Challenges in Representation Learning: Facial Expression Recognition Challenge

August 19, 2019

Challenges in Representation Learning: Facial Expression Recognition Challenge from *https://www.kaggle.com/c/challenges-in-representation-learning-facial-expression-recognition-challenge/data*

1 Data Exploration

Some data exploration, looking at the structure of the files etc.

```
In [2]: # loading packages
        import numpy as np
        import pandas as pd
        import os
        import torch as th

        import warnings
        warnings.simplefilter('ignore')

        indir = '/home/eileen/udacity/challenge2/FacialExpressions/fer2013'

        #listing data files
        for dirname, _, filenames in os.walk(indir):
            for filename in filenames:
                print(os.path.join(dirname, filename))
```

```
/home/eileen/udacity/challenge2/FacialExpressions/fer2013/fer2013.bib
/home/eileen/udacity/challenge2/FacialExpressions/fer2013/README
/home/eileen/udacity/challenge2/FacialExpressions/fer2013/fer2013.csv
```

```
In [3]: #looking at readme file
        with open(indir+'/README','r') as readme:
            contents = readme.read()
            print(contents)
```

```
If you use this dataset in your research work, please cite
```

"Challenges in Representation Learning: A report on three machine learning
contests." I Goodfellow, D Erhan, PL Carrier, A Courville, M Mirza, B
Hamner, W Cukierski, Y Tang, DH Lee, Y Zhou, C Ramaiah, F Feng, R Li,
X Wang, D Athanasakis, J Shawe-Taylor, M Milakov, J Park, R Ionescu,
M Popescu, C Grozea, J Bergstra, J Xie, L Romaszko, B Xu, Z Chuang, and
Y. Bengio. arXiv 2013.

See fer2013.bib for a bibtex entry.

```
In [4]: #looking at data file
        with open(indir+'/fer2013.csv','r') as f:
            firstline = f.readline()
            print(firstline)   # print header
            contents = f.readline()
            print(contents)    # print first row with data
```

```
emotion,pixels,Usage

0,70 80 82 72 58 58 60 63 54 58 60 48 89 115 121 119 115 110 98 91 84 84 90 99 110 126 143 153 1
171 177 178 180 194 101 55 65 60 47 55 65 63 59 58 63 57 52 90 105 117 122 130 143 153 157 163 1
164 158 159 154 140 78 21 11 61 144 168 173 157 138 150 148 132 159 182 183 136 106 116 95 106 1
```

2 Data Preparation

```
In [5]: #opening as panda dataframe and looking at "usage" column
        df = pd.read_csv(indir+'/fer2013.csv')
        df.Usage.unique()

Out[5]: array(['Training', 'PublicTest', 'PrivateTest'], dtype=object)

In [6]: df.shape

Out[6]: (35887, 3)

In [7]: df.head()

Out[7]:    emotion                                             pixels     Usage
        0        0  70 80 82 72 58 58 60 63 54 58 60 48 89 115 121...  Training
        1        0  151 150 147 155 148 133 111 140 170 174 182 15...  Training
        2        2  231 212 156 164 174 138 161 173 182 200 106 38...  Training
        3        4  24 32 36 30 32 23 19 20 30 41 21 22 32 34 21 1...  Training
        4        6  4 0 0 0 0 0 0 0 0 0 0 0 3 15 23 28 48 50 58 84...  Training

In [8]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 35887 entries, 0 to 35886
Data columns (total 3 columns):
emotion    35887 non-null int64
pixels     35887 non-null object
Usage      35887 non-null object
dtypes: int64(1), object(2)
memory usage: 841.2+ KB
```

2.1 creating 3 dataframes for training data, public testing data and private testing data

```
In [9]: train = df.query('Usage == "Training"')
        train.drop(columns=['Usage'], inplace=True)
        train.reset_index(drop=True, inplace=True)
        train.head()

Out[9]:    emotion                                             pixels
        0        0  70 80 82 72 58 58 60 63 54 58 60 48 89 115 121...
        1        0  151 150 147 155 148 133 111 140 170 174 182 15...
        2        2  231 212 156 164 174 138 161 173 182 200 106 38...
        3        4  24 32 36 30 32 23 19 20 30 41 21 22 32 34 21 1...
        4        6  4 0 0 0 0 0 0 0 0 0 0 0 3 15 23 28 48 50 58 84...

In [10]: public_test = df.query('Usage == "PublicTest"')
         public_test.drop(columns=['Usage'], inplace=True)
         public_test.reset_index(drop=True, inplace=True)
         public_test.head()

Out[10]:    emotion                                             pixels
         0        0  254 254 254 254 254 249 255 160 2 58 53 70 77 ...
         1        1  156 184 198 202 204 207 210 212 213 214 215 21...
         2        4  69 118 61 60 96 121 103 87 103 88 70 90 115 12...
         3        6  205 203 236 157 83 158 120 116 94 86 155 180 2...
         4        3  87 79 74 66 74 96 77 80 80 84 83 89 102 91 84 ...

In [11]: private_test = df.query('Usage == "PrivateTest"')
         private_test.drop(columns=['Usage'], inplace=True)
         private_test.reset_index(drop=True, inplace=True)
         private_test.head()

Out[11]:    emotion                                             pixels
         0        0  170 118 101 88 88 75 78 82 66 74 68 59 63 64 6...
         1        5  7 5 8 6 7 3 2 6 5 4 4 5 7 5 5 5 6 7 7 7 10 10 ...
         2        6  232 240 241 239 237 235 246 117 24 24 22 13 12...
         3        4  200 197 149 139 156 89 111 58 62 95 113 117 11...
         4        2  40 28 33 56 45 33 31 78 152 194 200 186 196 20...

In [12]: train.shape
```

Out[12]: (28709, 2)

In [13]: public_test.shape

Out[13]: (3589, 2)

In [14]: private_test.shape

Out[14]: (3589, 2)

2.2 converting to PyTorch tensors

In [15]:
```
def mk_labeltensor(dframe):
    """ creating a torch tensor from the emotion column
    dframe = dataframe
    """
    emotions = dframe['emotion'].values
    return th.tensor(emotions)
```

In [16]:
```
def mk_imagetensor(dframe):
    """ creating a torch tensor from the pixels column
    dframe = dataframe
    """
    pixels = dframe['pixels'].str.split(' ')
    dframe_images_list = pixels.apply(lambda x: list(int(i) for i in x))
    return th.tensor(dframe_images_list)
```

In [17]:
```
train_labels = mk_labeltensor(train)
train_images = mk_imagetensor(train)
print(train_labels.shape)
print(train_images.shape)
```

```
torch.Size([28709])
torch.Size([28709, 2304])
```

In [18]:
```
public_test_labels = mk_labeltensor(public_test)
public_test_images = mk_imagetensor(public_test)
print(public_test_labels.shape)
print(public_test_images.shape)
```

```
torch.Size([3589])
torch.Size([3589, 2304])
```

In [19]:
```
private_test_labels = mk_labeltensor(private_test)
private_test_images = mk_imagetensor(private_test)
print(private_test_labels.shape)
print(private_test_images.shape)
```

```
torch.Size([3589])
torch.Size([3589, 2304])
```

3 Linear Model

At first we will try out a linear model to recognize facial expressions.

3.1 Defining the Model

In [20]:
```
from torch import nn, optim
import torch.nn.functional as F
```

In [21]:
```
df.emotion.nunique()
```

Out[21]: 7

In [23]:
```
# for reproducible results:
seed = 30
np.random.seed(seed)
th.manual_seed(seed)
```

Out[23]: <torch._C.Generator at 0x7f01728beeb0>

In [24]:
```
# input: 48x48 pixels = 2304
# output: 7 different emotions
class Classifier(nn.Module):
    def __init__(self):
        super().__init__()
        self.fc1 = nn.Linear(2304, 1024)
        self.fc2 = nn.Linear(1024, 256)
        self.fc3 = nn.Linear(256, 64)
        self.fc4 = nn.Linear(64, 7)

        # Dropout module with 0.2 drop probability
        self.dropout = nn.Dropout(p=0.2)

    def forward(self, x):
        # making sure input tensor is flattened
        x = x.view(x.shape[0], -1)

        x = self.dropout(F.relu(self.fc1(x)))
        x = self.dropout(F.relu(self.fc2(x)))
        x = self.dropout(F.relu(self.fc3(x)))

        x = F.log_softmax(self.fc4(x), dim=1)

        return x
```

