CNN 实验报告

朱浩泽 1911530

June 17, 2022

1 老师提供的基础 CNN 网络

1.1 网络结构

我们通过 Pycharm 软件的 python 控制台查看运行时的变量，可以看到网络结构如下:

```
Net(
  (conv1): Conv2d(3, 6, kernel_size=(5, 5), stride=(1, 1))
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (conv2): Conv2d(6, 16, kernel_size=(5, 5), stride=(1, 1))
  (fc1): Linear(in_features=400, out_features=120, bias=True)
  (fc2): Linear(in_features=120, out_features=84, bias=True)
  (fc3): Linear(in_features=84, out_features=10, bias=True)
)
```

1.2 训练结果

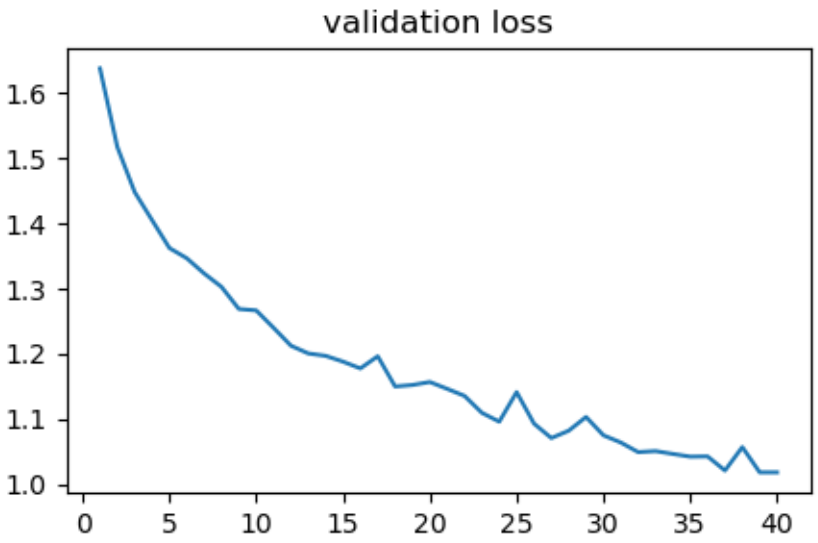


Figure 1: 基础网络在测试集上的损失

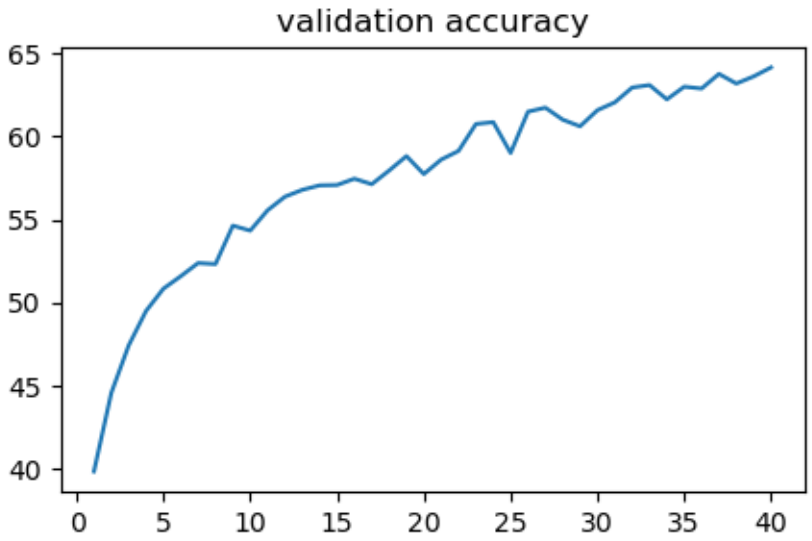


Figure 2: 基础网络在测试集上的准确率

可以看到，在经历 40 轮次的训练后，基础网络对 cifar10 数据集分类的准确率为 64.14%。

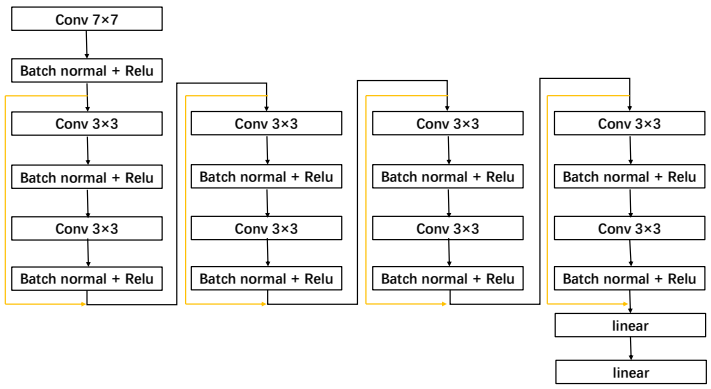
2 个人实现的 ResNet 网络

2.1 网络结构

```
ResNet(
  (conv): Conv2d(3, 32, kernel_size=(7, 7), stride=(1, 1), padding=(3, 3))
  (bn): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (relu1): ReLU()
  (basic1): BasicBlock(
    (conv1): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (bn1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu1): ReLU()
    (conv2): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (relu2): ReLU()
    (bn2): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
  (basic2): BasicBlock(
    (conv1): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu1): ReLU()
    (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
    (relu2): ReLU()
    (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (sample): DownSample(
      (conv): Conv2d(32, 64, kernel_size=(1, 1), stride=(2, 2))
      (batch_normal): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
```

```
    )
  )
  (basic3): BasicBlock(
    (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu1): ReLU()
    (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (relu2): ReLU()
    (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
  (basic4): BasicBlock(
    (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu1): ReLU()
    (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
    (relu2): ReLU()
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (sample): DownSample(
      (conv): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2))
      (batch_normal): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (basic5): BasicBlock(
    (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu1): ReLU()
    (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (relu2): ReLU()
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
  (fc1): Linear(in_features=8192, out_features=1024, bias=True)
  (fc2): Linear(in_features=1024, out_features=100, bias=True)
  (relu2): ReLU()
)
```

