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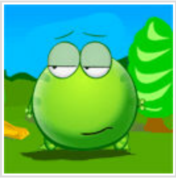

fengbingchun

卷积神经网络(CNN)代码实现(MNIST)解析

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分类： Caffe（19） Deep Learning（8） Neural Network（12）

在http://blog.csdn.net/fengbingchun/article/details/50814710中给出了CNN的简单实现，这里对每一步的实现作个说明：

共7层：依次为输入层、C1层、S2层、C3层、S4层、C5层、输出层，C代表卷积层(特征提取)，S代表降采样层或池化层(Pooling)，输出层为全连接层。

1. 各层权值、偏置(阈值)初始化：

各层权值、偏置个数计算如下：

(1)、输入层：预处理后的32*32图像数据，无权值和偏置；

(2)、C1层：卷积窗大小5*5，输出特征图数量6，卷积窗种类1*6=6，输出特征图大小28*28，因此可训练参数(权值+偏置)：(5*5*1)*6+6=150+6；

(3)、S2层：卷积窗大小2*2，输出下采样图数量6，卷积窗种类6，输出下采样图大小14*14，因此可训练参数(权值+偏置)：1*6+6=6+6；

(4)、C3层：卷积窗大小5*5，输出特征图数量16，卷积窗种类6*16=96，输出特征图大小10*10，因此可训练参数(权值+偏置)：(5*5*6)*16+16=2400+16；

(5)、S4层：卷积窗大小2*2，输出下采样图数量16，卷积窗种类16，输出下采样图大小5*5，因此可训练参数(权值+偏置)：1*16+16=16+16；

(6)、C5层：卷积窗大小5*5，输出特征图数量120，卷积窗种类16*120=1920，输出特征图大小1*1，因此可训练参数(权值+偏置)：(5*5*16)*120+120=48000+120；

(7)、输出层：卷积窗大小1*1，输出特征图数量10，卷积窗种类120*10=1200，输出特征图大小1*1，因此可训练参数(权值+偏置)：(1*120)*10+10=1200+10.

代码段如下：

[cpp]

```cpp
#define num_map_input_CNN       1 //输入层map个数
#define num_map_C1_CNN          6 //C1层map个数
#define num_map_S2_CNN          6 //S2层map个数
#define num_map_C3_CNN          16 //C3层map个数
#define num_map_S4_CNN          16 //S4层map个数
#define num_map_C5_CNN          120 //C5层map个数
#define num_map_output_CNN      10 //输出层map个数

#define len_weight_C1_CNN       150 //C1层权值数，(5*5*1)*6=150
#define len_bias_C1_CNN         6 //C1层阈值数，6
```

```
#define len_weight_S2_CNN       6 //S2层权值数,1*6=6
#define len_bias_S2_CNN         6 //S2层阈值数,6
#define len_weight_C3_CNN       2400 //C3层权值数，(5*5*6)*16=2400
#define len_bias_C3_CNN         16 //C3层阈值数,16
#define len_weight_S4_CNN       16 //S4层权值数，1*16=16
#define len_bias_S4_CNN         16 //S4层阈值数，16
#define len_weight_C5_CNN       48000 //C5层权值数，(5*5*16)*120=48000
#define len_bias_C5_CNN         120 //C5层阈值数，120
#define len_weight_output_CNN   1200 //输出层权值数，(1*120)*10=1200
#define len_bias_output_CNN     10 //输出层阈值数，10

#define num_neuron_input_CNN    1024 //输入层神经元数，(32*32)*1=1024
#define num_neuron_C1_CNN       4704 //C1层神经元数，(28*28)*6=4704
#define num_neuron_S2_CNN       1176 //S2层神经元数，(14*14)*6=1176
#define num_neuron_C3_CNN       1600 //C3层神经元数，(10*10)*16=1600
#define num_neuron_S4_CNN       400 //S4层神经元数，(5*5)*16=400
#define num_neuron_C5_CNN       120 //C5层神经元数，(1*1)*120=120
#define num_neuron_output_CNN   10 //输出层神经元数，(1*1)*10=10
```

权值、偏置初始化：

(1)、权值使用函数uniform_real_distribution均匀分布初始化，tiny-cnn中每次初始化权值数值都相同，这里作了调整，使每次初始化的权值均不同。每层权值初始化大小范围都不一样；

(2)、所有层的偏置均初始化为0.

代码段如下：

[cpp]

```cpp
double CNN::uniform_rand(double min, double max)
{
    //static std::mt19937 gen(1);
    std::random_device rd;
    std::mt19937 gen(rd());
    std::uniform_real_distribution<double> dst(min, max);
    return dst(gen);
}

bool CNN::uniform_rand(double* src, int len, double min, double max)
{
    for (int i = 0; i < len; i++) {
        src[i] = uniform_rand(min, max);
    }

    return true;
}

bool CNN::initWeightThreshold()
{
    srand(time(0) + rand());
    const double scale = 6.0;

    double min_ = -std::sqrt(scale / (25.0 + 150.0));
    double max_ = std::sqrt(scale / (25.0 + 150.0));
    uniform_rand(weight_C1, len_weight_C1_CNN, min_, max_);
    for (int i = 0; i < len_bias_C1_CNN; i++) {
        bias_C1[i] = 0.0;
    }

    min_ = -std::sqrt(scale / (4.0 + 1.0));
    max_ = std::sqrt(scale / (4.0 + 1.0));
    uniform_rand(weight_S2, len_weight_S2_CNN, min_, max_);
    for (int i = 0; i < len_bias_S2_CNN; i++) {
        bias_S2[i] = 0.0;
    }

    min_ = -std::sqrt(scale / (150.0 + 400.0));
    max_ = std::sqrt(scale / (150.0 + 400.0));
    uniform_rand(weight_C3, len_weight_C3_CNN, min_, max_);
    for (int i = 0; i < len_bias_C3_CNN; i++) {
        bias_C3[i] = 0.0;
    }

    min_ = -std::sqrt(scale / (4.0 + 1.0));
    max_ = std::sqrt(scale / (4.0 + 1.0));
    uniform_rand(weight_S4, len_weight_S4_CNN, min_, max_);
    for (int i = 0; i < len_bias_S4_CNN; i++) {
```