3.2 Training the Model

In [25]:
```
model = Classifier()
criterion = nn.NLLLoss()
```

```python
optimizer = optim.Adam(model.parameters(), lr=0.001)

epochs = 15
batch_size = 100
batches = round(train.shape[0]/batch_size)

acc, train_losses, test_losses = [], [], []
for e in range(epochs):
    running_loss = 0
    for i in range(batches):

        # Clear gradients
        optimizer.zero_grad()

        # Forward propagation
        start = i * batch_size
        end = start + batch_size
        log_ps = model(train_images[start:end].float())

        # Calculate loss
        loss = criterion(log_ps, train_labels[start:end])

        # Calculate gradients
        loss.backward()

        # Update parameters
        optimizer.step()

        running_loss += loss.item()

    else:
        test_loss = 0
        accuracy = 0

        # Validation
        with th.no_grad():
            model.eval()
            # Predict test dataset
            log_ps = model(public_test_images.float())
            test_loss += criterion(log_ps,public_test_labels)

            ps = th.exp(log_ps)
            top_p, top_class = ps.topk(1,dim=1)
            equals = top_class == public_test_labels.view(*top_class.shape)
            accuracy += th.mean(equals.type(th.FloatTensor))

        model.train()
```

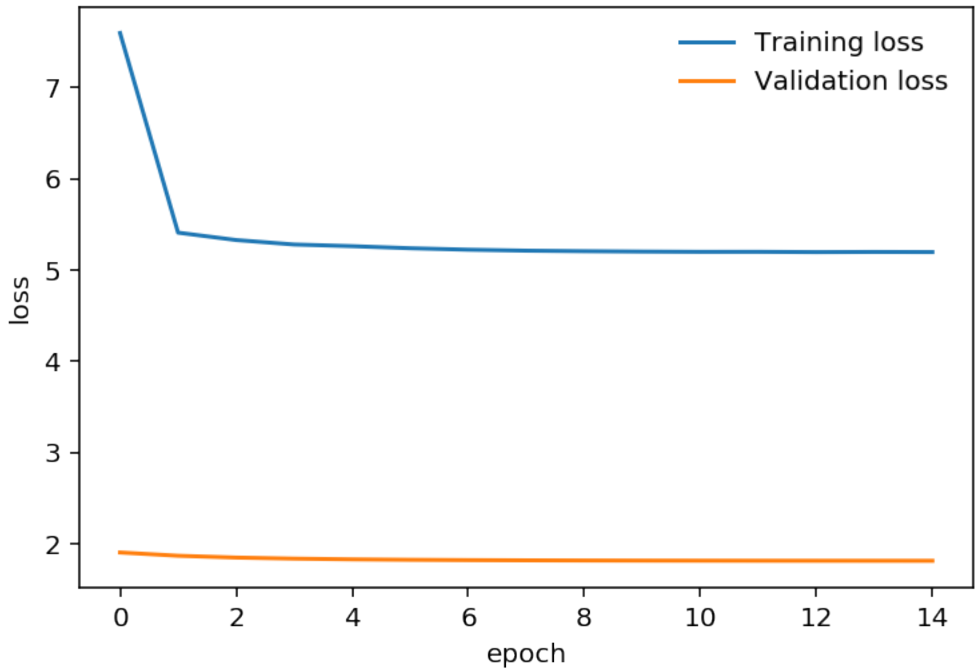
```
            train_losses.append(running_loss/batch_size)
            test_losses.append(test_loss)
            acc.append(accuracy)

            print("Epoch: {}/{}.. ".format(e+1, epochs),
                  "Training Loss: {:.3f}.. ".format(running_loss/batch_size),
                  "Test Loss: {:.3f}.. ".format(test_loss),
                  "Test Accuracy: {:.3f}".format(accuracy))
```

```
Epoch: 1/15..  Training Loss: 7.599..  Test Loss: 1.902..  Test Accuracy: 0.249
Epoch: 2/15..  Training Loss: 5.410..  Test Loss: 1.866..  Test Accuracy: 0.249
Epoch: 3/15..  Training Loss: 5.329..  Test Loss: 1.846..  Test Accuracy: 0.249
Epoch: 4/15..  Training Loss: 5.280..  Test Loss: 1.834..  Test Accuracy: 0.250
Epoch: 5/15..  Training Loss: 5.261..  Test Loss: 1.827..  Test Accuracy: 0.250
Epoch: 6/15..  Training Loss: 5.239..  Test Loss: 1.822..  Test Accuracy: 0.250
Epoch: 7/15..  Training Loss: 5.223..  Test Loss: 1.818..  Test Accuracy: 0.250
Epoch: 8/15..  Training Loss: 5.212..  Test Loss: 1.816..  Test Accuracy: 0.250
Epoch: 9/15..  Training Loss: 5.206..  Test Loss: 1.814..  Test Accuracy: 0.250
Epoch: 10/15..  Training Loss: 5.202..  Test Loss: 1.813..  Test Accuracy: 0.250
Epoch: 11/15..  Training Loss: 5.199..  Test Loss: 1.812..  Test Accuracy: 0.250
Epoch: 12/15..  Training Loss: 5.199..  Test Loss: 1.812..  Test Accuracy: 0.250
Epoch: 13/15..  Training Loss: 5.196..  Test Loss: 1.811..  Test Accuracy: 0.250
Epoch: 14/15..  Training Loss: 5.198..  Test Loss: 1.811..  Test Accuracy: 0.250
Epoch: 15/15..  Training Loss: 5.197..  Test Loss: 1.811..  Test Accuracy: 0.250
```

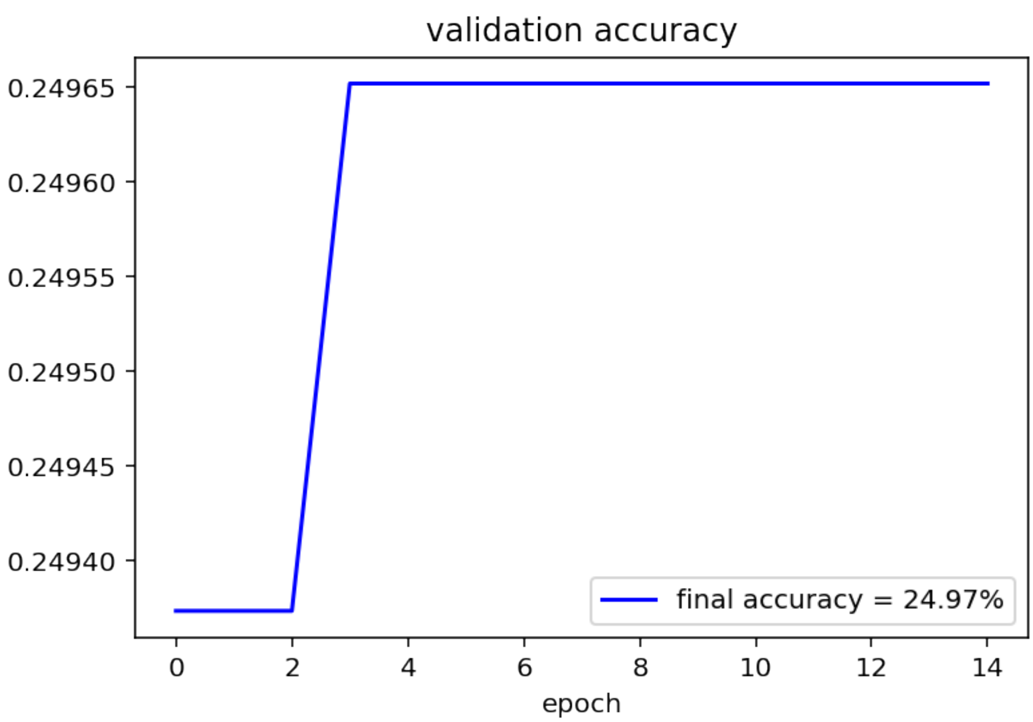
3.3 Plotting the Loss and the Accuracy

In [26]:
```
%matplotlib inline
%config InlineBackend.figure_format = 'retina'

import matplotlib.pyplot as plt
```

In [27]:
```
eps = range(epochs)
plt.plot(eps, train_losses, label='Training loss')
plt.plot(eps, test_losses, label='Validation loss')
plt.xlabel('epoch')
plt.ylabel('loss')
#plt.ylim(0,6.0)
plt.legend(frameon=False);
```




```
In [28]: plt.plot(eps, acc, 'b', label='Validation acc')
         plt.title('validation accuracy');
         plt.legend(['final accuracy = {:.2f}%'.format(accuracy * 100.0)])
         plt.xlabel('epoch');
```



3.3.1 Result

The accuracy does not go above 25%. That is better than guesswork (7 choices of emotions would give about 14-15% accuracy when guessing), but not really great. A different model structure might lead to better results.