具体结构可以画草图如下



2.2 实验结果

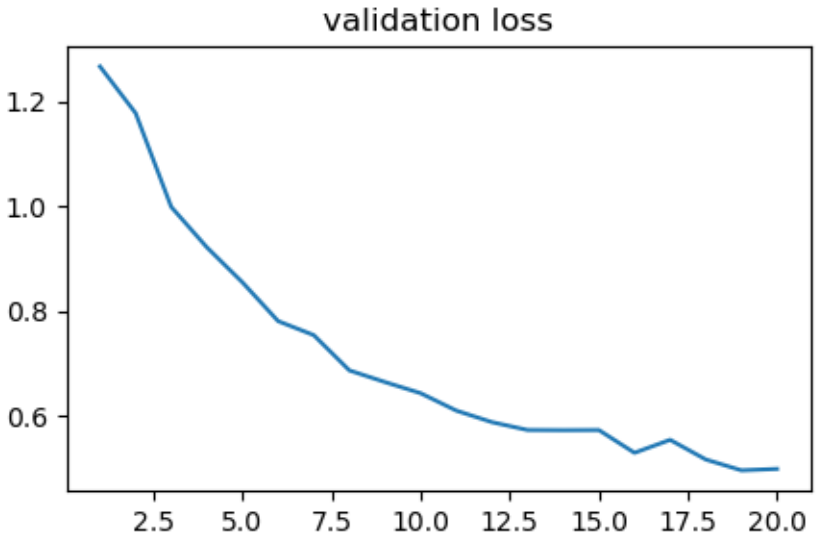


Figure 3: 个人实现的 **ResNet** 网路在测试集上的损失

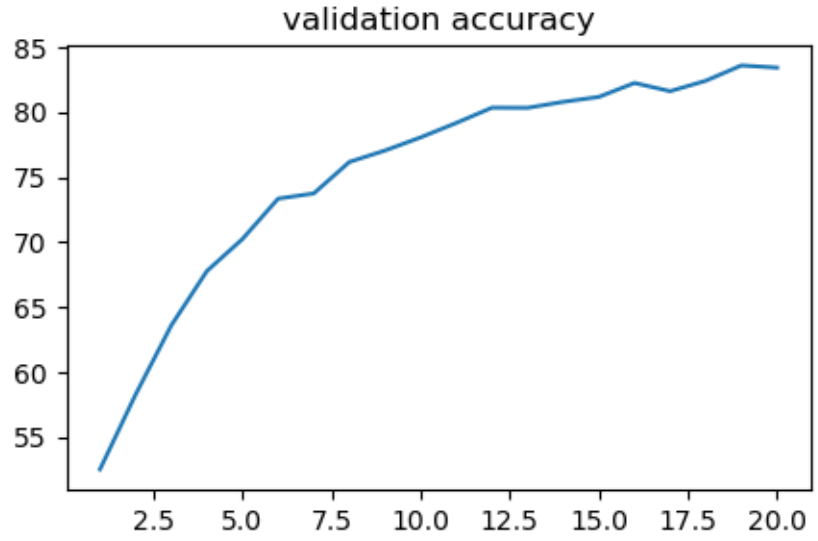


Figure 4: 个人实现的 **ResNet** 网路在测试集上的准确率

可以看到，在经历 40 轮次的训练后，个人实现的 ResNet 对 cifar10 数据集分类的准确率为 83.43%。

3 个人实现的 DenseNet 网络

3.1 网络结构

我们根据 Densely connected convolutional networks 原文中描述的网络结构进行简单设计，因为计算力有限，所以只采用了两个 DenseBlock 和一个 TransitionBlock。

利用 pycharm 打印网络结构如下：

```
DenseNet(
  (conv): Conv2d(3, 32, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3))
  (bn1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (max_pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (relu): ReLU()
  (denseblock1): DenseBlock(
    (denseblock): Sequential(
      (0): DenseBasic(
        (layer): Sequential(
          (0): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
          (1): ReLU()
          (2): Conv2d(32, 128, kernel_size=(1, 1), stride=(1, 1))
          (3): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
          (4): ReLU()
          (5): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
        )
      )
      (1): DenseBasic(
        (layer): Sequential(
          (0): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
          (1): ReLU()
          (2): Conv2d(64, 128, kernel_size=(1, 1), stride=(1, 1))
          (3): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
          (4): ReLU()
          (5): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
        )
      )
      (2): DenseBasic(
        (layer): Sequential(
          (0): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
          (1): ReLU()
          (2): Conv2d(96, 128, kernel_size=(1, 1), stride=(1, 1))
          (3): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
          (4): ReLU()
          (5): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
        )
      )
      (3): DenseBasic(
        (layer): Sequential(
```

```
        (0): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (1): ReLU()
        (2): Conv2d(128, 128, kernel_size=(1, 1), stride=(1, 1))
        (3): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (4): ReLU()
        (5): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      )
    )
    (4): DenseBasic(
      (layer): Sequential(
        (0): BatchNorm2d(160, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (1): ReLU()
        (2): Conv2d(160, 128, kernel_size=(1, 1), stride=(1, 1))
        (3): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (4): ReLU()
        (5): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      )
    )
    (5): DenseBasic(
      (layer): Sequential(
        (0): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (1): ReLU()
