In [1]:
```
#安装相应package
#!pip install numpy pandas matplotlib requests tqdm opencv-python
# !pip install numpy pandas matplotlib seaborn plotly requests tqdm opencv-python pillow wandb -i https://pypi.tuna.tsinghua.edu.cn/simple
```

In [2]:
```
#测试torch
# import torch
# torch.__version__
```

In [3]:
```
#中文字体文件
!wget https://zihao-openmmlab.obs.cn-east-3.myhuaweicloud.com/20220716-mmclassification/dataset/SimHei.ttf --no-check-certificate
```

```
--2023-04-01 16:08:18--  https://zihao-openmmlab.obs.cn-east-3.myhuaweicloud.com/20220716-mmclassification/dataset/SimHei.ttf (https://zihao-openmmlab.obs.cn-east-3.myhuaweicloud.com/20220716-mmclassification/dataset/SimHei.ttf)
正在解析主机 zihao-openmmlab.obs.cn-east-3.myhuaweicloud.com (zihao-openmmlab.obs.cn-east-3.myhuaweicloud.com)... 121.36.235.132
正在连接 zihao-openmmlab.obs.cn-east-3.myhuaweicloud.com (zihao-openmmlab.obs.cn-east-3.myhuaweicloud.com)|121.36.235.132|:443... 已连接。
已发出 HTTP 请求，正在等待回应... 200 OK
长度： 10050868 (9.6M) [application/x-font-ttf]
正在保存至: “SimHei.ttf.3”

SimHei.ttf.3        100%[===================>]   9.58M  38.1MB/s    用时 0.3s

2023-04-01 16:08:19 (38.1 MB/s) - 已保存 “SimHei.ttf.3” [10050868/10050868])
```

In [4]:
```
import os
```

In [5]:
```

# 存放结果文件
os.mkdir('output1')

# 存放训练得到的模型权重
os.mkdir('checkpoint1')


# 存放生成的图表
os.mkdir('图表1')
```

准备数据集

In [6]:
```
# !git clone https://github.com/JasonYangCode/AppleLeaf9
```

导入工具包

In [7]:
```
import time
import os

import numpy as np
from tqdm import tqdm

import torch
import torchvision
import torch.nn as nn
import torch.nn.functional as F

import matplotlib.pyplot as plt
%matplotlib inline

# 忽略烦人的红色提示
import warnings
warnings.filterwarnings("ignore")
# 有 GPU 就用 GPU，没有就用 CPU
device = torch.device('cuda:0' if torch.cuda.is_available() else 'cpu')
print('device', device)
```

```
device cuda:0
```

图像预处理

In [8]:
```
from torchvision import transforms
target_size = (224,224)
# 训练集图像预处理：缩放裁剪、图像增强、转 Tensor、归一化
train_transform = transforms.Compose([transforms.Resize(target_size),
                                      transforms.RandomHorizontalFlip(),
                                      transforms.ToTensor(),
                                      transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
                                     ])

# 测试集图像预处理-RCTN：缩放、裁剪、转 Tensor、归一化
test_transform = transforms.Compose([transforms.Resize(256),
                                     transforms.CenterCrop(224),
                                     transforms.ToTensor(),
                                     transforms.Normalize(
                                         mean=[0.485, 0.456, 0.406],
                                         std=[0.229, 0.224, 0.225])
                                    ])
```

加载数据集

In [9]:
```
# 数据集文件夹路径
dataset_dir = 'AppleLeaf9_split'
#训练集路径
train_path = os.path.join(dataset_dir, 'train')
#测试集路径
test_path = os.path.join(dataset_dir, 'val')
print('训练集路径', train_path)
print('测试集路径', test_path)
```

```
训练集路径 AppleLeaf9_split/train
测试集路径 AppleLeaf9_split/val
```

In [10]:
```
from torchvision import datasets
#是否输入train_transform、test_transform参数可以选择是否对训练集和测试集进行数据增强，目前是未进行数据增强
# 载入训练集
train_dataset = datasets.ImageFolder(train_path, train_transform)

# 载入测试集
test_dataset = datasets.ImageFolder(test_path, test_transform)

print('训练集图像数量', len(train_dataset))
print('类别个数', len(train_dataset.classes))
print('各类别名称', train_dataset.classes)
print('测试集图像数量', len(test_dataset))
print('类别个数', len(test_dataset.classes))
print('各类别名称', test_dataset.classes)
```

```
训练集图像数量 11669
类别个数 9
各类别名称 ['Alternaria leaf spot', 'Brown spot', 'Frogeye leaf spot', 'Grey spot', 'Health', 'Mosaic', 'Powdery mildew', 'Rust', 'Scab']
测试集图像数量 2913
类别个数 9
各类别名称 ['Alternaria leaf spot', 'Brown spot', 'Frogeye leaf spot', 'Grey spot', 'Health', 'Mosaic', 'Powdery mildew', 'Rust', 'Scab']
```

In [11]:
```
print('测试集图像数量', len(test_dataset))
print('类别个数', len(test_dataset.classes))
print('各类别名称', test_dataset.classes)
```

```
测试集图像数量 2913
类别个数 9
各类别名称 ['Alternaria leaf spot', 'Brown spot', 'Frogeye leaf spot', 'Grey spot', 'Health', 'Mosaic', 'Powdery mildew', 'Rust', 'Scab']
```

In [12]:
```
# 各类别名称
class_names = train_dataset.classes
n_class = len(class_names)
# 映射关系：类别 到 索引号
train_dataset.class_to_idx
# 映射关系：索引号 到 类别
idx_to_labels = {y:x for x,y in train_dataset.class_to_idx.items()}
# 保存为本地的 npy 文件
np.save('idx_to_labels.npy', idx_to_labels)
np.save('labels_to_idx.npy', train_dataset.class_to_idx)
class_names
```