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```
        bias_S4[i] = 0.0;
    }

    min_ = -std::sqrt(scale / (400.0 + 3000.0));
    max_ = std::sqrt(scale / (400.0 + 3000.0));
    uniform_rand(weight_C5, len_weight_C5_CNN, min_, max_);
    for (int i = 0; i < len_bias_C5_CNN; i++) {
        bias_C5[i] = 0.0;
    }

    min_ = -std::sqrt(scale / (120.0 + 10.0));
    max_ = std::sqrt(scale / (120.0 + 10.0));
    uniform_rand(weight_output, len_weight_output_CNN, min_, max_);
    for (int i = 0; i < len_bias_output_CNN; i++) {
        bias_output[i] = 0.0;
    }

    return true;
}
```

2. 加载MNIST数据：

关于MNIST的介绍可以参考：http://blog.csdn.net/fengbingchun/article/details/49611549

使用MNIST库作为训练集和测试集，训练样本集为60000个，测试样本集为10000个。

(1)、MNIST库中图像原始大小为28*28，这里缩放为32*32，数据取值范围为[-1,1]，扩充值均取-1，作为输入层输入数据。

代码段如下：

[cpp]

```cpp
static void readMnistImages(std::string filename, double* data_dst, int num_image)
{
    const int width_src_image = 28;
    const int height_src_image = 28;
    const int x_padding = 2;
    const int y_padding = 2;
    const double scale_min = -1;
    const double scale_max = 1;

    std::ifstream file(filename, std::ios::binary);
    assert(file.is_open());

    int magic_number = 0;
    int number_of_images = 0;
    int n_rows = 0;
    int n_cols = 0;
    file.read((char*)&magic_number, sizeof(magic_number));
    magic_number = reverseInt(magic_number);
    file.read((char*)&number_of_images, sizeof(number_of_images));
    number_of_images = reverseInt(number_of_images);
    assert(number_of_images == num_image);
    file.read((char*)&n_rows, sizeof(n_rows));
    n_rows = reverseInt(n_rows);
    file.read((char*)&n_cols, sizeof(n_cols));
    n_cols = reverseInt(n_cols);
    assert(n_rows == height_src_image && n_cols == width_src_image);

    int size_single_image = width_image_input_CNN * height_image_input_CNN;

    for (int i = 0; i < number_of_images; ++i) {
        int addr = size_single_image * i;

        for (int r = 0; r < n_rows; ++r) {
            for (int c = 0; c < n_cols; ++c) {
                unsigned char temp = 0;
                file.read((char*)&temp, sizeof(temp));
                data_dst[addr + width_image_input_CNN * (r + y_padding) + c + x_padding] =
            }
        }
    }
}
```

关闭

(2)、对于Label,输出层有10个节点，对应位置的节点值设为0.8，其它节点设为-0.8，作为输出层数据。

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代码段如下：

[cpp]

```cpp
static void readMnistLabels(std::string filename, double* data_dst, int num_image)
{
    const double scale_max = 0.8;

    std::ifstream file(filename, std::ios::binary);
    assert(file.is_open());

    int magic_number = 0;
    int number_of_images = 0;
    file.read((char*)&magic_number, sizeof(magic_number));
    magic_number = reverseInt(magic_number);
    file.read((char*)&number_of_images, sizeof(number_of_images));
    number_of_images = reverseInt(number_of_images);
    assert(number_of_images == num_image);

    for (int i = 0; i < number_of_images; ++i) {
        unsigned char temp = 0;
        file.read((char*)&temp, sizeof(temp));
        data_dst[i * num_map_output_CNN + temp] = scale_max;
    }
}static void readMnistLabels(std::string filename, double* data_dst, int num_image)
{
    const double scale_max = 0.8;

    std::ifstream file(filename, std::ios::binary);
    assert(file.is_open());

    int magic_number = 0;
    int number_of_images = 0;
    file.read((char*)&magic_number, sizeof(magic_number));
    magic_number = reverseInt(magic_number);
    file.read((char*)&number_of_images, sizeof(number_of_images));
    number_of_images = reverseInt(number_of_images);
    assert(number_of_images == num_image);

    for (int i = 0; i < number_of_images; ++i) {
        unsigned char temp = 0;
        file.read((char*)&temp, sizeof(temp));
        data_dst[i * num_map_output_CNN + temp] = scale_max;
    }
}
```

3. 前向传播：主要计算每层的神经元值；其中C1层、C3层、C5层操作过程相同；S2层、S4层操作过程相同。

(1)、输入层：神经元数为(32*32)*1=1024。

(2)、C1层：神经元数为(28*28)*6=4704，分别用每一个5*5的卷积图像去乘以32*32的图像，获得一个28*28的图像，即对应位置相加再求和，stride长度为1；一共6个5*5的卷积图像，然后对每一个神经元加上一个阈值，最后再通过tanh激活函数对每一神经元进行运算得到最终每一个神经元的结果。

激活函数的作用：它是用来加入非线性因素的，解决线性模型所不能解决的问题，提供网络的非线性建模能力。如果没有激活函数，那么该网络仅能够表达线性映射，此时即便有再多的隐藏层，其整个网络跟单层神经网络也是等价的。因此也可以认为，只有加入了激活函数之后，深度神经网络才具备了分层的非线性映射学习能力。

代码段如下：

[cpp]

关闭

```cpp
double CNN::activation_function_tanh(double x)
{
    double ep = std::exp(x);
    double em = std::exp(-x);

    return (ep - em) / (ep + em);
}

bool CNN::Forward_C1()
{
    init_variable(neuron_C1, 0.0, num_neuron_C1_CNN);

```