4 Convolutional Neural Network (CNN)

A CNN model is our next try. Here we get very different results with different optimizers and learning rates. We have to try different structures.

```
In [29]: # we need to restructure the data, so that pixels are represented in a 48x48 format:
         train_images = train_images.view(train_images.shape[0],48,48)
         public_test_images = public_test_images.view(public_test_images.shape[0],48,48)
         private_test_images = private_test_images.view(private_test_images.shape[0],48,48)
         print(train_images.shape)
         print(public_test_images.shape)
         print(private_test_images.shape)
```

```
torch.Size([28709, 48, 48])
torch.Size([3589, 48, 48])
torch.Size([3589, 48, 48])
```

```
In [30]: # using dataloader for the images and labels
         import torch.utils.data

         def make_dataloader(data, batch_size, shuffle):
             images, labels = data['pixels'], data['emotion']
             images = np.array([np.fromstring(image, np.uint8, sep=' ') for image in images])
             images = images.reshape(images.shape[0], 1, 48, 48)
             dataset = torch.utils.data.TensorDataset(th.Tensor(images), th.Tensor(np.array(labe
             return th.utils.data.DataLoader(dataset=dataset, batch_size=batch_size, shuffle=shu

         trainloader = make_dataloader(train, 100, True)
         testloader = make_dataloader(public_test, 100, True)
         validloader = make_dataloader(private_test, 100, False)
```

4.1 With Adam Optimizer

4.1.1 Defining the Model

```
In [31]: # for reproducible results:
         seed = 30
         np.random.seed(seed)
         torch.manual_seed(seed)
```

```
Out[31]: <torch._C.Generator at 0x7f01728beeb0>
```

```
In [32]: class NetAdam(nn.Module):
             def __init__(self):
                 super(NetAdam, self).__init__()

                 self.conv1 = nn.Conv2d(1, 32, kernel_size=3)
                 self.conv2 = nn.Conv2d(32, 64, kernel_size=3)
                 self.conv3 = nn.Conv2d(64, 128, kernel_size=3)

                 self.fc1 = nn.Linear(2048, 1024) #784, 256)
                 self.fc2 = nn.Linear(1024, 256) #256, 128)
                 self.fc3 = nn.Linear(256, 64) #128, 64)
                 self.fc4 = nn.Linear(64, 7) #64, 10)

                 # Dropout module with 0.2 drop probability
                 self.dropout = nn.Dropout(p=0.2)

                 self.pool = nn.MaxPool2d(2)

             def forward(self, x):

                 x = self.pool(F.relu(self.conv1(x)))
                 x = self.pool(F.relu(self.conv2(x)))
                 x = self.pool(F.relu(self.conv3(x)))

                 x = x.view(x.shape[0], -1)
                 x = self.dropout(F.relu(self.fc1(x)))
                 x = self.dropout(F.relu(self.fc2(x)))
                 x = self.dropout(F.relu(self.fc3(x)))
                 x = F.log_softmax(self.fc4(x), dim=1)
                 return x
```

4.1.2 Training the Model

```
In [33]: model = NetAdam()
         criterion = nn.NLLLoss()
         optimizer = optim.Adam(model.parameters(), lr=0.001)

         epochs = 15

         acc, train_losses, test_losses = [], [], []
         for e in range(epochs):
             running_loss = 0
             for images, labels in trainloader:

                 # Clear gradients
                 optimizer.zero_grad()
```

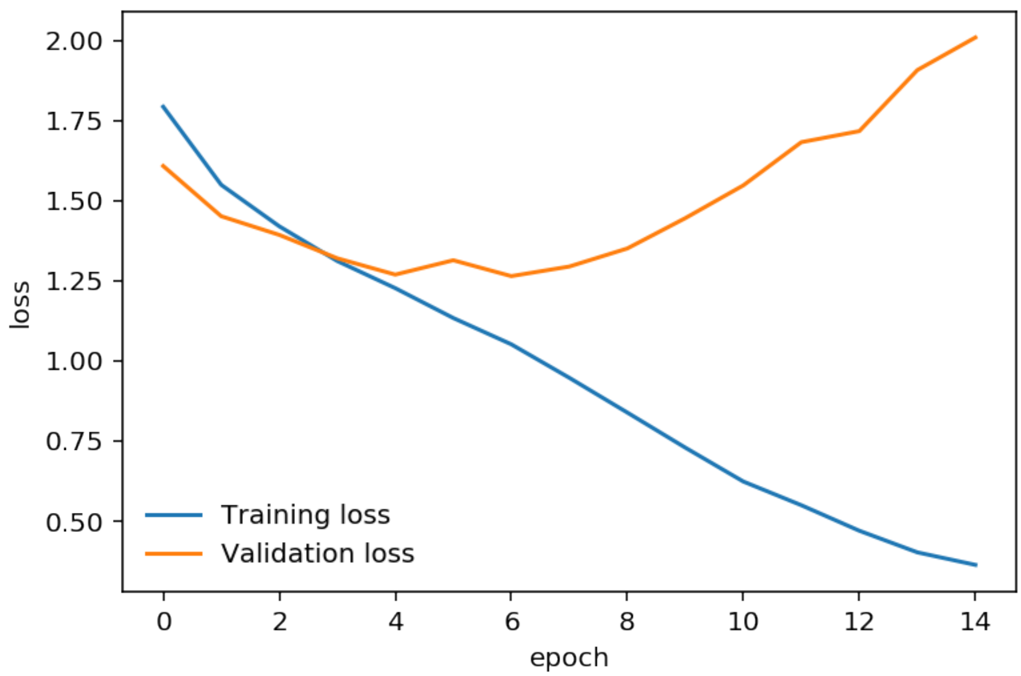
```
            # Forward propagation
            log_ps = model(images)

            # Calculate loss
            loss = criterion(log_ps, labels)

            # Calculate gradients
            loss.backward()

            # Update parameters
            optimizer.step()

            running_loss += loss.item()

        else:
            test_loss = 0
            accuracy = 0

            # Validation
            with th.no_grad():
                for images, labels in testloader:
                    model.eval()
                    # Predict test dataset
                    log_ps = model(images)
                    test_loss += criterion(log_ps,labels)

                    ps = th.exp(log_ps)
                    top_p, top_class = ps.topk(1,dim=1)
                    equals = top_class == labels.view(*top_class.shape)
                    accuracy += th.mean(equals.type(th.FloatTensor))

            model.train()

            train_losses.append(running_loss/len(trainloader))
            test_losses.append(test_loss/len(testloader))
            acc.append(accuracy/len(testloader))

            print("Epoch: {}/{}.. ".format(e+1, epochs),
                  "Training Loss: {:.3f}.. ".format(running_loss/len(trainloader)),
                  "Test Loss: {:.3f}.. ".format(test_loss/len(testloader)),
                  "Test Accuracy: {:.3f}".format(accuracy/len(testloader)))
```

```
Epoch: 1/15..  Training Loss: 1.793..  Test Loss: 1.608..  Test Accuracy: 0.376
Epoch: 2/15..  Training Loss: 1.549..  Test Loss: 1.451..  Test Accuracy: 0.444
Epoch: 3/15..  Training Loss: 1.420..  Test Loss: 1.393..  Test Accuracy: 0.473
Epoch: 4/15..  Training Loss: 1.311..  Test Loss: 1.320..  Test Accuracy: 0.497
Epoch: 5/15..  Training Loss: 1.226..  Test Loss: 1.269..  Test Accuracy: 0.520
```

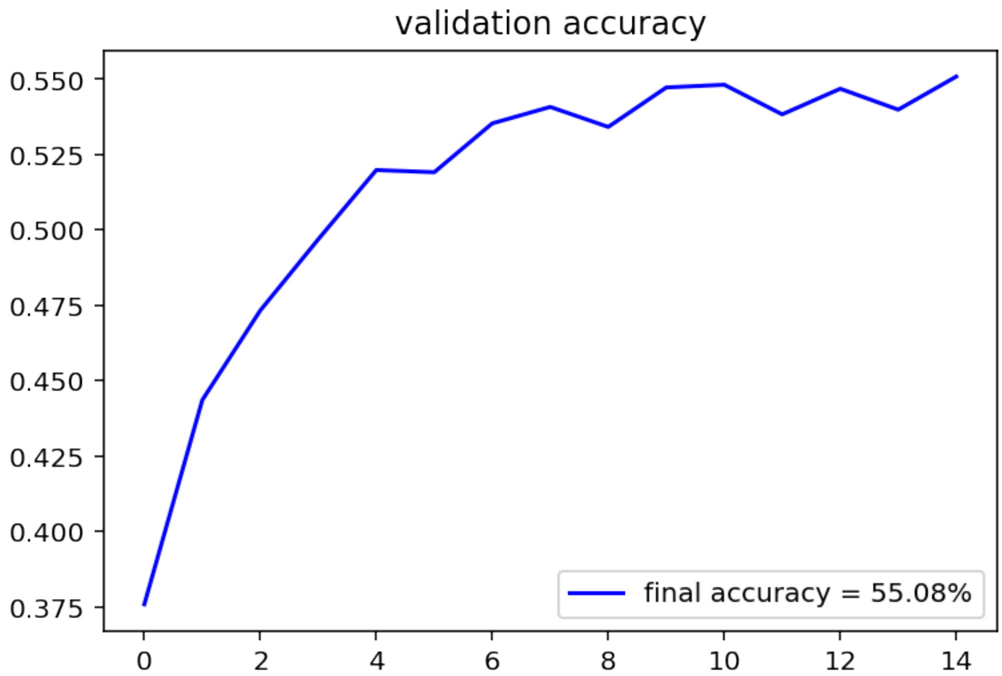
```
Epoch: 6/15..  Training Loss: 1.133..  Test Loss: 1.314..  Test Accuracy: 0.519
Epoch: 7/15..  Training Loss: 1.051..  Test Loss: 1.264..  Test Accuracy: 0.535
Epoch: 8/15..  Training Loss: 0.947..  Test Loss: 1.294..  Test Accuracy: 0.541
Epoch: 9/15..  Training Loss: 0.838..  Test Loss: 1.350..  Test Accuracy: 0.534
Epoch: 10/15..  Training Loss: 0.729..  Test Loss: 1.445..  Test Accuracy: 0.547
Epoch: 11/15..  Training Loss: 0.623..  Test Loss: 1.547..  Test Accuracy: 0.548
Epoch: 12/15..  Training Loss: 0.549..  Test Loss: 1.682..  Test Accuracy: 0.538
Epoch: 13/15..  Training Loss: 0.469..  Test Loss: 1.717..  Test Accuracy: 0.547
Epoch: 14/15..  Training Loss: 0.402..  Test Loss: 1.907..  Test Accuracy: 0.540
Epoch: 15/15..  Training Loss: 0.363..  Test Loss: 2.009..  Test Accuracy: 0.551
```