Out[12]:
```
['Alternaria leaf spot',
 'Brown spot',
 'Frogeye leaf spot',
 'Grey spot',
 'Health',
 'Mosaic',
 'Powdery mildew',
 'Rust',
 'Scab']
```

In [13]:
```
# 映射关系：类别 到 索引号
train_dataset.class_to_idx
```

Out[13]:
```
{'Alternaria leaf spot': 0,
 'Brown spot': 1,
 'Frogeye leaf spot': 2,
 'Grey spot': 3,
 'Health': 4,
 'Mosaic': 5,
 'Powdery mildew': 6,
 'Rust': 7,
 'Scab': 8}
```

In [14]:
```
# 映射关系：索引号 到 类别
idx_to_labels = {y:x for x,y in train_dataset.class_to_idx.items()}
idx_to_labels
```

Out[14]:
```
{0: 'Alternaria leaf spot',
 1: 'Brown spot',
 2: 'Frogeye leaf spot',
 3: 'Grey spot',
 4: 'Health',
 5: 'Mosaic',
 6: 'Powdery mildew',
 7: 'Rust',
 8: 'Scab'}
```

定义数据加载器

In [15]:
```
from torch.utils.data import DataLoader

BATCH_SIZE = 32

# 训练集的数据加载器
train_loader = DataLoader(train_dataset,
                          batch_size=BATCH_SIZE,
                          shuffle=True,
                          num_workers=4
                         )

# 测试集的数据加载器
test_loader = DataLoader(test_dataset,
                         batch_size=BATCH_SIZE,
                         shuffle=False,
                         num_workers=4
                        )
```

查看一个batch中的img和label

In [16]:
```
# DataLoader 是 python生成器，每次调用返回一个 batch 的数据
images, labels = next(iter(train_loader))
```

In [17]:
```
images.shape
```

Out[17]:
```
torch.Size([32, 3, 224, 224])
```

In [18]:
```
labels
```

Out[18]:
```
tensor([8, 8, 8, 8, 2, 8, 2, 8, 8, 2, 7, 7, 8, 2, 7, 7, 7, 2, 8, 2, 6, 2, 7, 2,
        2, 7, 8, 2, 2, 6, 8, 7])
```

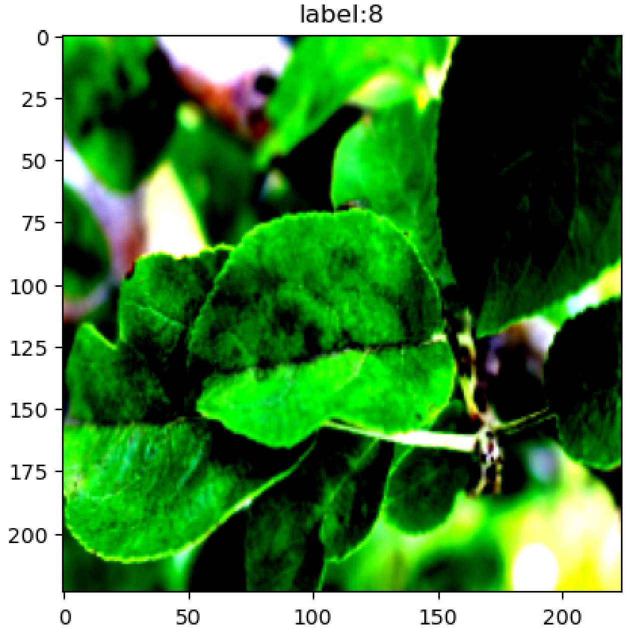
可视化一个batch的图像和标注

In [19]:
```
# 将数据集中的Tensor张量转为numpy的array数据类型
images = images.numpy()
```

In [20]:
```
# batch 中经过预处理的图像
idx = 2
plt.imshow(images[idx].transpose((1,2,0))) # 转为(224, 224, 3)
plt.title('label:'+str(labels[idx].item()))
```

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
```

Out[20]:
```
Text(0.5, 1.0, 'label:8')
```



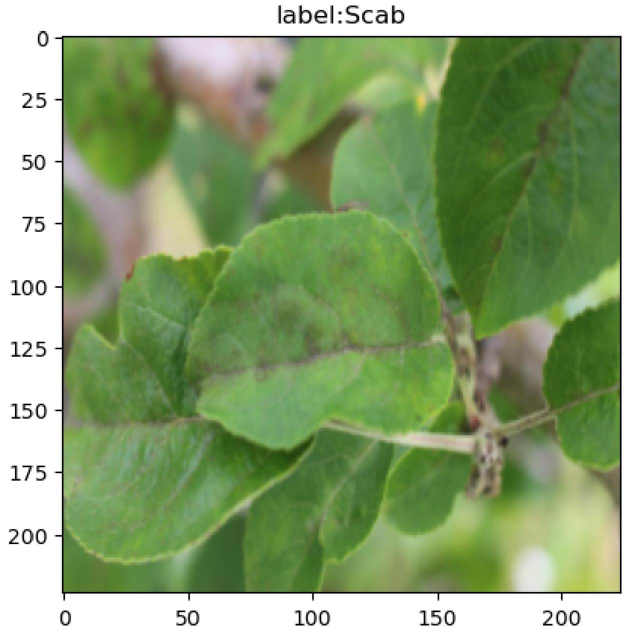
In [21]:
```
# 显示类别数字
label = labels[idx].item()
label
```

Out[21]:
```
8
```

In [22]:
```
# 显示类别数字对应的类别
pred_classname = idx_to_labels[label]
pred_classname
```

Out[22]:
```
'Scab'
```

In [23]:
```
# 原始图像
idx = 2
mean = np.array([0.485, 0.456, 0.406])
std = np.array([0.229, 0.224, 0.225])
plt.imshow(np.clip(images[idx].transpose((1,2,0)) * std + mean, 0, 1))
plt.title('label:'+ pred_classname)
plt.show()
```



导入train所需包

In [24]:
```
from torchvision import models
import torch.optim as optim
from torch.optim import lr_scheduler
```

CBAM

In [25]:
```
import torch
import torch.nn as nn
import copy
import torch.nn.functional as F
import math