```cpp
    for (int o = 0; o < num_map_C1_CNN; o++) {
        for (int inc = 0; inc < num_map_input_CNN; inc++) {
            int addr1 = get_index(0, 0, num_map_input_CNN * o + inc, width_kernel_conv_CNN
            int addr2 = get_index(0, 0, inc, width_image_input_CNN, height_image_input_CNN
            int addr3 = get_index(0, 0, o, width_image_C1_CNN, height_image_C1_CNN, num_ma

            const double* pw = &weight_C1[0] + addr1;
            const double* pi = data_single_image + addr2;
            double* pa = &neuron_C1[0] + addr3;

            for (int y = 0; y < height_image_C1_CNN; y++) {
                for (int x = 0; x < width_image_C1_CNN; x++) {
                    const double* ppw = pw;
                    const double* ppi = pi + y * width_image_input_CNN + x;
                    double sum = 0.0;

                    for (int wy = 0; wy < height_kernel_conv_CNN; wy++) {
                        for (int wx = 0; wx < width_kernel_conv_CNN; wx++) {
                            sum += *ppw++ * ppi[wy * width_image_input_CNN + wx];
                        }
                    }

                    pa[y * width_image_C1_CNN + x] += sum;
                }
            }
        }

        int addr3 = get_index(0, 0, o, width_image_C1_CNN, height_image_C1_CNN, num_map_C
        double* pa = &neuron_C1[0] + addr3;
        double b = bias_C1[o];
        for (int y = 0; y < height_image_C1_CNN; y++) {
            for (int x = 0; x < width_image_C1_CNN; x++) {
                pa[y * width_image_C1_CNN + x] += b;
            }
        }
    }

    for (int i = 0; i < num_neuron_C1_CNN; i++) {
        neuron_C1[i] = activation_function_tanh(neuron_C1[i]);
    }

    return true;
}
```

(3)、S2层：神经元数为(14*14)*6=1176，对C1中6个28*28的特征图生成6个14*14的下采样图，相邻四个神经元分别乘以同一个权值再进行相加求和，再求均值即除以4，然后再加上一个阈值，最后再通过tanh激活函数对每一神经元进行运算得到最终每一个神经元的结果。

代码段如下：

[cpp]

```cpp
bool CNN::Forward_S2()
{
    init_variable(neuron_S2, 0.0, num_neuron_S2_CNN);
    double scale_factor = 1.0 / (width_kernel_pooling_CNN * height_kernel_pooling_CNN);

    assert(out2wi_S2.size() == num_neuron_S2_CNN);
    assert(out2bias_S2.size() == num_neuron_S2_CNN);

    for (int i = 0; i < num_neuron_S2_CNN; i++) {
        const wi_connections& connections = out2wi_S2[i];
        neuron_S2[i] = 0;

        for (int index = 0; index < connections.size(
            neuron_S2[i] += weight_S2[connections[index].first] * neuron_C1[connections[in
        }

        neuron_S2[i] *= scale_factor;
        neuron_S2[i] += bias_S2[out2bias_S2[i]];
    }

    for (int i = 0; i < num_neuron_S2_CNN; i++) {
        neuron_S2[i] = activation_function_tanh(neuron_S2[i]);
    }

    return true;
}
```

(4)、C3层：神经元数为(10*10)*16=1600，C3层实现方式与C1层完全相同，由S2中的6个14*14下采样图生成16个10*10特征图，对于生成的每一个10*10的特征图，是由6个5*5的卷积图像去乘以6个14*14的下采样图，然后对应位置相加求和，然后对每一个神经元加上一个阈值，最后再通过tanh激活函数对每一神经元进行运算得到最终每一个神经元的结果。

也可按照Y.Lecun给出的表进行计算，即对于生成的每一个10*10的特征图，是由n个5*5的卷积图像去乘以n个14*14的下采样图，其中n是小于6的，即不完全连接。这样做的原因：第一，不完全的连接机制将连接的数量保持在合理的范围内。第二，也是最重要的，其破坏了网络的对称性。由于不同的特征图有不同的输入，所以迫使他们抽取不同的特征。

代码段如下：

[cpp]

```cpp
// connection table [Y.Lecun, 1998 Table.1]
#define O true
#define X false
static const bool tbl[6][16] = {
    O, X, X, X, O, O, O, X, X, O, O, O, O, X, O, O,
    O, O, X, X, X, O, O, O, X, X, O, O, O, O, X, O,
    O, O, O, X, X, X, O, O, O, X, X, O, X, O, O, O,
    X, O, O, O, X, X, O, O, O, O, X, X, O, X, O, O,
    X, X, O, O, O, X, X, O, O, O, O, X, O, O, X, O,
    X, X, X, O, O, O, X, X, O, O, O, O, X, O, O, O
};
#undef O
#undef X

bool CNN::Forward_C3()
{
    init_variable(neuron_C3, 0.0, num_neuron_C3_CNN);

    for (int o = 0; o < num_map_C3_CNN; o++) {
        for (int inc = 0; inc < num_map_S2_CNN; inc++) {
            if (!tbl[inc][o]) continue;

            int addr1 = get_index(0, 0, num_map_S2_CNN * o + inc, width_kernel_conv_CNN, h
            int addr2 = get_index(0, 0, inc, width_image_S2_CNN, height_image_S2_CNN, num_
            int addr3 = get_index(0, 0, o, width_image_C3_CNN, height_image_C3_CNN, num_ma

            const double* pw = &weight_C3[0] + addr1;
            const double* pi = &neuron_S2[0] + addr2;
            double* pa = &neuron_C3[0] + addr3;

            for (int y = 0; y < height_image_C3_CNN; y++) {
                for (int x = 0; x < width_image_C3_CNN; x++) {
                    const double* ppw = pw;
                    const double* ppi = pi + y * width_image_S2_CNN + x;
                    double sum = 0.0;

                    for (int wy = 0; wy < height_kernel_conv_CNN; wy++) {
                        for (int wx = 0; wx < width_kernel_conv_CNN; wx++) {
                            sum += *ppw++ * ppi[wy * width_image_S2_CNN + wx];
                        }
                    }

                    pa[y * width_image_C3_CNN + x] += sum;
                }
            }
        }

        int addr3 = get_index(0, 0, o, width_image_C3_
        double* pa = &neuron_C3[0] + addr3;
        double b = bias_C3[o];
        for (int y = 0; y < height_image_C3_CNN; y++) {
            for (int x = 0; x < width_image_C3_CNN; x++) {
                pa[y * width_image_C3_CNN + x] += b;
            }
        }
    }

    for (int i = 0; i < num_neuron_C3_CNN; i++) {
        neuron_C3[i] = activation_function_tanh(neuron_C3[i]);
    }

    return true;
```

关闭

```
}
```

(5)、S4层：神经元数为(5*5)*16=400，S4层实现方式与S2层完全相同，由C3中16个10*10的特征图生成16个5*5下采样图，相邻四个神经元分别乘以同一个权值再进行相加求和，再求均值即除以4，然后再加上一个阈值，最后再通过tanh激活函数对每一神经元进行运算得到最终每一个神经元的结果。

代码段如下：

[cpp]