4.1.3 Plotting Loss and Accuracy

In [34]:
```python
eps = range(epochs)
plt.plot(eps, train_losses, label='Training loss')
plt.plot(eps, test_losses, label='Validation loss')
plt.xlabel('epoch')
plt.ylabel('loss')
plt.legend(frameon=False);
```



In [39]:
```python
plt.plot(eps, acc, 'b', label='Validation accuracy')
plt.title('validation accuracy');
plt.legend(['final accuracy = {:.2f}%'.format(acc[-1]*100)]);
```



This gives us an **accuracy of 55.1%** on the test set. This is already quite good, but we want to try if we can get better results with the SGD optimizer.

4.2 With SGD Optimizer

4.2.1 Defining the Model

```
In [40]: class NetSGD(nn.Module):
             def __init__(self):
                 super(NetSGD, self).__init__()

                 self.conv1 = nn.Conv2d(1, 32, kernel_size=3)
                 self.conv2 = nn.Conv2d(32, 64, kernel_size=3)
                 self.conv3 = nn.Conv2d(64, 128, kernel_size=3)

                 self.fc1 = nn.Linear(2048, 1024)
                 self.fc2 = nn.Linear(1024, 256)
                 self.fc3 = nn.Linear(256, 64)
                 self.fc4 = nn.Linear(64, 7)

                 # Dropout module with 0.3 drop probability
                 self.dropout = nn.Dropout(p=0.3)

                 self.pool = nn.MaxPool2d(2)

             def forward(self, x):
```

```
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = self.pool(F.relu(self.conv3(x)))

        x = x.view(x.shape[0], -1)
        x = self.dropout(F.relu(self.fc1(x)))
        x = self.dropout(F.relu(self.fc2(x)))
        x = self.dropout(F.relu(self.fc3(x)))
        x = F.log_softmax(self.fc4(x), dim=1)
        return x
```

4.2.2 Training the Model

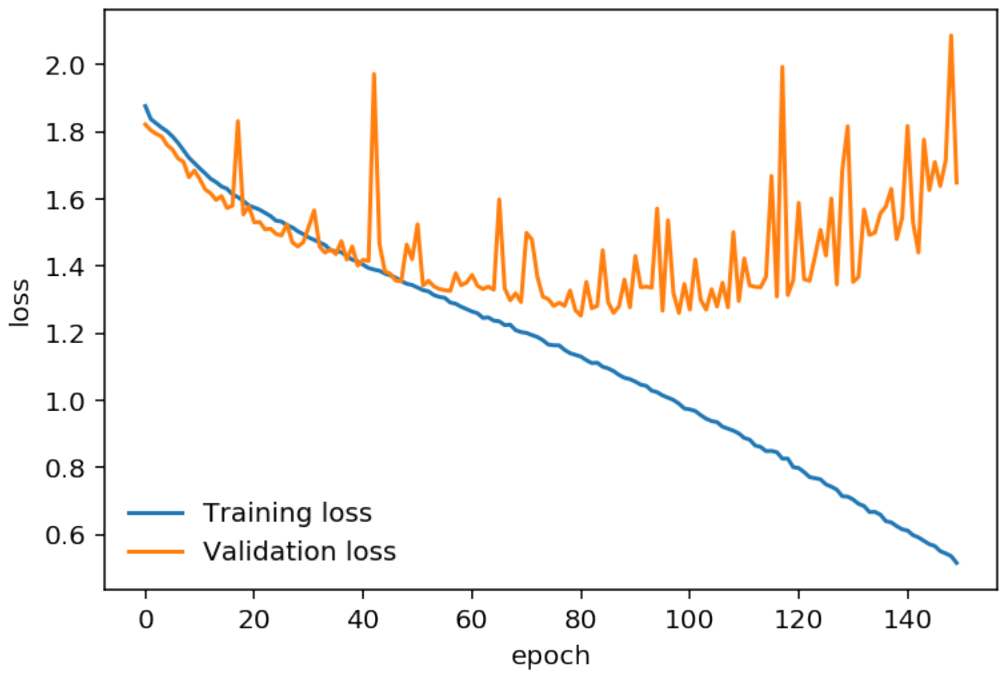
```
In [32]: modelSGD = NetSGD()
         criterion = nn.NLLLoss()
         optimizer = optim.SGD(model.parameters(), lr=0.001)

         epochs = 150

         acc, train_losses, test_losses = [], [], []
         for e in range(epochs):
             running_loss = 0
             for images, labels in trainloader:

                 # Clear gradients
                 optimizer.zero_grad()

                 # Forward propagation
                 log_ps = modelSGD(images)

                 # Calculate loss
                 loss = criterion(log_ps, labels)

                 # Calculate gradients
                 loss.backward()

                 # Update parameters
                 optimizer.step()

                 running_loss += loss.item()

             else:
                 test_loss = 0
                 accuracy = 0

                 # Validation
                 with th.no_grad():
```

```
                for images, labels in testloader:
                    model.eval()
                    # Predict test dataset
                    log_ps = modelSGD(images)
                    test_loss += criterion(log_ps,labels)

                    ps = th.exp(log_ps)
                    top_p, top_class = ps.topk(1,dim=1)
                    equals = top_class == labels.view(*top_class.shape)
                    accuracy += th.mean(equals.type(th.FloatTensor))

            model.train()

            train_losses.append(running_loss/len(trainloader))
            test_losses.append(test_loss/len(testloader))
            acc.append(accuracy/len(testloader))

            print("Epoch: {}/{}.. ".format(e+1, epochs),
                  "Training Loss: {:.3f}.. ".format(running_loss/len(trainloader)),
                  "Test Loss: {:.3f}.. ".format(test_loss/len(testloader)),
                  "Test Accuracy: {:.3f}".format(accuracy/len(testloader)))
```