        (2): Conv2d(192, 128, kernel_size=(1, 1), stride=(1, 1))
        (3): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (4): ReLU()
        (5): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      )
    )
  )
)
(bn2): BatchNorm2d(224, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
(conv1): Conv2d(224, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(avg1): AvgPool2d(kernel_size=2, stride=2, padding=0)
(denseblock2): DenseBlock(
  (denseblock): Sequential(
    (0): DenseBasic(
      (layer): Sequential(
        (0): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (1): ReLU()
        (2): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1))
        (3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (4): ReLU()
        (5): Conv2d(256, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      )
    )
    (1): DenseBasic(
      (layer): Sequential(
        (0): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
```

```
        (1): ReLU()
        (2): Conv2d(128, 256, kernel_size=(1, 1), stride=(1, 1))
        (3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (4): ReLU()
        (5): Conv2d(256, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      )
    )
    (2): DenseBasic(
      (layer): Sequential(
        (0): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (1): ReLU()
        (2): Conv2d(192, 256, kernel_size=(1, 1), stride=(1, 1))
        (3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (4): ReLU()
        (5): Conv2d(256, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      )
    )
    (3): DenseBasic(
      (layer): Sequential(
        (0): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (1): ReLU()
        (2): Conv2d(256, 256, kernel_size=(1, 1), stride=(1, 1))
        (3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (4): ReLU()
        (5): Conv2d(256, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      )
    )
    (4): DenseBasic(
      (layer): Sequential(
        (0): BatchNorm2d(320, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (1): ReLU()
        (2): Conv2d(320, 256, kernel_size=(1, 1), stride=(1, 1))
        (3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (4): ReLU()
        (5): Conv2d(256, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      )
    )
    (5): DenseBasic(
      (layer): Sequential(
        (0): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (1): ReLU()
        (2): Conv2d(384, 256, kernel_size=(1, 1), stride=(1, 1))
        (3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (4): ReLU()
        (5): Conv2d(256, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      )
    )
  )
```

```
  )
  (fc1): Linear(in_features=7168, out_features=10, bias=True)
)
```