```cpp
bool CNN::Forward_S4()
{
    double scale_factor = 1.0 / (width_kernel_pooling_CNN * height_kernel_pooling_CNN);
    init_variable(neuron_S4, 0.0, num_neuron_S4_CNN);

    assert(out2wi_S4.size() == num_neuron_S4_CNN);
    assert(out2bias_S4.size() == num_neuron_S4_CNN);

    for (int i = 0; i < num_neuron_S4_CNN; i++) {
        const wi_connections& connections = out2wi_S4[i];
        neuron_S4[i] = 0.0;

        for (int index = 0; index < connections.size(); index++) {
            neuron_S4[i] += weight_S4[connections[index].first] * neuron_C3[connections[i
        }

        neuron_S4[i] *= scale_factor;
        neuron_S4[i] += bias_S4[out2bias_S4[i]];
    }

    for (int i = 0; i < num_neuron_S4_CNN; i++) {
        neuron_S4[i] = activation_function_tanh(neuron_S4[i]);
    }

    return true;
}
```

(6)、C5层：神经元数为(1*1)*120=120，也可看为全连接层，C5层实现方式与C1、C3层完全相同，由S4中16个5*5下采样图生成120个1*1特征图，对于生成的每一个1*1的特征图，是由16个5*5的卷积图像去乘以16个5*5的下采用图，然后相加求和，然后对每一个神经元加上一个阈值，最后再通过tanh激活函数对每一神经元进行运算得到最终每一个神经元的结果。

代码段如下：

[cpp]

```cpp
bool CNN::Forward_C5()
{
    init_variable(neuron_C5, 0.0, num_neuron_C5_CNN);

    for (int o = 0; o < num_map_C5_CNN; o++) {
        for (int inc = 0; inc < num_map_S4_CNN; inc++) {
            int addr1 = get_index(0, 0, num_map_S4_CNN * o + inc, width_kernel_conv_CNN, h
            int addr2 = get_index(0, 0, inc, width_image_S4_CNN, height_image_S4_CNN, num_
            int addr3 = get_index(0, 0, o, width_image_C5_CNN, height_image_C5_CNN, num_ma

            const double *pw = &weight_C5[0] + addr1;
            const double *pi = &neuron_S4[0] + addr2;
            double *pa = &neuron_C5[0] + addr3;

            for (int y = 0; y < height_image_C5_CNN; y++) {
                for (int x = 0; x < width_image_C5_CNN
                    const double *ppw = pw;
                    const double *ppi = pi + y * width_image_S4_CNN + x;
                    double sum = 0.0;

                    for (int wy = 0; wy < height_kernel_conv_CNN; wy++) {
                        for (int wx = 0; wx < width_kernel_conv_CNN; wx++) {
                            sum += *ppw++ * ppi[wy * width_image_S4_CNN + wx];
                        }
                    }

                    pa[y * width_image_C5_CNN + x] += sum;
                }
            }
        }
```

关闭

```

        int addr3 = get_index(0, 0, o, width_image_C5_CNN, height_image_C5_CNN, num_map_C!
        double *pa = &neuron_C5[0] + addr3;
        double b = bias_C5[o];
        for (int y = 0; y < height_image_C5_CNN; y++) {
            for (int x = 0; x < width_image_C5_CNN; x++) {
                pa[y * width_image_C5_CNN + x] += b;
            }
        }
    }

    for (int i = 0; i < num_neuron_C5_CNN; i++) {
        neuron_C5[i] = activation_function_tanh(neuron_C5[i]);
    }

    return true;
}
```

(7)、输出层：神经元数为(1*1)*10=10，为全连接层，输出层中的每一个神经元均是由C5层中的120个神经元乘以相对应的权值，然后相加求和；然后对每一个神经元加上一个阈值，最后再通过tanh激活函数对每一神经元进行运算得到最终每一个神经元的结果。

代码段如下：

[cpp]

```cpp
bool CNN::Forward_output()
{
    init_variable(neuron_output, 0.0, num_neuron_output_CNN);

    for (int i = 0; i < num_neuron_output_CNN; i++) {
        neuron_output[i] = 0.0;

        for (int c = 0; c < num_neuron_C5_CNN; c++) {
            neuron_output[i] += weight_output[c * num_neuron_output_CNN + i] * neuron_C5[(
        }

        neuron_output[i] += bias_output[i];
    }

    for (int i = 0; i < num_neuron_output_CNN; i++) {
        neuron_output[i] = activation_function_tanh(neuron_output[i]);
    }

    return true;
}
```

4. 反向传播：主要计算每层权值和偏置的误差以及每层神经元的误差；其中输入层、S2层、S4层操作过程相同；C1层、C3层操作过程相同。

(1)、输出层：计算输出层神经元误差；通过mse损失函数的导数函数和tanh激活函数的导数函数来计算输出层神经元误差，即a、已计算出的输出层神经元值减去对应label值，b、1.0减去输出层神经元值的平方，c、a与c的乘积和。

损失函数作用：在统计学中损失函数是一种衡量损失和错误(这种损失与"错误地"估计有关)程度的函数。损失函数在实践中最重要的运用，在于协助我们通过过程的改善而持续减少目标值的变异，并非仅仅追求符合逻辑。在深度学习中，对于损失函数的收敛特性，我们期望是当误差越大的时候，收敛(学习)速度应该越快。成为损失函数需要满足两点要求：非负性；预测值和期望值接近时，函数值趋于0.

代码段如下：

关闭

[cpp]

```cpp
double CNN::loss_function_mse_derivative(double y, double t)
{
    return (y - t);
}

void CNN::loss_function_gradient(const double* y, const double* t, double* dst, int len)
{
    for (int i = 0; i < len; i++) {
        dst[i] = loss_function_mse_derivative(y[i], t[i]);
    }
}
```

```cpp

double CNN::activation_function_tanh_derivative(double x)
{
    return (1.0 - x * x);
}

double CNN::dot_product(const double* s1, const double* s2, int len)
{
    double result = 0.0;

    for (int i = 0; i < len; i++) {
        result += s1[i] * s2[i];
    }

    return result;
}

bool CNN::Backward_output()
{
    init_variable(delta_neuron_output, 0.0, num_neuron_output_CNN);

    double dE_dy[num_neuron_output_CNN];
    init_variable(dE_dy, 0.0, num_neuron_output_CNN);
    loss_function_gradient(neuron_output, data_single_label, dE_dy, num_neuro
失函数: mean squared error(均方差)