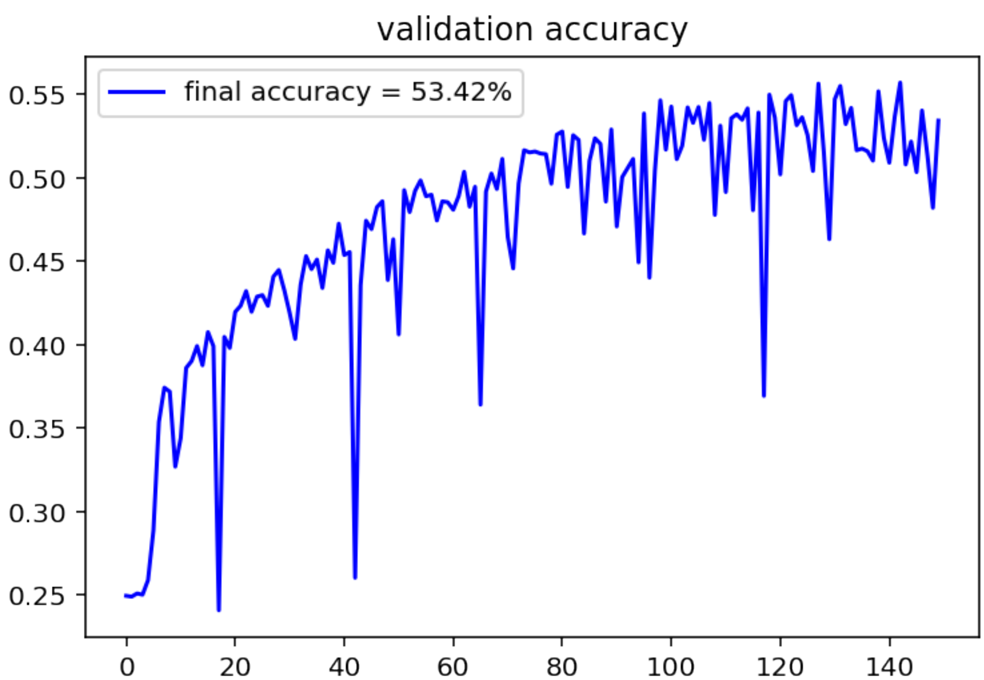
```
Epoch: 1/150..  Training Loss: 1.876..  Test Loss: 1.821..  Test Accuracy: 0.249
Epoch: 10/150..  Training Loss: 1.706..  Test Loss: 1.684..  Test Accuracy: 0.327
Epoch: 20/150..  Training Loss: 1.580..  Test Loss: 1.577..  Test Accuracy: 0.398
Epoch: 30/150..  Training Loss: 1.495..  Test Loss: 1.470..  Test Accuracy: 0.433
Epoch: 40/150..  Training Loss: 1.413..  Test Loss: 1.401..  Test Accuracy: 0.472
Epoch: 50/150..  Training Loss: 1.343..  Test Loss: 1.420..  Test Accuracy: 0.463
Epoch: 60/150..  Training Loss: 1.271..  Test Loss: 1.350..  Test Accuracy: 0.485
Epoch: 70/150..  Training Loss: 1.203..  Test Loss: 1.292..  Test Accuracy: 0.511
Epoch: 80/150..  Training Loss: 1.135..  Test Loss: 1.268..  Test Accuracy: 0.526
Epoch: 90/150..  Training Loss: 1.063..  Test Loss: 1.277..  Test Accuracy: 0.529
Epoch: 100/150..  Training Loss: 0.975..  Test Loss: 1.346..  Test Accuracy: 0.517
Epoch: 110/150..  Training Loss: 0.901..  Test Loss: 1.296..  Test Accuracy: 0.531
Epoch: 120/150..  Training Loss: 0.800..  Test Loss: 1.358..  Test Accuracy: 0.536
Epoch: 130/150..  Training Loss: 0.713..  Test Loss: 1.816..  Test Accuracy: 0.463
Epoch: 140/150..  Training Loss: 0.615..  Test Loss: 1.543..  Test Accuracy: 0.524
Epoch: 150/150..  Training Loss: 0.515..  Test Loss: 1.648..  Test Accuracy: 0.534
```

4.2.3 Plotting the Loss and Accuracy

```
In [48]: eps = range(epochs)
         plt.plot(eps, train_losses, label='Training loss')
         plt.plot(eps, test_losses, label='Validation loss')
         plt.xlabel('epoch')
         plt.ylabel('loss')
         plt.legend(frameon=False);
```




```
In [49]: plt.plot(eps, acc, 'b', label='Validation accuracy')
         plt.title('validation accuracy');
         plt.legend(['final accuracy = {:.2f}%'.format(acc[-1]*100)]);
```



Even after 150 epochs the **accuracy of 53.4%** is not higher than with Adam-Optimizer model with just 15 epochs, but training takes a lot longer. Therefore this model is not an improvement. We will try another model.

5 Another CNN Model

5.1 Data Preparation

```
In [52]: data = pd.read_csv(indir+'/fer2013.csv')
         print(data.shape)
```

```
(35887, 3)
```

```
In [53]: val_orig, test_orig, train_orig = data.groupby('Usage')
         print('val:',   val_orig[0])
         print('test:',  test_orig[0])
         print('train:', train_orig[0])
         print(val_orig[1].head(2))
```

```
val: PrivateTest
test: PublicTest
train: Training
       emotion                                             pixels        Usage
32298        0  170 118 101 88 88 75 78 82 66 74 68 59 63 64 6...  PrivateTest
32299        5  7 5 8 6 7 3 2 6 5 4 4 5 7 5 5 5 6 7 7 7 10 10 ...  PrivateTest
```

```
In [54]: val_data_orig, test_data_orig, train_data_orig = val_orig[1], test_orig[1], train_orig[
         print('val_data_orig.shape:  ', val_data_orig.shape)
         print('test_data_orig.shape: ',  test_data_orig.shape)
         print('train_data_orig.shape:', train_data_orig.shape)
```

```
val_data_orig.shape:   (3589, 3)
test_data_orig.shape:  (3589, 3)
train_data_orig.shape: (28709, 3)
```

```
In [55]: def prepare(data):
             images = np.array([np.fromstring(image, np.uint8, sep=' ') for image in data['pixel
             images = images.reshape(images.shape[0], 48, 48)
             images = np.stack((images,) * 3, axis=-1)
             labels = np.array(data['emotion'])
             return images, labels.reshape(len(labels), 1)

         val_data_orig_X,   val_data_orig_Y   = prepare(val_data_orig)
         test_data_orig_X,  test_data_orig_Y  = prepare(test_data_orig)
```

```
train_data_orig_X, train_data_orig_Y = prepare(train_data_orig)

print('val_data_orig_X.shape:   ', val_data_orig_X.shape)
print('val_data_orig_Y.shape:   ', val_data_orig_Y.shape)
print('test_data_orig_X.shape:  ', test_data_orig_X.shape)
print('test_data_orig_Y.shape:  ', test_data_orig_Y.shape)
print('train_data_orig_X.shape:', train_data_orig_X.shape)
print('train_data_orig_Y.shape:', train_data_orig_Y.shape)
```

```
val_data_orig_X.shape:   (3589, 48, 48, 3)
val_data_orig_Y.shape:   (3589, 1)
test_data_orig_X.shape:  (3589, 48, 48, 3)
test_data_orig_Y.shape:  (3589, 1)
train_data_orig_X.shape: (28709, 48, 48, 3)
train_data_orig_Y.shape: (28709, 1)
```

```
In [56]: train_data_Y = np.eye(7)[train_data_orig_Y.reshape(-1)]
         train_data_Y
```

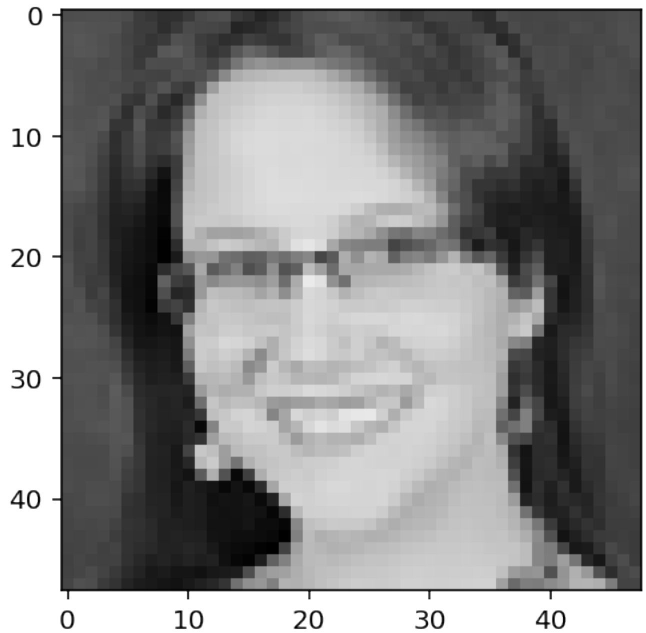
```
Out[56]: array([[1., 0., 0., ..., 0., 0., 0.],
                [1., 0., 0., ..., 0., 0., 0.],
                [0., 0., 1., ..., 0., 0., 0.],
                ...,
                [0., 0., 0., ..., 1., 0., 0.],
                [1., 0., 0., ..., 0., 0., 0.],
                [0., 0., 0., ..., 1., 0., 0.]])
```

```
In [57]: val_data_Y  = np.eye(7)[val_data_orig_Y.reshape(-1)]
         test_data_Y = np.eye(7)[test_data_orig_Y.reshape(-1)]
```

```
In [58]: emotions = ['Angry', 'Disgust', 'Fear', 'Happy', 'Sad', 'Surprise', 'Neutral']
```

```
In [59]: index = 7
         plt.imshow(train_data_orig_X[index])
         print('train_data_orig_Y:', train_data_orig_Y[index][0])
         print('emotion:', emotions[np.where(train_data_Y[index, :] == 1)[0][0]])
```

```
train_data_orig_Y: 3
emotion: Happy
```