3.2 实验结果

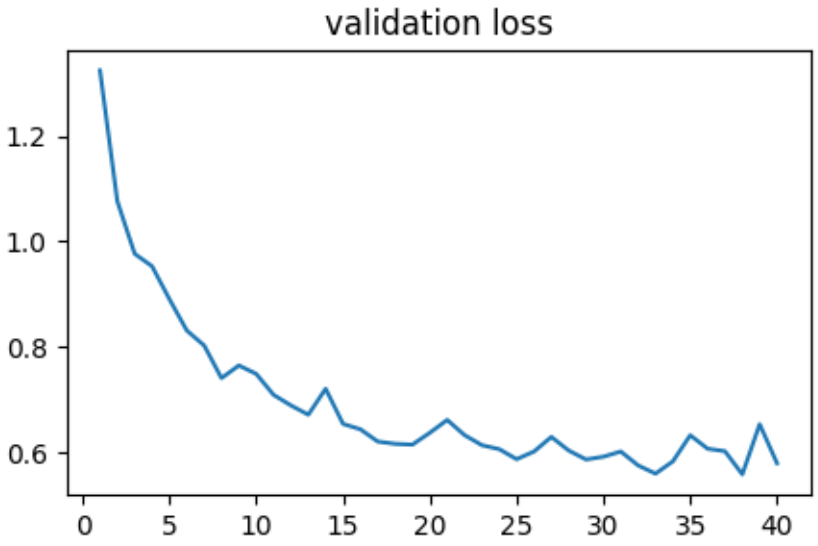


Figure 5: 个人实现的 **DenseNet** 在测试集上的损失

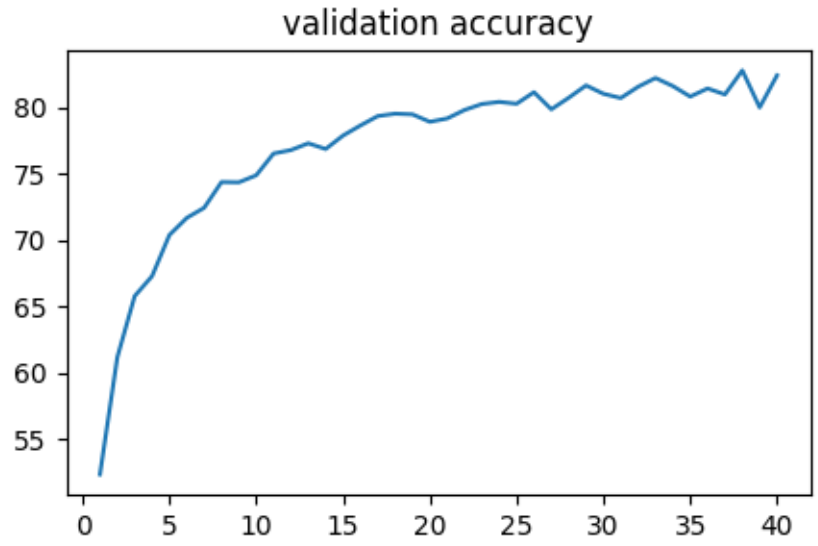


Figure 6: 个人实现的 **DenseNet** 在测试集上的准确率

可以看到，在经历 40 轮次的训练后，个人实现的 DenseNet 对 cifar10 数据集分类的准确率为 82.82%。

4 解释没有跳跃连接的卷积网络、ResNet、DenseNet 在训练过程中有什么不同

残差网络　正如在 [1] 一文中指出的那样，残差网络是指在每两个卷积层之间，即几个特征抽取模块之间，加入了短路链接，这就是残差的由来，又称为恒等映射。这种操作可以将梯度之间传导给下一个模块块，避免了梯度消失的问题。于此同时，在训练的过程中某些卷积层可能已经达到了最优解，此时没有再进行训练的必要。通过这种操作，我们可以在接下来的训练中，直接跳过这两个卷积层，不会破坏之前训练出来的最优解。

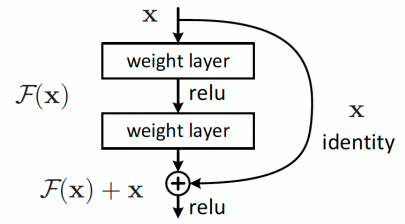


Figure 7: 基于 **ResNet** 的基础结构 **[1]**

$$y = \mathcal{F}(x) + x$$

其中，y 代表的是通过残差网络后输出的特征值，x 代表的是输入的特征值，$\mathcal{F}$ 代表的是卷积操作。其中，有一些卷积改变了图像的形状，这时候我们需要对输入的残差连接进行下采样，具体就是用一个 1×1 的卷积，设置步长为 2 来改变残差的形状，使其可以顺利的与卷积层的输出进行相加。