    // delta = dE/da = (dE/dy) * (dy/da)
    for (int i = 0; i < num_neuron_output_CNN; i++) {
        double dy_da[num_neuron_output_CNN];
        init_variable(dy_da, 0.0, num_neuron_output_CNN);

        dy_da[i] = activation_function_tanh_derivative(neuron_output[i]);
        delta_neuron_output[i] = dot_product(dE_dy, dy_da, num_neuron_output_CNN);
    }

    return true;
}
```

(2)、C5层：计算C5层神经元误差、输出层权值误差、输出层偏置误差；通过输出层神经元误差乘以输出层权值，求和，结果再乘以C5层神经元的tanh激活函数的导数(即1-C5层神经元值的平方)，获得C5层每一个神经元误差；通过输出层神经元误差乘以C5层神经元获得输出层权值误差；输出层偏置误差即为输出层神经元误差。

代码段如下：

[cpp]

```cpp
bool CNN::muladd(const double* src, double c, int len, double* dst)
{
    for (int i = 0; i < len; i++) {
        dst[i] += (src[i] * c);
    }

    return true;
}

bool CNN::Backward_C5()
{
    init_variable(delta_neuron_C5, 0.0, num_neuron_C5_CNN);
    init_variable(delta_weight_output, 0.0, len_weight_output_CNN);
    init_variable(delta_bias_output, 0.0, len_bias_output_CNN);

    for (int c = 0; c < num_neuron_C5_CNN; c++) {
        // propagate delta to previous layer
        // prev_delta[c] += current_delta[r] * W_[c *
        delta_neuron_C5[c] = dot_product(&
delta_neuron_output[0], &weight_output[c * num_neuron_output_CNN], num_neuron_output_CNN)
        delta_neuron_C5[c] *= activation_function_tanh_derivative(neuron_C5[c]);
    }

    // accumulate weight-step using delta
    // dW[c * out_size + i] += current_delta[i] * prev_out[c]
    for (int c = 0; c < num_neuron_C5_CNN; c++) {
        muladd(&delta_neuron_output[0], neuron_C5[c], num_neuron_output_CNN, &delta_weigh
    }

    for (int i = 0; i < len_bias_output_CNN; i++) {
        delta_bias_output[i] += delta_neuron_output[i];
    }
```

```

    return true;
}
```

(3)、S4层：计算S4层神经元误差、C5层权值误差、C5层偏置误差；通过C5层权值乘以C5层神经元误差，求和，结果再乘以S4层神经元的tanh激活函数的导数(即1-S4神经元的平方)，获得S4层每一个神经元误差；通过S4层神经元乘以C5层神经元误差，求和，获得C5层权值误差；C5层偏置误差即为C5层神经元误差。

代码段如下：

[cpp]

```cpp
bool CNN::Backward_S4()
{
    init_variable(delta_neuron_S4, 0.0, num_neuron_S4_CNN);
    init_variable(delta_weight_C5, 0.0, len_weight_C5_CNN);
    init_variable(delta_bias_C5, 0.0, len_bias_C5_CNN);

    // propagate delta to previous layer
    for (int inc = 0; inc < num_map_S4_CNN; inc++) {
        for (int outc = 0; outc < num_map_C5_CNN; outc++) {
            int addr1 = get_index(0, 0, num_map_S4_CNN * outc + inc, width_ke
            int addr2 = get_index(0, 0, outc, width_image_C5_CNN, height_image_C5_CNN, num
            int addr3 = get_index(0, 0, inc, width_image_S4_CNN, height_image_S4_CNN, num_

            const double* pw = &weight_C5[0] + addr1;
            const double* pdelta_src = &delta_neuron_C5[0] + addr2;
            double* pdelta_dst = &delta_neuron_S4[0] + addr3;

            for (int y = 0; y < height_image_C5_CNN; y++) {
                for (int x = 0; x < width_image_C5_CNN; x++) {
                    const double* ppw = pw;
                    const double ppdelta_src = pdelta_src[y * width_image_C5_CNN + x];
                    double* ppdelta_dst = pdelta_dst + y * width_image_S4_CNN + x;

                    for (int wy = 0; wy < height_kernel_conv_CNN; wy++) {
                        for (int wx = 0; wx < width_kernel_conv_CNN; wx++) {
                            ppdelta_dst[wy * width_image_S4_CNN + wx] += *ppw++ * ppdelta_
                        }
                    }
                }
            }
        }
    }

    for (int i = 0; i < num_neuron_S4_CNN; i++) {
        delta_neuron_S4[i] *= activation_function_tanh_derivative(neuron_S4[i]);
    }

    // accumulate dw
    for (int inc = 0; inc < num_map_S4_CNN; inc++) {
        for (int outc = 0; outc < num_map_C5_CNN; outc++) {
            for (int wy = 0; wy < height_kernel_conv_CNN; wy++) {
                for (int wx = 0; wx < width_kernel_conv_CNN; wx++) {
                    int addr1 = get_index(wx, wy, inc, width_image_S4_CNN, height_image_S4
                    int addr2 = get_index(0, 0, outc, width_image_C5_CNN, height_image_C5_
                    int addr3 = get_index(wx, wy, num_map_S4_CNN * outc + inc, width_kerne

                    double dst = 0.0;
                    const double* prevo = &neuron_S4[0] + addr1;
                    const double* delta = &delta_neuron_C5[0] + addr2;

                    for (int y = 0; y < height_image_C5_CNN; y++) {
                        dst += dot_product(prevo + y
                    }

                    delta_weight_C5[addr3] += dst;
                }
            }
        }
    }

    // accumulate db
    for (int outc = 0; outc < num_map_C5_CNN; outc++) {
        int addr2 = get_index(0, 0, outc, width_image_C5_CNN, height_image_C5_CNN, num_ma
        const double* delta = &delta_neuron_C5[0] + addr2;

        for (int y = 0; y < height_image_C5_CNN; y++) {
```

关闭

```cpp
            for (int x = 0; x < width_image_C5_CNN; x++) {
                delta_bias_C5[outc] += delta[y * width_image_C5_CNN + x];
            }
        }
    }

    return true;
}
```

(4)、C3层：计算C3层神经元误差、S4层权值误差、S4层偏置误差；通过S4层权值乘以S4层神经元误差，求和，结果再乘以C3层神经元的tanh激活函数的导数(即1-S4神经元的平方)，然后再乘以1/4，获得C3层每一个神经元误差；通过C3层神经元乘以S4神经元误差，求和，再乘以1/4，获得S4层权值误差；通过S4层神经元误差求和，来获得S4层偏置误差。

代码段如下：

[cpp]