## 以下是CBAM代码
import torch
import torch.nn as nn
import copy
import torch.nn.functional as F

class ChannelAttentionModule(nn.Module):
    def __init__(self, channel, ratio=16):
        super(ChannelAttentionModule, self).__init__()
        #使用自适应池化缩减map的大小，保持通道不变
        self.avg_pool = nn.AdaptiveAvgPool2d(1)
        self.max_pool = nn.AdaptiveMaxPool2d(1)

        self.shared_MLP = nn.Sequential(
            nn.Conv2d(channel, channel // ratio, 1, bias=False),
            nn.ReLU(),
            nn.Conv2d(channel // ratio, channel, 1, bias=False)
        )
        self.sigmoid = nn.Sigmoid()

    def forward(self, x):
        avgout = self.shared_MLP(self.avg_pool(x))
        maxout = self.shared_MLP(self.max_pool(x))
        return self.sigmoid(avgout + maxout)

class SpatialAttentionModule(nn.Module):
    def __init__(self):
        super(SpatialAttentionModule, self).__init__()
        self.conv2d = nn.Conv2d(in_channels=2, out_channels=1, kernel_size=7, stride=1, padding=3)
        self.sigmoid = nn.Sigmoid()

    def forward(self, x):
        #map尺寸不变，缩减通道
        avgout = torch.mean(x, dim=1, keepdim=True)
        maxout, _ = torch.max(x, dim=1, keepdim=True)
        out = torch.cat([avgout, maxout], dim=1)
        out = self.sigmoid(self.conv2d(out))
        return out

class CBAM(nn.Module):
    def __init__(self, channel):
        super(CBAM, self).__init__()
        self.channel_attention = ChannelAttentionModule(channel)
        self.spatial_attention = SpatialAttentionModule()

    def forward(self, x):
        out = self.channel_attention(x) * x
        out = self.spatial_attention(out) * out
        return out
```

```
class InceptionA(nn.Module):
    def __init__(self, in_channels):
        super(InceptionA,self).__init__()
        # 第二个分支
        self.branch1_1 = nn.Conv2d(in_channels, 16, kernel_size=1)
        # 第三个分支
        self.branch5_5_1 = nn.Conv2d(in_channels, 16, kernel_size=1)
        self.branch5_5_2 = nn.Conv2d(16, 24, kernel_size=5, padding=2)
        # 第四个分支
        self.branch3_3_1 = nn.Conv2d(in_channels, 16, kernel_size=1)
        self.branch3_3_2 = nn.Conv2d(16, 24, kernel_size=3, padding=1)
        self.branch3_3_3 = nn.Conv2d(24, 24, kernel_size=3, padding=1)
        # 第一个分支
        self.branch_pool = nn.Conv2d(in_channels, 24, kernel_size=1)
    def forward(self, x):

        branch1_1 = self.branch1_1(x)

        branch5_5 = self.branch5_5_1(x)
        branch5_5 = self.branch5_5_2(branch5_5)

        branch3_3 = self.branch3_3_1(x)
        branch3_3 = self.branch3_3_2(branch3_3)
        branch3_3 = self.branch3_3_3(branch3_3)

        branch_pool = F.avg_pool2d(x, kernel_size=3, stride=1, padding=1)
        branch_pool = self.branch_pool(branch_pool)

        outputs = [branch1_1, branch5_5, branch3_3, branch_pool]
        return torch.cat(outputs, dim=1) # (b, c, w, h),则dim=1, 即按照通道进行拼接。
```

In [26]:

```
cbam_custom_64 = CBAM(256)
```

迁移学习模型设置

In [27]:

```
model = models.resnet50(pretrained=True) # 载入预训练模型
# 加入CBAM
# model.layer1 = nn.Sequential(model.layer1[0],cbam_custom_64,model.layer1[1],cbam_custom_64)
model.fc = nn.Linear(model.fc.in_features, n_class)

optimizer = optim.Adam(model.parameters())
```

In [28]:
```
model
```

Out[28]:
```
ResNet(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
  (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (relu): ReLU(inplace=True)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
  (layer1): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(64, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (downsample): Sequential(
        (0): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
```

训练参数配置

In [29]:
```
model = model.to(device)

# 交叉熵损失函数
criterion = nn.CrossEntropyLoss()

# 训练轮次 Epoch
EPOCHS = 30

# 学习率降低策略
lr_scheduler = lr_scheduler.StepLR(optimizer, step_size=5, gamma=0.5)
```

训练集上训练

In [30]:
```
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import f1_score
from sklearn.metrics import roc_auc_score
def train_one_batch(images, labels):
    '''
    运行一个 batch 的训练，返回当前 batch 的训练日志
    '''

    # 获得一个 batch 的数据和标注
    images = images.to(device)
    labels = labels.to(device)

    outputs = model(images) # 输入模型，执行前向预测
    loss = criterion(outputs, labels) # 计算当前 batch 中，每个样本的平均交叉熵损失函数值