5.2 Training the Model

```
In [61]: import tensorflow as tf
         from tensorflow.python.framework import ops
         import math
```

```
In [62]: def create_placeholders(n_H0, n_W0, n_C0, n_y):
             X = tf.placeholder(tf.float32, shape=[None, n_H0, n_W0, n_C0])
             Y = tf.placeholder(tf.float32, shape=[None, n_y])

             return X, Y
         X, Y = create_placeholders(48, 48, 3, 7)
         print('X:', X)
         print('Y:', Y)
```

```
X: Tensor("Placeholder:0", shape=(?, 48, 48, 3), dtype=float32)
Y: Tensor("Placeholder_1:0", shape=(?, 7), dtype=float32)
```

```
In [64]: def initialize_parameters():
             W1 = tf.get_variable('W1', [4, 4, 3, 8], initializer=tf.contrib.layers.xavier_initi
             W2 = tf.get_variable('W2', [2, 2, 8, 16], initializer=tf.contrib.layers.xavier_init

             parameters = {'W1' : W1,
                           'W2' : W2}

             return parameters
```

```
In [65]: tf.reset_default_graph()
         with tf.Session() as sess_test:
             parameters = initialize_parameters()
             init = tf.global_variables_initializer()
             sess_test.run(init)
             print("W1 = " + str(parameters["W1"].eval()[1, 1, 1]))
             print("W2 = " + str(parameters["W2"].eval()[1, 1, 1]))
```

```
WARNING: Logging before flag parsing goes to stderr.
W0819 13:40:09.734265 139644989413120 lazy_loader.py:50]
The TensorFlow contrib module will not be included in TensorFlow 2.0.
For more information, please see:
  * https://github.com/tensorflow/community/blob/master/rfcs/20180907-contrib-sunset.md
  * https://github.com/tensorflow/addons
  * https://github.com/tensorflow/io (for I/O related ops)
If you depend on functionality not listed there, please file an issue.



W1 = [-0.1320848   0.10930885 -0.00154065  0.15939452 -0.18380184  0.15448336
  0.02520965 -0.0548813 ]
W2 = [ 0.01906937 -0.09174544 -0.10848433 -0.08736813  0.01733667  0.03061759
 -0.029899    0.13276094  0.21292257  0.02214384  0.11686075  0.14175373
 -0.02699548 -0.18018472  0.16310841 -0.17431891]
```

```
In [66]: def forward_propagation(X, parameters):
             W1 = parameters['W1']
             W2 = parameters['W2']

             Z1 = tf.nn.conv2d(X, W1, strides=[1,1,1,1], padding='SAME')
             A1 = tf.nn.relu(Z1)
             P1 = tf.nn.max_pool(A1, ksize = [1,4,4,1], strides = [1,4,4,1], padding = 'SAME')

             Z2 = tf.nn.conv2d(P1, W2, strides=[1,1,1,1], padding='SAME')
             A2 = tf.nn.relu(Z2)
             P2 = tf.nn.max_pool(A2, ksize = [1,2,2,1], strides = [1,2,2,1], padding = 'SAME')

             F = tf.contrib.layers.flatten(P2)
             Z3 = tf.contrib.layers.fully_connected(F,   120, activation_fn=tf.nn.relu)
             Z4 = tf.contrib.layers.fully_connected(Z3,   64, activation_fn=tf.nn.relu)
             Z5 = tf.contrib.layers.fully_connected(Z4,    7,   activation_fn=None)

             return Z5
```

```
In [67]: tf.reset_default_graph()

         with tf.Session() as sess:
             X, Y = create_placeholders(48, 48, 3, 7)
```

```
    parameters = initialize_parameters()
    Z3 = forward_propagation(X, parameters)
    init = tf.global_variables_initializer()
    sess.run(init)
    a = sess.run(Z3, {X: np.random.randn(2, 48, 48, 3), Y: np.random.randn(2, 7)})
    print("Z = " + str(a))
```

```
W0819 13:40:18.304095 139644989413120 deprecation.py:323] From /home/eileen/anaconda3/lib/python
Instructions for updating:
Use keras.layers.flatten instead.


Z = [[ 0.17071213 -1.5759544   0.2636412  -0.85942864  0.29739666  0.14196292
  -0.62942433]
 [ 0.24379545 -1.5965977  -0.12846392 -0.6421461   0.56848305 -0.07953613
  -0.45063743]]
```

```
In [68]: def compute_cost(Z, Y):

             cost = tf.reduce_mean( tf.nn.softmax_cross_entropy_with_logits(logits = Z, labels =

             return cost
```

```
In [69]: tf.reset_default_graph()

         with tf.Session() as sess:
             X, Y = create_placeholders(48, 48, 3, 7)
             parameters = initialize_parameters()
             Z3 = forward_propagation(X, parameters)
             cost = compute_cost(Z3, Y)
             init = tf.global_variables_initializer()
             sess.run(init)
             a = sess.run(cost, {X: np.random.randn(4, 48, 48, 3), Y: np.random.randn(4, 7)})
             print("cost = " + str(a))
```

```
W0819 13:40:22.518725 139644989413120 deprecation.py:323] From <ipython-input-68-91edf5235ec9>:3
Instructions for updating:

Future major versions of TensorFlow will allow gradients to flow
into the labels input on backprop by default.

See `tf.nn.softmax_cross_entropy_with_logits_v2`.



cost = -2.501046
```

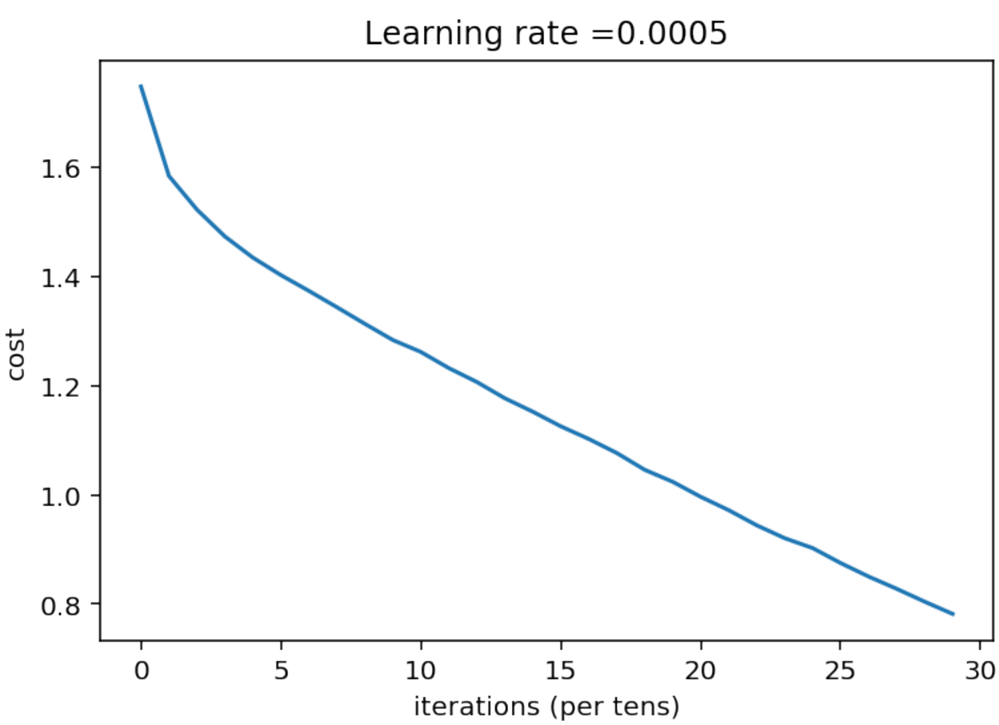
```
In [70]: def random_mini_batches(X, Y, mini_batch_size = 64):
             m = X.shape[0]                  # number of training examples
             mini_batches = []

             # Step 1: Shuffle (X, Y)
             permutation = list(np.random.permutation(m))
             shuffled_X = X[permutation,:,:,:]
             shuffled_Y = Y[permutation,:]

             # Step 2: Partition (shuffled_X, shuffled_Y). Minus the end case.
             num_complete_minibatches = math.floor(m/mini_batch_size) # number of mini batches c
             for k in range(0, num_complete_minibatches):
                 mini_batch_X = shuffled_X[k * mini_batch_size : k * mini_batch_size + mini_batc
                 mini_batch_Y = shuffled_Y[k * mini_batch_size : k * mini_batch_size + mini_batc
                 mini_batch = (mini_batch_X, mini_batch_Y)
                 mini_batches.append(mini_batch)

             # Handling the end case (last mini-batch < mini_batch_size)
             if m % mini_batch_size != 0:
                 mini_batch_X = shuffled_X[num_complete_minibatches * mini_batch_size : m,:,:,:]
                 mini_batch_Y = shuffled_Y[num_complete_minibatches * mini_batch_size : m,:]
                 mini_batch = (mini_batch_X, mini_batch_Y)
                 mini_batches.append(mini_batch)

             return mini_batches

In [71]: def model(X_train, Y_train, X_test, Y_test, learning_rate = 0.0005,
                   num_epochs = 30, minibatch_size = 50, print_cost = True):
             ops.reset_default_graph()                        # to be able to rerun the model w
             (m, n_H0, n_W0, n_C0) = X_train.shape
             n_y = Y_train.shape[1]
             costs = []                                       # To keep track of the cost
             accurancies = []

             X, Y = create_placeholders(n_H0, n_W0, n_C0, n_y)

             parameters = initialize_parameters()

             Z3 = forward_propagation(X, parameters)

             cost = compute_cost(Z3, Y)

             optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate).minimize(cost)

             init = tf.global_variables_initializer()
             gpu_options = tf.GPUOptions(per_process_gpu_memory_fraction=0.333)
```