```cpp
bool CNN::Backward_C3()
{
    init_variable(delta_neuron_C3, 0.0, num_neuron_C3_CNN);
    init_variable(delta_weight_S4, 0.0, len_weight_S4_CNN);
    init_variable(delta_bias_S4, 0.0, len_bias_S4_CNN);

    double scale_factor = 1.0 / (width_kernel_pooling_CNN * height_kernel_pooling_CNN);

    assert(in2wo_C3.size() == num_neuron_C3_CNN);
    assert(weight2io_C3.size() == len_weight_S4_CNN);
    assert(bias2out_C3.size() == len_bias_S4_CNN);

    for (int i = 0; i < num_neuron_C3_CNN; i++) {
        const wo_connections& connections = in2wo_C3[i];
        double delta = 0.0;

        for (int j = 0; j < connections.size(); j++) {
            delta += weight_S4[connections[j].first] * delta_neuron_S4[connections[j].sec
        }

        delta_neuron_C3[i] = delta * scale_factor * activation_function_tanh_derivative(ne
    }

    for (int i = 0; i < len_weight_S4_CNN; i++) {
        const io_connections& connections = weight2io_C3[i];
        double diff = 0;

        for (int j = 0; j < connections.size(); j++) {
            diff += neuron_C3[connections[j].first] * delta_neuron_S4[connections[j].secor
        }

        delta_weight_S4[i] += diff * scale_factor;
    }

    for (int i = 0; i < len_bias_S4_CNN; i++) {
        const std::vector<int>& outs = bias2out_C3[i];
        double diff = 0;

        for (int o = 0; o < outs.size(); o++) {
            diff += delta_neuron_S4[outs[o]];
        }

        delta_bias_S4[i] += diff;
    }

    return true;
}
```


(5)、S2层：计算S2层神经元误差、C3层权值误差、C3层偏置误差；通过C3层权值乘以C3层神经元误差，求和，结果再乘以S2层神经元的tanh激活函数的导数(即1-S2神经元的平方)，获得S2层每一个神经元误差；通过S2层神经元乘以C3层神经元误差，求和，获得C3层权值误差；C3层偏置误差即为C3层神经元误差和。

代码段如下：

[cpp]

```cpp
bool CNN::Backward_S2()
{
```

```
    init_variable(delta_neuron_S2, 0.0, num_neuron_S2_CNN);
    init_variable(delta_weight_C3, 0.0, len_weight_C3_CNN);
    init_variable(delta_bias_C3, 0.0, len_bias_C3_CNN);

    // propagate delta to previous layer
    for (int inc = 0; inc < num_map_S2_CNN; inc++) {
        for (int outc = 0; outc < num_map_C3_CNN; outc++) {
            if (!tbl[inc][outc]) continue;

            int addr1 = get_index(0, 0, num_map_S2_CNN * outc + inc, width_kernel_conv_CNN
            int addr2 = get_index(0, 0, outc, width_image_C3_CNN, height_image_C3_CNN, nur
            int addr3 = get_index(0, 0, inc, width_image_S2_CNN, height_image_S2_CNN, num_

            const double *pw = &weight_C3[0] + addr1;
            const double *pdelta_src = &delta_neuron_C3[0] + addr2;;
            double* pdelta_dst = &delta_neuron_S2[0] + addr3;

            for (int y = 0; y < height_image_C3_CNN; y++) {
                for (int x = 0; x < width_image_C3_CNN; x++) {
                    const double* ppw = pw;
                    const double ppdelta_src = pdelta_src[y * width_image_C3_CNN + x];
                    double* ppdelta_dst = pdelta_dst + y * width_image_S2_CNN + x;

                    for (int wy = 0; wy < height_kernel_conv_CNN; wy++) {
                        for (int wx = 0; wx < width_kernel_conv_CNN; wx++) {
                            ppdelta_dst[wy * width_image_S2_CNN + wx] += *ppw++ * ppdelta_
                        }
                    }
                }
            }
        }
    }

    for (int i = 0; i < num_neuron_S2_CNN; i++) {
        delta_neuron_S2[i] *= activation_function_tanh_derivative(neuron_S2[i]);
    }

    // accumulate dw
    for (int inc = 0; inc < num_map_S2_CNN; inc++) {
        for (int outc = 0; outc < num_map_C3_CNN; outc++) {
            if (!tbl[inc][outc]) continue;

            for (int wy = 0; wy < height_kernel_conv_CNN; wy++) {
                for (int wx = 0; wx < width_kernel_conv_CNN; wx++) {
                    int addr1 = get_index(wx, wy, inc, width_image_S2_CNN, height_image_S2
                    int addr2 = get_index(0, 0, outc, width_image_C3_CNN, height_image_C3_
                    int addr3 = get_index(wx, wy, num_map_S2_CNN * outc + inc, width_kerne

                    double dst = 0.0;
                    const double* prevo = &neuron_S2[0] + addr1;
                    const double* delta = &delta_neuron_C3[0] + addr2;

                    for (int y = 0; y < height_image_C3_CNN; y++) {
                        dst += dot_product(prevo + y * width_image_S2_CNN, delta + y * wid
                    }

                    delta_weight_C3[addr3] += dst;
                }
            }
        }
    }

    // accumulate db
    for (int outc = 0; outc < len_bias_C3_CNN; outc++) {
        int addr1 = get_index(0, 0, outc, width_image_C3_CNN, height_image_C3_CNN, num_map
        const double* delta = &delta_neuron_C3[0] + a

        for (int y = 0; y < height_image_C3_CNN; y++) {
            for (int x = 0; x < width_image_C3_CNN; x++) {
                delta_bias_C3[outc] += delta[y * width_image_C3_CNN + x];
            }
        }
    }

    return true;
}
```

关闭

(6)、C1层：计算C1层神经元误差、S2层权值误差、S2层偏置误差；通过S2层权值乘以S2层神经元误差，求

和，结果再乘以C1层神经元的tanh激活函数的导数(即1-C1神经元的平方)，然后再乘以1/4，获得C1层每一个神经元误差；通过C1层神经元乘以S2神经元误差，求和，再乘以1/4，获得S2层权值误差；通过S2层神经元误差求和，来获得S4层偏置误差。

代码段如下：

[cpp]