    # 优化更新权重
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

    # 获取当前 batch 的标签类别和预测类别
    _, preds = torch.max(outputs, 1) # 获得当前 batch 所有图像的预测类别
    preds = preds.cpu().numpy()
    loss = loss.detach().cpu().numpy()
    outputs = outputs.detach().cpu().numpy()
    labels = labels.detach().cpu().numpy()

    log_train = {}
    log_train['epoch'] = epoch
    log_train['batch'] = batch_idx
    # 计算分类评估指标
    log_train['train_loss'] = loss
    log_train['train_accuracy'] = accuracy_score(labels, preds)
    log_train['train_precision'] = precision_score(labels, preds, average='macro')
    log_train['train_recall'] = recall_score(labels, preds, average='macro')
    log_train['train_f1-score'] = f1_score(labels, preds, average='macro')

    return log_train
```

测试集上测试

In [31]:
```
def evaluate_testset():
    '''
    在整个测试集上评估，返回分类评估指标日志
    '''

    loss_list = []
    labels_list = []
    preds_list = []

    with torch.no_grad():
        for images, labels in test_loader: # 生成一个 batch 的数据和标注
            images = images.to(device)
            labels = labels.to(device)
            outputs = model(images) # 输入模型，执行前向预测

            # 获取整个测试集的标签类别和预测类别
            _, preds = torch.max(outputs, 1) # 获得当前 batch 所有图像的预测类别
            preds = preds.cpu().numpy()
            loss = criterion(outputs, labels) # 由 logit，计算当前 batch 中，每个样本的平均交叉熵损失函数值
            loss = loss.detach().cpu().numpy()
            outputs = outputs.detach().cpu().numpy()
            labels = labels.detach().cpu().numpy()

            loss_list.append(loss)
            labels_list.extend(labels)
            preds_list.extend(preds)

    log_test = {}
    log_test['epoch'] = epoch

    # 计算分类评估指标
    log_test['test_loss'] = np.mean(loss_list)
    log_test['test_accuracy'] = accuracy_score(labels_list, preds_list)
    log_test['test_precision'] = precision_score(labels_list, preds_list, average='macro')
    log_test['test_recall'] = recall_score(labels_list, preds_list, average='macro')
    log_test['test_f1-score'] = f1_score(labels_list, preds_list, average='macro')

    return log_test
```

训练集之前，记录训练日志

In [32]:
```
import pandas as pd
epoch = 0
batch_idx = 0
best_test_accuracy = 0
```

In [33]:
```
# 训练日志-训练集
df_train_log = pd.DataFrame()
log_train = {}
log_train['epoch'] = 0
log_train['batch'] = 0
images, labels = next(iter(train_loader))
log_train.update(train_one_batch(images, labels))
df_train_log = df_train_log.append(log_train, ignore_index=True)
```

In [34]:
```
df_train_log
```

Out[34]:

	epoch	batch	train_loss	train_accuracy	train_precision	train_recall	train_f1-score
0	0.0	0.0	2.1326554	0.21875	0.215278	0.163462	0.151786

In [35]:
```
# 训练日志-测试集
df_test_log = pd.DataFrame()
log_test = {}
log_test['epoch'] = 0
log_test.update(evaluate_testset())
df_test_log = df_test_log.append(log_test, ignore_index=True)
```

In [36]:
```
df_test_log
```

Out[36]:

	epoch	test_loss	test_accuracy	test_precision	test_recall	test_f1-score
0	0.0	1.972587	0.319945	0.247351	0.119376	0.092848

安装wandb

In [37]:
```
import wandb

wandb.init(project='appleleaf', name=time.strftime('%m%d%H%M%S'))
```

```
wandb: Currently logged in as: pet. Use `wandb login --relogin` to force relogin
```

Tracking run with wandb version 0.14.0

Run data is saved locally in `/home/maoml/part_time_workspace/wandb/run-20230401_160838-obr7ag21`

Syncing run **0401160837 (https://wandb.ai/pet/appleleaf/runs/obr7ag21)** to Weights & Biases (https://wandb.ai/pet/appleleaf) (docs (https://wandb.me/run))

View project at https://wandb.ai/pet/appleleaf (https://wandb.ai/pet/appleleaf)

View run at https://wandb.ai/pet/appleleaf/runs/obr7ag21 (https://wandb.ai/pet/appleleaf/runs/obr7ag21)

Out[37]:

Display W&B run

开始训练

In [38]:
```
for epoch in range(1, EPOCHS+1):

    print(f'Epoch {epoch}/{EPOCHS}')

    ## 训练阶段
    model.train()
    for images, labels in tqdm(train_loader): # 获得一个 batch 的数据和标注
        batch_idx += 1
        log_train = train_one_batch(images, labels)
        df_train_log = df_train_log.append(log_train, ignore_index=True)
        wandb.log(log_train)

    lr_scheduler.step()

    ## 测试阶段
    model.eval()
    log_test = evaluate_testset()
    df_test_log = df_test_log.append(log_test, ignore_index=True)
    wandb.log(log_test)

    # 保存最新的最佳模型文件
    if log_test['test_accuracy'] > best_test_accuracy:
        # 删除旧的最佳模型文件(如有)
        old_best_checkpoint_path = 'checkpoint/best-{:.3f}.pth'.format(best_test_accuracy)
        if os.path.exists(old_best_checkpoint_path):
            os.remove(old_best_checkpoint_path)
        # 保存新的最佳模型文件
        best_test_accuracy = log_test['test_accuracy']
        new_best_checkpoint_path = 'checkpoint/best-{:.3f}.pth'.format(log_test['test_accuracy'])
        torch.save(model, new_best_checkpoint_path)
        print('保存新的最佳模型', 'checkpoint/best-{:.3f}.pth'.format(best_test_accuracy))
        # best_test_accuracy = log_test['test_accuracy']

df_train_log.to_csv('训练日志-训练集.csv', index=False)
df_test_log.to_csv('训练日志-测试集.csv', index=False)
```

可视化训练日志

In [39]:
```
import pandas as pd