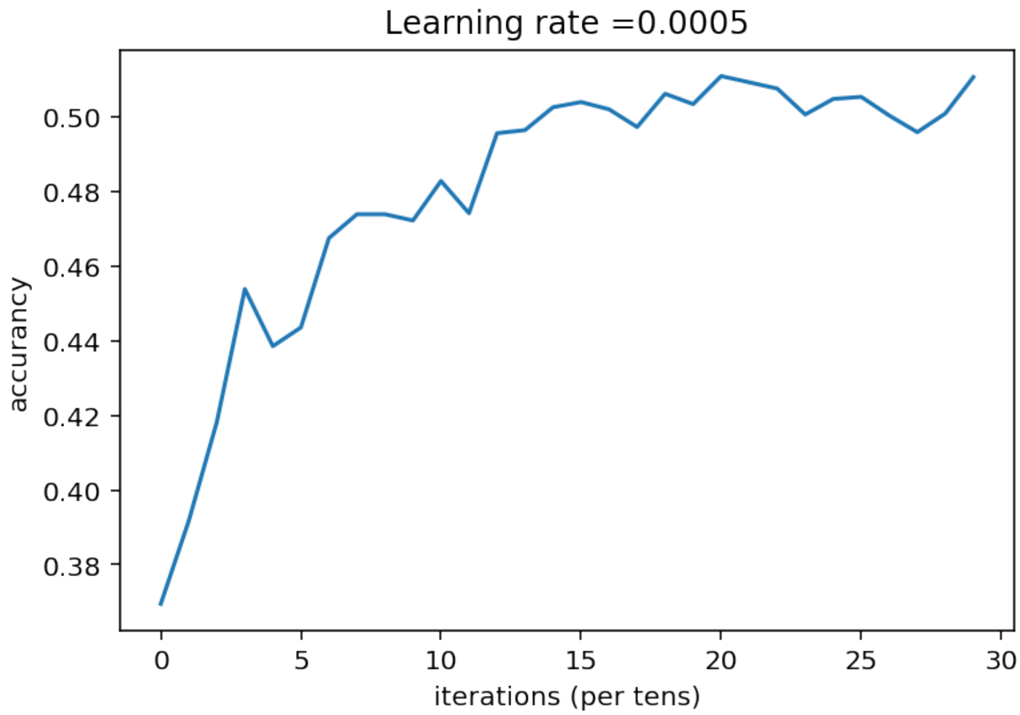
```
with tf.Session() as sess:
        # Run the initialization
        sess.run(init)

        # Do the training loop
        for epoch in range(num_epochs):

            minibatch_cost = 0.
            num_minibatches = int(m / minibatch_size) # number of minibatches of si
            minibatches = random_mini_batches(X_train, Y_train, minibatch_size)

            for minibatch in minibatches:

                # Select a minibatch
                (minibatch_X, minibatch_Y) = minibatch

                _ , temp_cost = sess.run([optimizer, cost], feed_dict={X: minibatch

                minibatch_cost += temp_cost / num_minibatches


            # Print the cost every epoch
            if print_cost == True and epoch % 5 == 0:
                print ("Cost after epoch %i: %f" % (epoch, minibatch_cost))

            if print_cost == True and epoch % 1 == 0:
                costs.append(minibatch_cost)
                # Calculate the correct predictions
                predict_op = tf.argmax(Z3, 1)
                correct_prediction = tf.equal(predict_op, tf.argmax(Y, 1))

                # Calculate accuracy on the test set
                accuracy = tf.reduce_mean(tf.cast(correct_prediction, "float"))
                test_accuracy = accuracy.eval({X: X_test, Y: Y_test})
                accurancies.append(test_accuracy)


        # plot the cost
        plt.plot(np.squeeze(costs))
        plt.ylabel('cost')
        plt.xlabel('iterations (per tens)')
        plt.title("Learning rate =" + str(learning_rate))
        plt.show()

        # plot the accurancies
        plt.plot(np.squeeze(accurancies))
        plt.ylabel('accurancy')
        plt.xlabel('iterations (per tens)')
```

```
    plt.title("Learning rate =" + str(learning_rate))
    plt.show()

    # Calculate the correct predictions
    predict_op = tf.argmax(Z3, 1)
    correct_prediction = tf.equal(predict_op, tf.argmax(Y, 1))

    # Calculate accuracy on the test set
    accuracy = tf.reduce_mean(tf.cast(correct_prediction, "float"))
    print(accuracy)
    train_accuracy = accuracy.eval({X: X_train, Y: Y_train})
    test_accuracy = accuracy.eval({X: X_test, Y: Y_test})
    print("Train Accuracy:", train_accuracy)
    print("Test Accuracy:", test_accuracy)

    return train_accuracy, test_accuracy, parameters
```

```
In [72]: _, _, parameters = model(train_data_orig_X/255, train_data_Y, test_data_orig_X/255, tes
```

```
Cost after epoch 0: 1.747928
Cost after epoch 5: 1.402561
Cost after epoch 10: 1.261864
Cost after epoch 15: 1.125621
Cost after epoch 20: 0.996478
Cost after epoch 25: 0.875181
```






```
Tensor("Mean_31:0", shape=(), dtype=float32)
Train Accuracy: 0.74561983
Test Accuracy: 0.5107272
```

This model gives us an **accuracy score of 51.1%**, but with much faster training. We will try another model type to see if we can improve our accuracy.

```
In [ ]:
```

6 ResNet Models

6.1 Data Preparation

We start with loading packages and setting seeds to 0 for reproducible results

```
In [1]: import random
        import numpy as np # linear algebra
        import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
        import torch
        import torch.utils.data
```

```
import matplotlib.pyplot as plt

# set all seed to 0
random.seed(0)
np.random.seed(0)
torch.manual_seed(0)
torch.cuda.manual_seed(0)
torch.backends.cudnn.deterministic = True
```

We import data from csv file and split it into 3 groups: training - for our models training, validation - for models' evaluation and tuning hyperparametrs during training, testing - for evaluation of the final model.

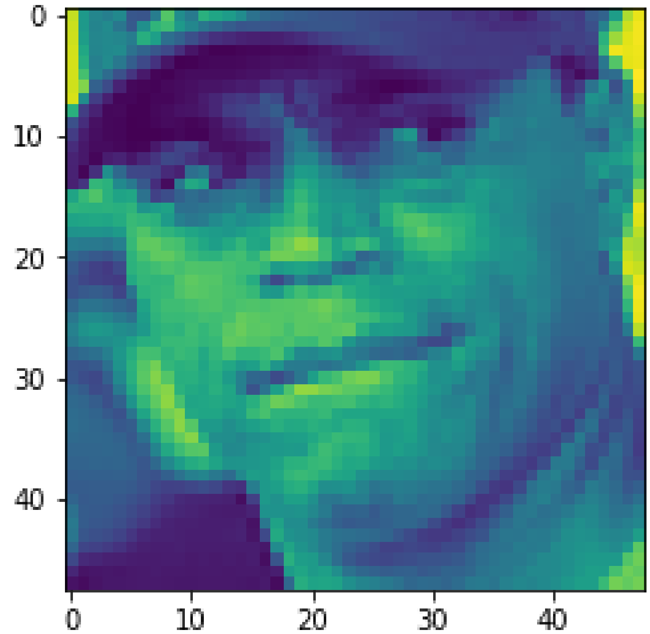
```
In [2]: # read data
        all_data = pd.read_csv("../input/fer2013/fer2013.csv")

In [3]: # split to 3 parts
        groups = [g for _, g in all_data.groupby('Usage')]
        training_data = groups[2]
        validation_data = groups[1]
        testing_data = groups[0]
```

As last step of data preparation, we process groups: transform Dataframes to DataLoader and reshape images array from 1D to 2D. At the same time data will be moved to GPU if it is available:

```
In [4]: device = torch.device('cuda:0' if torch.cuda.is_available() else 'cpu')
        label_names = ['Angry', 'Disgust', 'Fear', 'Happy', 'Sad', 'Surprise', 'Neutral']
        def make_dataloader(data, batch_size, shuffle):
            images, labels = data['pixels'], data['emotion']
            images = np.array([np.fromstring(image, np.uint8, sep=' ') for image in images]) / 2
            images = torch.FloatTensor(images.reshape(images.shape[0], 1, 48, 48)).to(device) #
            dataset = torch.utils.data.TensorDataset(images, torch.LongTensor(np.array(labels)).
            return torch.utils.data.DataLoader(dataset=dataset, batch_size=batch_size, shuffle=s

In [5]: train_loader = make_dataloader(training_data, 100, True)
        valid_loader = make_dataloader(validation_data, 100, False)
```

Let's look at data:

```
In [6]: dataiter = iter(train_loader)
        images, labels = dataiter.next()
        print(label_names[labels[1]])
        plt.imshow(images[1].view(48, 48).cpu());

Angry
```



6.2 Training the Models

In this project we will be using ResNet models from torchvision package. Models will be trained in two steps: 1. ResNet18 model trained with different learning rate 2. ResNet50 and ResNet152 models trained with learning rate that showed the best result with ResNet18 For all models, we will be using CrossEntropyLoss loss function and SGD optimizer. Results of training of different models will be compared and the best performing one will be selected for final tests.