```cpp
bool CNN::Backward_C1()
{
    init_variable(delta_neuron_C1, 0.0, num_neuron_C1_CNN);
    init_variable(delta_weight_S2, 0.0, len_weight_S2_CNN);
    init_variable(delta_bias_S2, 0.0, len_bias_S2_CNN);

    double scale_factor = 1.0 / (width_kernel_pooling_CNN * height_kernel_pooling_CNN);

    assert(in2wo_C1.size() == num_neuron_C1_CNN);
    assert(weight2io_C1.size() == len_weight_S2_CNN);
    assert(bias2out_C1.size() == len_bias_S2_CNN);

    for (int i = 0; i < num_neuron_C1_CNN; i++) {
        const wo_connections& connections = in2wo_C1[i];
        double delta = 0.0;

        for (int j = 0; j < connections.size(); j++) {
            delta += weight_S2[connections[j].first] * delta_neuron_S2[connections[j].seco
        }

        delta_neuron_C1[i] = delta * scale_factor * activation_function_tanh_derivative(ne
    }

    for (int i = 0; i < len_weight_S2_CNN; i++) {
        const io_connections& connections = weight2io_C1[i];
        double diff = 0.0;

        for (int j = 0; j < connections.size(); j++) {
            diff += neuron_C1[connections[j].first] * delta_neuron_S2[connections[j].secon
        }

        delta_weight_S2[i] += diff * scale_factor;
    }

    for (int i = 0; i < len_bias_S2_CNN; i++) {
        const std::vector<int>& outs = bias2out_C1[i];
        double diff = 0;

        for (int o = 0; o < outs.size(); o++) {
            diff += delta_neuron_S2[outs[o]];
        }

        delta_bias_S2[i] += diff;
    }

    return true;
}
```

(7)、输入层：计算输入层神经元误差、C1层权值误差、C1层偏置误差；通过C1层权值乘以C1层神经元误差，求和，结果再乘以输入层神经元的tanh激活函数的导数(即1-输入层神经元的平方)，获得输入层每一个神经元误差；通过输入层层神经元乘以C1层神经元误差，求和，获得C1层权值误差；C1层偏置误差即为C1层神经元误差和。

[cpp]

```cpp
bool CNN::Backward_input()
{
    init_variable(delta_neuron_input, 0.0, num_neuron_input_CNN);
    init_variable(delta_weight_C1, 0.0, len_weight_C1_CNN);
    init_variable(delta_bias_C1, 0.0, len_bias_C1_CNN);

    // propagate delta to previous layer
    for (int inc = 0; inc < num_map_input_CNN; inc++) {
        for (int outc = 0; outc < num_map_C1_CNN; outc++) {
            int addr1 = get_index(0, 0, num_map_input_CNN * outc + inc, width_kernel_conv_
            int addr2 = get_index(0, 0, outc, width_image_C1_CNN, height_image_C1_CNN, nu
            int addr3 = get_index(0, 0, inc, width_image_input_CNN, height_image_input_CN

            const double* pw = &weight_C1[0] + addr1;
```

关闭

```cpp
            const double* pdelta_src = &delta_neuron_C1[0] + addr2;
            double* pdelta_dst = &delta_neuron_input[0] + addr3;

            for (int y = 0; y < height_image_C1_CNN; y++) {
                for (int x = 0; x < width_image_C1_CNN; x++) {
                    const double* ppw = pw;
                    const double ppdelta_src = pdelta_src[y * width_image_C1_CNN + x];
                    double* ppdelta_dst = pdelta_dst + y * width_image_input_CNN + x;

                    for (int wy = 0; wy < height_kernel_conv_CNN; wy++) {
                        for (int wx = 0; wx < width_kernel_conv_CNN; wx++) {
                            ppdelta_dst[wy * width_image_input_CNN + wx] += *ppw++ * ppde
                        }
                    }
                }
            }
        }
    }

    for (int i = 0; i < num_neuron_input_CNN; i++) {
        delta_neuron_input[i] *= activation_function_identity_derivative(data_single_image
    }

    // accumulate dw
    for (int inc = 0; inc < num_map_input_CNN; inc++) {
        for (int outc = 0; outc < num_map_C1_CNN; outc++) {
            for (int wy = 0; wy < height_kernel_conv_CNN; wy++) {
                for (int wx = 0; wx < width_kernel_conv_CNN; wx++) {
                    int addr1 = get_index(wx, wy, inc, width_image_input_CNN, height_image
                    int addr2 = get_index(0, 0, outc, width_image_C1_CNN, height_image_C1_
                    int addr3 = get_index(wx, wy, num_map_input_CNN * outc + inc, width_ke

                    double dst = 0.0;
                    const double* prevo = data_single_image + addr1;//&neuron_input[0]
                    const double* delta = &delta_neuron_C1[0] + addr2;

                    for (int y = 0; y < height_image_C1_CNN; y++) {
                        dst += dot_product(prevo + y * width_image_input_CNN, delta + y *
                    }

                    delta_weight_C1[addr3] += dst;
                }
            }
        }
    }

    // accumulate db
    for (int outc = 0; outc < len_bias_C1_CNN; outc++) {
        int addr1 = get_index(0, 0, outc, width_image_C1_CNN, height_image_C1_CNN, num_ma
        const double* delta = &delta_neuron_C1[0] + addr1;

        for (int y = 0; y < height_image_C1_CNN; y++) {
            for (int x = 0; x < width_image_C1_CNN; x++) {
                delta_bias_C1[outc] += delta[y * width_image_C1_CNN + x];
            }
        }
    }

    return true;
}
```

5. 更新各层权值、偏置：通过之前计算的各层权值、各层权值误差；各层偏置、各层偏置误差以及学习率来更新各层权值和偏置。

代码段如下：

[cpp]