import matplotlib.pyplot as plt
%matplotlib inline
```

In [40]:
```
df_train = pd.read_csv('训练日志-训练集.csv')
df_test = pd.read_csv('训练日志-测试集.csv')
# #显示所有列
# pd.set_option('display.max_columns', None)
# #显示所有行
# pd.set_option('display.max_rows', None)
```

In [41]:
```
df_train
```

12	1.0	12.0	0.973099	0.656250	0.484014	0.606723	0.517898
13	1.0	13.0	1.313479	0.718750	0.685714	0.692708	0.652941
14	1.0	14.0	1.541294	0.500000	0.479798	0.497980	0.487279
15	1.0	15.0	0.691233	0.906250	0.891429	0.908333	0.898594
16	1.0	16.0	1.070463	0.625000	0.501961	0.488095	0.474064
17	1.0	17.0	1.283350	0.781250	0.576389	0.481481	0.506360
18	1.0	18.0	1.521462	0.562500	0.288889	0.304762	0.254938
19	1.0	19.0	0.873498	0.750000	0.533835	0.553571	0.540260
20	1.0	20.0	1.084308	0.625000	0.602641	0.536054	0.505200
21	1.0	21.0	0.863479	0.687500	0.434524	0.373016	0.374790
22	1.0	22.0	0.833528	0.593750	0.323810	0.295899	0.300067
23	1.0	23.0	0.778987	0.750000	0.323810	0.378571	0.344862
24	1.0	24.0	0.712643	0.781250	0.562500	0.552885	0.555320

In [42]:
```
df_test
```

Out[42]:

	epoch	test_loss	test_accuracy	test_precision	test_recall	test_f1-score
0	0.0	1.972587	0.319945	0.247351	0.119376	0.092848
1	1.0	0.465645	0.866117	0.853260	0.742245	0.772116
2	2.0	0.903600	0.726742	0.665690	0.772639	0.666799
3	3.0	0.434608	0.875043	0.836349	0.802603	0.806428
4	4.0	0.359228	0.894954	0.894779	0.838556	0.861790
5	5.0	0.261806	0.923447	0.877824	0.889384	0.876630
6	6.0	0.211836	0.943357	0.899597	0.914561	0.905404
7	7.0	0.182188	0.944387	0.918480	0.907048	0.909150
8	8.0	0.226739	0.933059	0.911741	0.903594	0.906946
9	9.0	0.207536	0.942671	0.908346	0.916257	0.909757
10	10.0	0.327165	0.923447	0.897461	0.869798	0.868000
11	11.0	0.185064	0.947477	0.938396	0.919084	0.927514
12	12.0	0.175527	0.957089	0.937634	0.933653	0.934806
13	13.0	0.187947	0.949537	0.927936	0.921627	0.924139
14	14.0	0.213478	0.953999	0.951255	0.922676	0.935402
15	15.0	0.173039	0.955029	0.932393	0.933664	0.932682
16	16.0	0.177972	0.957432	0.945861	0.933626	0.939302
17	17.0	0.169399	0.958462	0.930118	0.939559	0.934531
18	18.0	0.186875	0.958805	0.945256	0.938133	0.940361
19	19.0	0.198934	0.955372	0.934337	0.931292	0.932313
20	20.0	0.217568	0.949193	0.920667	0.933930	0.924089
21	21.0	0.198637	0.952626	0.922894	0.930168	0.925961
22	22.0	0.197136	0.957775	0.940173	0.939878	0.938160
23	23.0	0.206779	0.954343	0.940310	0.933087	0.935412
24	24.0	0.222307	0.949193	0.924985	0.931389	0.926726
25	25.0	0.195958	0.956402	0.929177	0.936421	0.932375
26	26.0	0.212796	0.953313	0.926970	0.933263	0.928276
27	27.0	0.216051	0.955716	0.935411	0.934809	0.934024
28	28.0	0.193601	0.956746	0.932502	0.939257	0.934789
29	29.0	0.216866	0.953999	0.931297	0.936233	0.932025
30	30.0	0.206769	0.952626	0.922032	0.931593	0.926048

训练集的准确率和损失函数

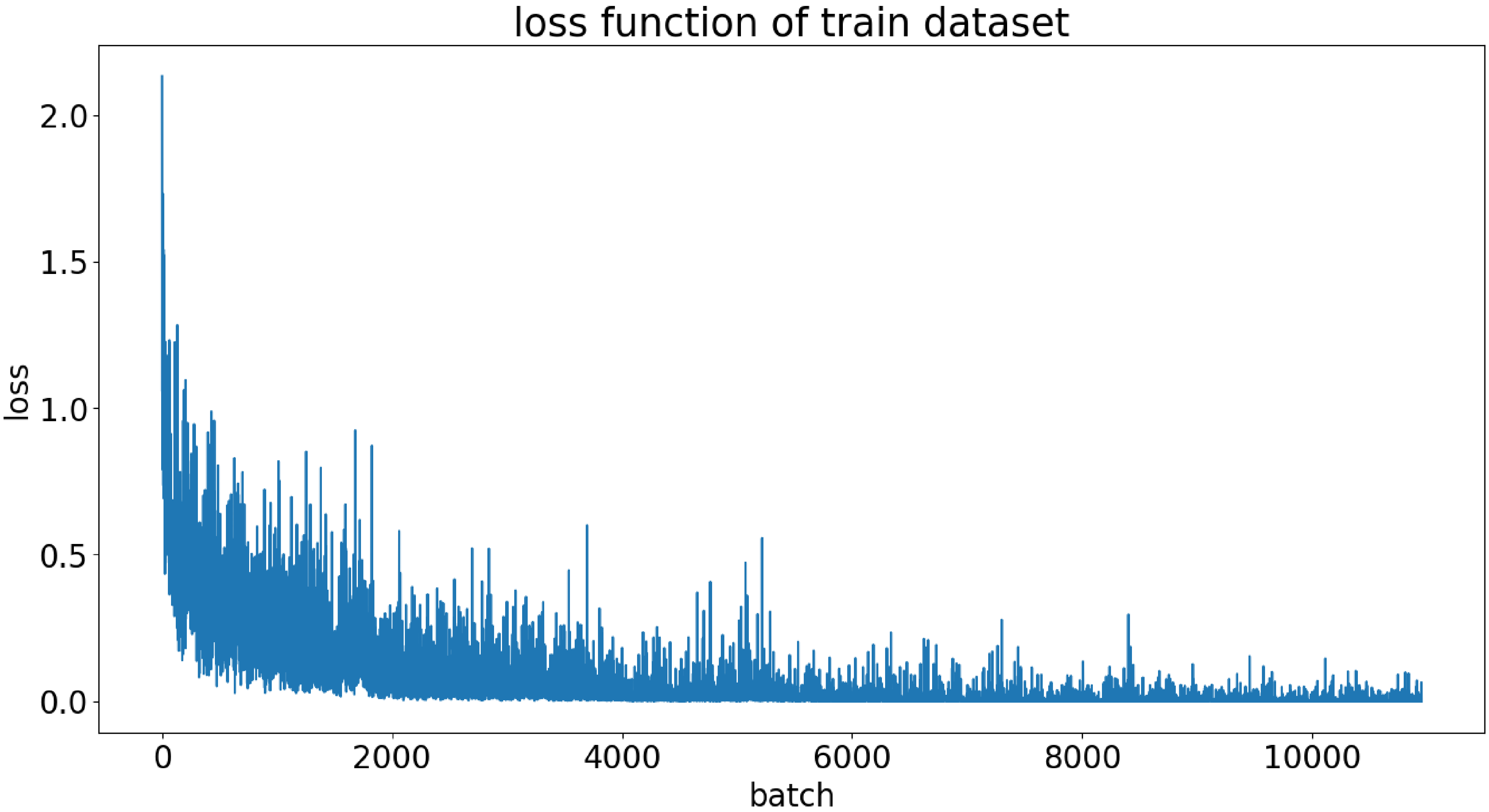
In [56]:
```
plt.figure(figsize=(16, 8))

