a new model with these hyperparameters: $ python train.py --hyp {yaml_file}')
```

检测效果：




划痕
多余物
划痕


叶片
划痕


划痕

划痕
划痕
划痕
划痕
划痕