```cpp
void CNN::update_weights_bias(const double* delta, double* e_weight, double* weight, int 
{
    for (int i = 0; i < len; i++) {
        e_weight[i] += delta[i] * delta[i];
        weight[i] -= learning_rate_CNN * delta[i] / (std::sqrt(e_weight[i]) + eps_CNN);
    }
}

bool CNN::UpdateWeights()
{
```

```cpp
    update_weights_bias(delta_weight_C1, E_weight_C1, weight_C1, len_weight_C1_CNN);
    update_weights_bias(delta_bias_C1, E_bias_C1, bias_C1, len_bias_C1_CNN);

    update_weights_bias(delta_weight_S2, E_weight_S2, weight_S2, len_weight_S2_CNN);
    update_weights_bias(delta_bias_S2, E_bias_S2, bias_S2, len_bias_S2_CNN);

    update_weights_bias(delta_weight_C3, E_weight_C3, weight_C3, len_weight_C3_CNN);
    update_weights_bias(delta_bias_C3, E_bias_C3, bias_C3, len_bias_C3_CNN);

    update_weights_bias(delta_weight_S4, E_weight_S4, weight_S4, len_weight_S4_CNN);
    update_weights_bias(delta_bias_S4, E_bias_S4, bias_S4, len_bias_S4_CNN);

    update_weights_bias(delta_weight_C5, E_weight_C5, weight_C5, len_weight_C5_CNN);
    update_weights_bias(delta_bias_C5, E_bias_C5, bias_C5, len_bias_C5_CNN);

    update_weights_bias(delta_weight_output, E_weight_output, weight_output, len_weight_ou
    update_weights_bias(delta_bias_output, E_bias_output, bias_output, len_bias_output_CNN

    return true;
}
```

6. 测试准确率是否达到要求或已达到循环次数：依次循环3至5中操作，根据训练集数量，每循环60000次时，通过计算的权值和偏置，来对10000个测试集进行测试，如果准确率达到0.985或者达到迭代次数时，保存权值和偏置。

代码段如下：

[cpp]

```cpp
bool CNN::train()
{
    out2wi_S2.clear();
    out2bias_S2.clear();
    out2wi_S4.clear();
    out2bias_S4.clear();
    in2wo_C3.clear();
    weight2io_C3.clear();
    bias2out_C3.clear();
    in2wo_C1.clear();
    weight2io_C1.clear();
    bias2out_C1.clear();

    calc_out2wi(width_image_C1_CNN, height_image_C1_CNN, width_image_S2_CNN, height_image_
    calc_out2bias(width_image_S2_CNN, height_image_S2_CNN, num_map_S2_CNN, out2bias_S2);
    calc_out2wi(width_image_C3_CNN, height_image_C3_CNN, width_image_S4_CNN, height_image_
    calc_out2bias(width_image_S4_CNN, height_image_S4_CNN, num_map_S4_CNN, out2bias_S4);
    calc_in2wo(width_image_C3_CNN, height_image_C3_CNN, width_image_S4_CNN, height_image_S
    calc_weight2io(width_image_C3_CNN, height_image_C3_CNN, width_image_S4_CNN, height_ima
    calc_bias2out(width_image_C3_CNN, height_image_C3_CNN, width_image_S4_CNN, height_imag
    calc_in2wo(width_image_C1_CNN, height_image_C1_CNN, width_image_S2_CNN, height_image_S
    calc_weight2io(width_image_C1_CNN, height_image_C1_CNN, width_image_S2_CNN, height_ima
    calc_bias2out(width_image_C1_CNN, height_image_C1_CNN, width_image_S2_CNN, height_imag

    int iter = 0;
    for (iter = 0; iter < num_epochs_CNN; iter++) {
        std::cout << "epoch: " << iter + 1;

        for (int i = 0; i < num_patterns_train_CNN; i++) {
            data_single_image = data_input_train + i * num_neuron_input_CNN;
            data_single_label = data_output_train + i * num_neuron_output_CNN;

            Forward_C1();
            Forward_S2();
            Forward_C3();
            Forward_S4();
            Forward_C5();
            Forward_output();

            Backward_output();
            Backward_C5();
            Backward_S4();
            Backward_C3();
            Backward_S2();
            Backward_C1();
            Backward_input();

            UpdateWeights();
        }
```

关闭

```cpp

        double accuracyRate = test();
        std::cout << ",    accuray rate: " << accuracyRate << std::endl;
        if (accuracyRate > accuracy_rate_CNN) {
            saveModelFile("E:/GitCode/NN_Test/data/cnn.model");
            std::cout << "generate cnn model" << std::endl;
            break;
        }
    }

    if (iter == num_epochs_CNN) {
        saveModelFile("E:/GitCode/NN_Test/data/cnn.model");
        std::cout << "generate cnn model" << std::endl;
    }

    return true;
}

double CNN::test()
{
    int count_accuracy = 0;

    for (int num = 0; num < num_patterns_test_CNN; num++) {
        data_single_image = data_input_test + num * num_neuron_input_CNN;
        data_single_label = data_output_test + num * num_neuron_output_CNN;

        Forward_C1();
        Forward_S2();
        Forward_C3();
        Forward_S4();
        Forward_C5();
        Forward_output();

        int pos_t = -1;
        int pos_y = -2;
        double max_value_t = -9999.0;
        double max_value_y = -9999.0;

        for (int i = 0; i < num_neuron_output_CNN; i++) {
            if (neuron_output[i] > max_value_y) {
                max_value_y = neuron_output[i];
                pos_y = i;
            }

            if (data_single_label[i] > max_value_t) {
                max_value_t = data_single_label[i];
                pos_t = i;
            }
        }

        if (pos_y == pos_t) {
            ++count_accuracy;
        }

        Sleep(1);
    }

    return (count_accuracy * 1.0 / num_patterns_test_CNN);
}
```

7. 对输入的图像数据进行识别：载入已保存的权值和偏置，对输入的数据进行识别，过程相当于前向传播。

代码段如下：

[cpp]

```cpp
int CNN::predict(const unsigned char* data, int width, int height)
{
    assert(data && width == width_image_input_CNN && height == height_image_input_CNN);

    const double scale_min = -1;
    const double scale_max = 1;

    double tmp[width_image_input_CNN * height_image_input_CNN];
    for (int y = 0; y < height; y++) {
        for (int x = 0; x < width; x++) {
            tmp[y * width + x] = (data[y * width + x] / 255.0) * (scale_max - scale_min) -
```

```
        }
    }

    data_single_image = &tmp[0];

    Forward_C1();
    Forward_S2();
    Forward_C3();
    Forward_S4();
    Forward_C5();
    Forward_output();

    int pos = -1;
    double max_value = -9999.0;

    for (int i = 0; i < num_neuron_output_CNN; i++) {
        if (neuron_output[i] > max_value) {
            max_value = neuron_output[i];
            pos = i;
        }
    }

    return pos;
}
```

GitHub：https://github.com/fengbingchun/NN_Test

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