x = df_train['batch']
y = df_train['train_loss']

plt.plot(x, y, label='train dataset')

plt.tick_params(labelsize=20)
plt.xlabel('batch', fontsize=20)
plt.ylabel('loss', fontsize=20)
plt.title('loss function of train dataset', fontsize=25)
plt.savefig('图表1/训练集损失函数.pdf', dpi=120, bbox_inches='tight')

plt.show()
```


loss function of train dataset
loss
2.0
1.5
1.0
0.5
0.0
0
2000
4000
6000
8000
10000
batch

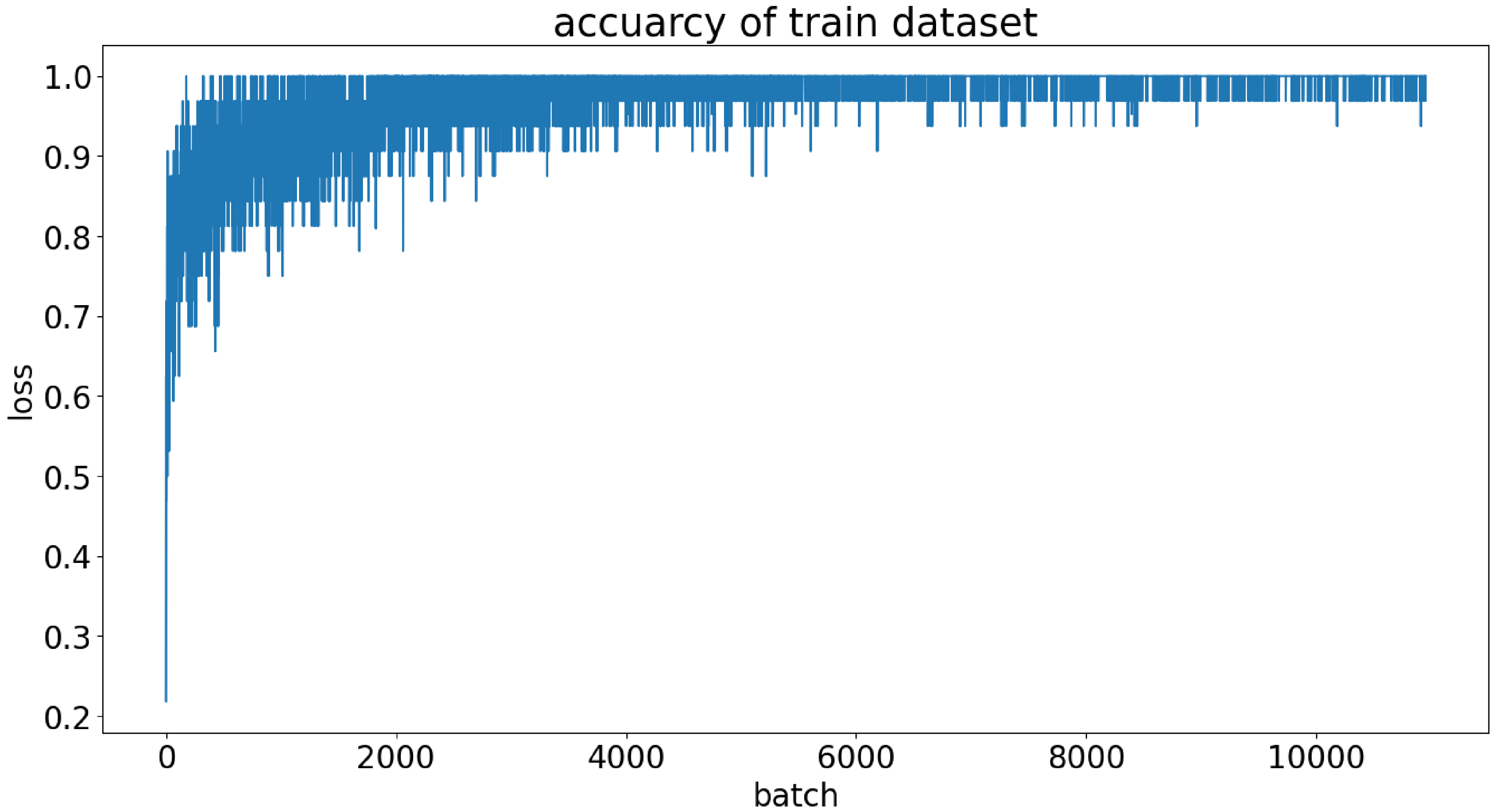
In [55]:
```
plt.figure(figsize=(16, 8))