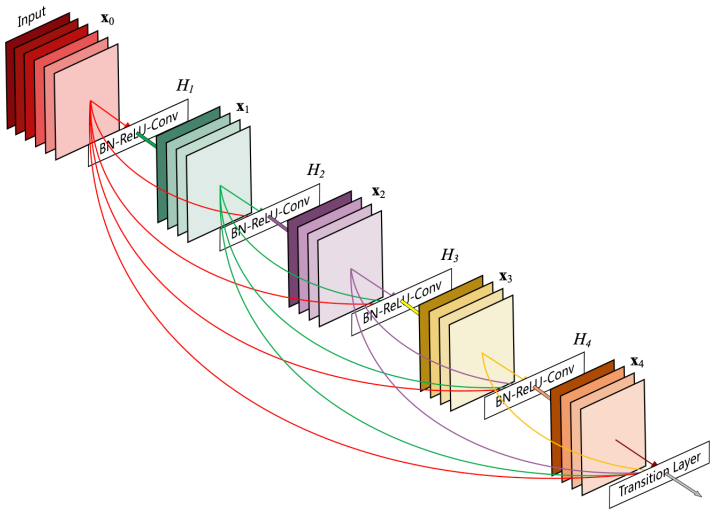


Figure 8: 基于 **DesnsNet** 的基础结构 **[2]**

DenseNet 如 [2] 一文中所说，当前馈卷积神经网络的深度过深的时候，信息通过许多层后，可能会被消失或“洗掉”。在借鉴的思想之后，Denset 也提出了一种残差结构，这种结构的每个层都从前面的层获得额外的输入，并将自己的特征图传递给所有后续层。这种与 ResNet 最大的不同是，ResNet 是将残差和输出进行相加，而 Desnet 则是将输出和残差进行拼接。

由于不需要重新学习冗余的特征，这种操作比传统的卷积需要更少的参数。传统的卷积网络的堆叠可以看作是具有具有状态的算法，并在层与层之间传递，但与此同时也会将保留信息进行传递。ResNet 可以通过残差使保留信息变得更加明确，并在训练中找出贡献非常小的层进行放弃，但参数量大大的增加。DenseNet 的框架则明确区分了在训练过程中可以将每一层的保留信息和传递的信息进行区分，在与 ResNet 具有共同的优先时，DenseNet 可以减少大量的参数量，且训练过程更加容易，过拟合的风险更小。

参考文献

[1] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770−778, 2016

[2] G.Huang,Z.Liu,L.VanDerMaaten,andK.Q.Weinberger. Densely connected convolutional networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 4700−4708, 2017.