x = df_train['batch']
y = df_train['train_accuracy']

plt.plot(x, y, label='训练集')

plt.tick_params(labelsize=20)
plt.xlabel('batch', fontsize=20)
plt.ylabel('loss', fontsize=20)
plt.title('accuarcy of train dataset', fontsize=25)
plt.savefig('图表1/训练集准确率.pdf', dpi=120, bbox_inches='tight')

plt.show()
```


accuarcy of train dataset
loss
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0
2000
4000
6000
8000
10000
batch

验证集损失函数

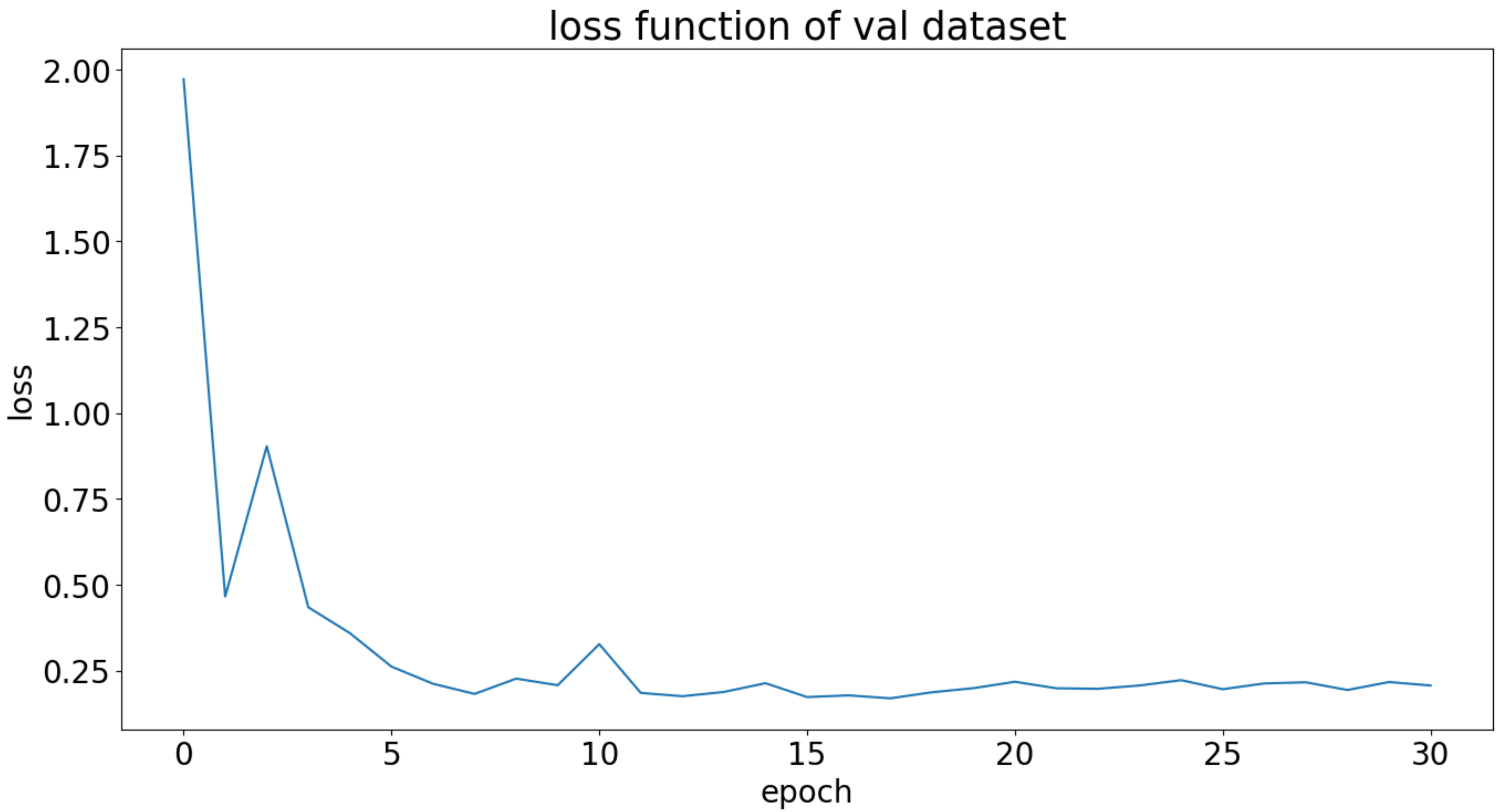
In [54]:
```
plt.figure(figsize=(16, 8))

x = df_test['epoch']
y = df_test['test_loss']

plt.plot(x, y, label='测试集')

plt.tick_params(labelsize=20)
plt.xlabel('epoch', fontsize=20)
plt.ylabel('loss', fontsize=20)
plt.title('loss function of val dataset', fontsize=25)
plt.savefig('图表1/测试集损失函数.pdf', dpi=120, bbox_inches='tight')

plt.show()
```


loss function of val dataset
loss
epoch
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0
5
10
15
20
25
30

验证集集评估指标

In [51]:

```
from matplotlib import colors as mcolors
import random
random.seed(124)
colors = ['b', 'g', 'r', 'c', 'm', 'y', 'k', 'tab:blue', 'tab:orange', 'tab:green', 'tab:red', 'tab:purple', 'tab:brown', 'tab:pink', 'tab:gray', 'tab:olive', 'tab:cyan', 'black', 'ir
markers = [".",",","o","v","^","<",">","1","2","3","4","8","s","p","P","*","h","H","+","x","X","D","d","|","_",0,1,2,3,4,5,6,7,8,9,10,11]
linestyle = ['--', '-.', '-']
def get_line_arg():
    '''
    随机产生一种绘图线型
    '''
    line_arg = {}
    line_arg['color'] = random.choice(colors)
    # line_arg['marker'] = random.choice(markers)
    line_arg['linestyle'] = random.choice(linestyle)
    line_arg['linewidth'] = random.randint(1, 4)
    # line_arg['markersize'] = random.randint(3, 5)
    return line_arg
```

In [47]:

```
metrics = ['test_accuracy', 'test_precision', 'test_recall', 'test_f1-score']
```

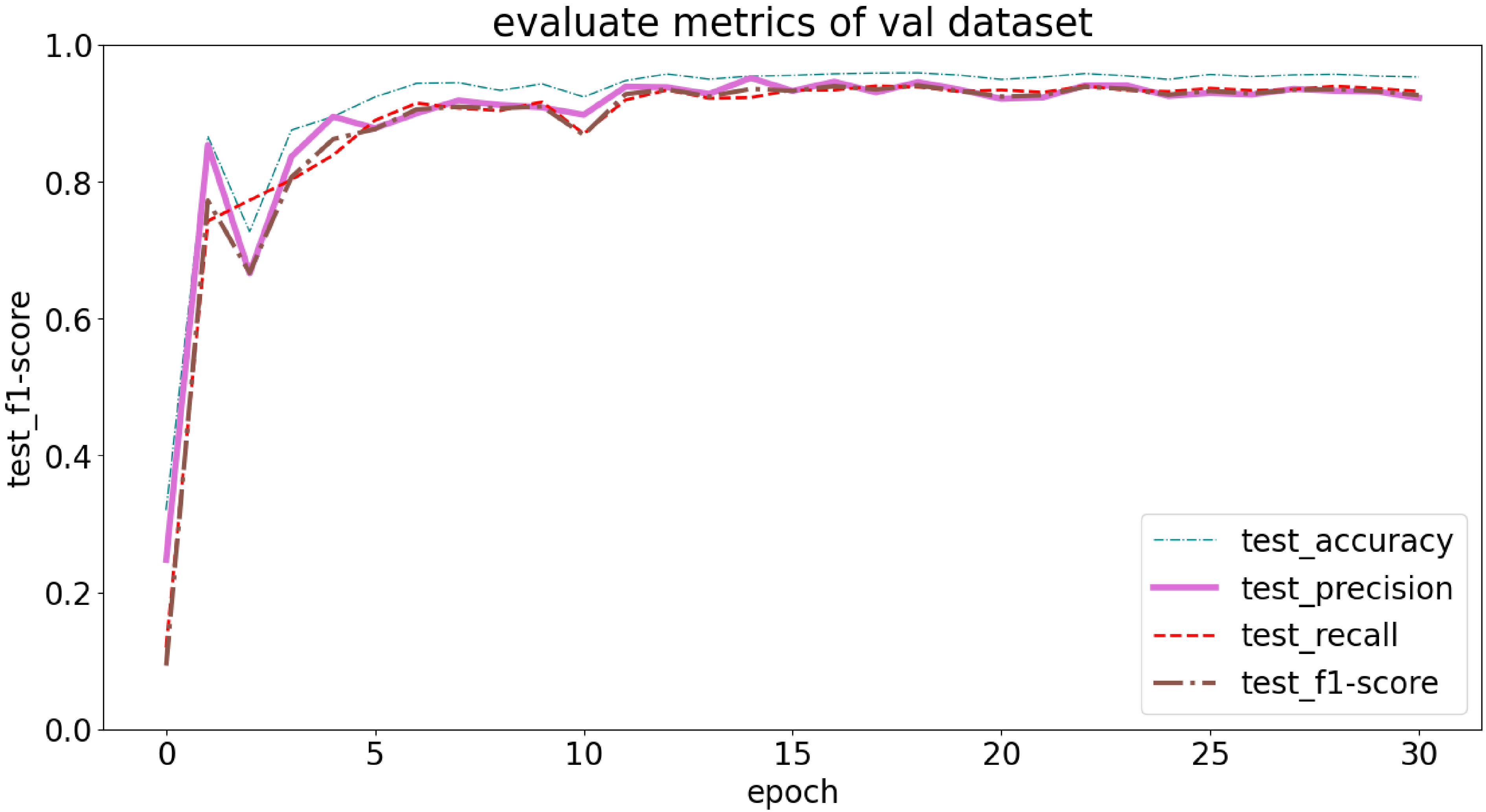
In [53]:
```
plt.figure(figsize=(16, 8))

x = df_test['epoch']
for y in metrics:
    plt.plot(x, df_test[y], label=y, **get_line_arg())

plt.tick_params(labelsize=20)
plt.ylim([0, 1])
plt.xlabel('epoch', fontsize=20)
plt.ylabel(y, fontsize=20)
plt.title('evaluate metrics of val dataset', fontsize=25)
plt.savefig('图表1/测试集分类评估指标.pdf', dpi=120, bbox_inches='tight')

plt.legend(fontsize=20)

plt.show()
```


evaluate metrics of val dataset
1.0
0.8
0.6
0.4
0.2
0.0
test_f1-score
0
5
10
15
20
25
30
epoch
test_accuracy
test_precision
test_recall
test_f1-score