We will need to change the first convolutional layer and the last fully connected layer n the loaded models to fit our data (1 color channel for pictures and 7 classes).

```
In [7]: import torch.nn as nn
        def adjust_model(model):
            model.conv1 = nn.Conv2d(1, 64, model.conv1.kernel_size, model.conv1.stride, model.co
            model.fc = nn.Linear(model.fc.in_features, 7, bias=False)
            return model
```

Each model will be trained with 100 epoches

```
In [8]: epochs = 100
```

```
In [9]: def eval_model(model, data_loader, criterion):
            model.eval()
            with torch.no_grad():
                accuracy = 0
                loss = 0
                for data, labels in data_loader:
```

```
                output = model(data)
                _, preds = torch.max(output.data, 1)
                equals = (preds == labels).cpu()
                accuracy += torch.mean(equals.type(torch.FloatTensor)).item()
                loss += criterion(output, labels).data.cpu()
            return accuracy/len(data_loader), loss/len(data_loader)

    def train_model(model, criterion, optimizer, data_loader, eval_loader):
        model = model.to(device)
        test_accuracy_history = []
        test_loss_history = []
        for epoch in range(epochs):
            model.train()
            for data, labels in data_loader:
                optimizer.zero_grad()
                output = model(data)
                loss = criterion(output, labels)
                loss.backward()
                optimizer.step()

            accuracy, loss = eval_model(model, eval_loader, criterion)
            test_accuracy_history.append(accuracy)
            test_loss_history.append(loss)
        return test_accuracy_history, test_loss_history
```

6.3 PART1: Same model - different learning rate

We start with ResNet18 model and five different learning rates:

```
In [10]: from torch import optim
         from torchvision import models
         criterion = nn.CrossEntropyLoss()
         lrs = [0.1, 0.01, 0.001, 0.0001, 0.000001]
         models_1 = [adjust_model(models.resnet18()) for i in range(len(lrs))]
         optimizers = [optim.SGD(models_1[i].parameters(), lr=lrs[i], momentum=0.9) for i in ran
```

```
In [ ]: for i in range(len(lrs)):
            accuracy, loss = train_model(models_1[i], criterion, optimizers[i], train_loader, va
            torch.save(accuracy, 'ResNet18_lr_'+ str(lrs[i]) + '_accuracy.pt')
            torch.save(loss, 'ResNet18_lr_'+ str(lrs[i]) + '_loss.pt')
            torch.save(models_1[i], 'ResNet18_lr_'+ str(lrs[i]) + '_model.pt')
```

Since it takes very long time to train model, it was done offline and the results were saved in files, that we can load now.

```
In [19]: resnet18_accuracy = [torch.load("../input/fer2013-results/results/ResNet18_lr_0.1_accur
                         torch.load("../input/fer2013-results/results/ResNet18_lr_0.01_accuracy.pt")
                         torch.load("../input/fer2013-results/results/ResNet18_lr_0.001_accuracy.pt"
                         torch.load("../input/fer2013-results/results/ResNet18_lr_0.0001_accuracy.pt
```

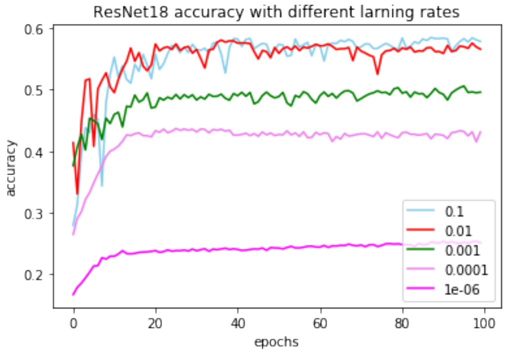
```
                torch.load("../input/fer2013-results/results/ResNet18_lr_1e-06_accuracy.pt"

resnet18_loss = [torch.load("../input/fer2013-results/results/ResNet18_lr_0.1_loss.pt")
                 torch.load("../input/fer2013-results/results/ResNet18_lr_0.01_loss.pt"
                 torch.load("../input/fer2013-results/results/ResNet18_lr_0.001_loss.pt
                 torch.load("../input/fer2013-results/results/ResNet18_lr_0.0001_loss.p
                 torch.load("../input/fer2013-results/results/ResNet18_lr_1e-06_loss.pt
```

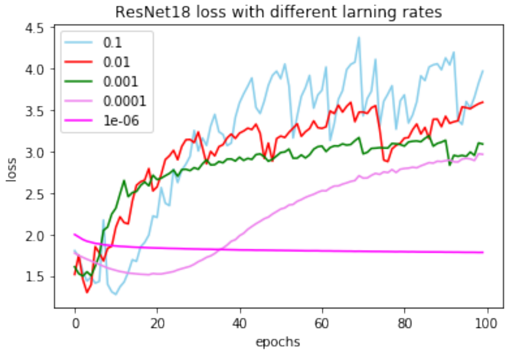
From the loss data we can see, that first model reach minimum loss at epoch 11. The second and third models reach minimum losses at 3d and 4th epochs. Even though loss starts to increase after this, the accuracy with the validation set is also growing for all three models. The model with 0.1 learning rate shows the best accuracy of all models - 57.81%. The model with 0.0001 learing rate has minimum loss at epoch 19, and model with least learning rate of 1e-06 doesn't reach minimum (the loss will keep going down if we increase number of epochs).

The results show that lower learning rate results in lower accuracy with ResNet18:

In [17]:
```
colors = ['skyblue', 'red', 'green', 'violet', 'magenta']

def make_plots(accuracy, losses, title1, title2, lbls):
    fig = plt.figure()
    ax1 = fig.add_subplot(1, 2, 1)
    ax1.title.set_text(title1)
    for i in range(len(accuracy)):
        ax1.plot(range(epochs),accuracy[i], color=colors[i],label=lbls[i])
    ax1.set_xlabel('epochs');
    ax1.set_ylabel('accuracy')
    ax1.legend(loc='lower right')

    ax2 = fig.add_subplot(1, 2, 2)
    ax2.title.set_text(title2)
    for i in range(len(losses)):
        ax2.plot(range(epochs),losses[i], color=colors[i],label=lbls[i])
    ax2.set_xlabel('epochs');
    ax2.set_ylabel('loss')
    ax2.legend(loc='upper left')
    plt.subplots_adjust(wspace=0.35, right=2.0)
    plt.show()
```

In [20]:
```
title1 = 'ResNet18 accuracy with different larning rates'
title2 = 'ResNet18 loss with different larning rates'
make_plots(resnet18_accuracy, resnet18_loss, title1, title2, [str(lr) for lr in lrs])
```






```
In [22]: def print_acc_loss_results(name_tag, var_s, accs, losses):
             min_inds = []
             print("Min losses:")
             for i in range (len(losses)):
                 min_v = min(losses[i])
                 min_ind = losses[i].index(min_v)
                 min_inds.append(min_ind)
                 print(name_tag + ' {}: Loss {:.5f} at the epoch # {}'.format(var_s[i],min_v, mi
             print("\nResulting accuracies:")
             for i in range (len(accs)):
                 print(name_tag + ' {}: Accuracy {:.2f}'.format(var_s[i],np.mean(accs[i][-10:-1]
             print("\nAccuracies at minimal loss epoch:")
             for i in range (len(accs)):
                 print(name_tag + ' {}: Accuracy {:.2f} at the epoch # {}'.format(var_s[i],accs[
```

```
In [23]: print_acc_loss_results('Learning rate', lrs, resnet18_accuracy, resnet18_loss)
```

```
Min losses:
Learning rate 0.1: Loss 1.27637 at the epoch # 11
Learning rate 0.01: Loss 1.29977 at the epoch # 4
Learning rate 0.001: Loss 1.49811 at the epoch # 3
Learning rate 0.0001: Loss 1.51452 at the epoch # 19
Learning rate 1e-06: Loss 1.78318 at the epoch # 99

Resulting accuracies:
Learning rate 0.1: Accuracy 57.81
Learning rate 0.01: Accuracy 56.77
Learning rate 0.001: Accuracy 49.62
Learning rate 0.0001: Accuracy 42.72
Learning rate 1e-06: Accuracy 25.22

Accuracies at minimal loss epoch:
Learning rate 0.1: Accuracy 55.29 at the epoch # 11
Learning rate 0.01: Accuracy 51.52 at the epoch # 4
```

```
Learning rate 0.001: Accuracy 42.77 at the epoch # 3
Learning rate 0.0001: Accuracy 42.52 at the epoch # 19
Learning rate 1e-06: Accuracy 25.37 at the epoch # 99
```

6.4 PART2: ResNet50 and ResNet152 models with best learning rate

The learning rate of 0.1 showed best results with ResNet18. We will use it to train ResNet50 and ResNet152 models and compare results with previously trained ResNet18 at the same learning rate.

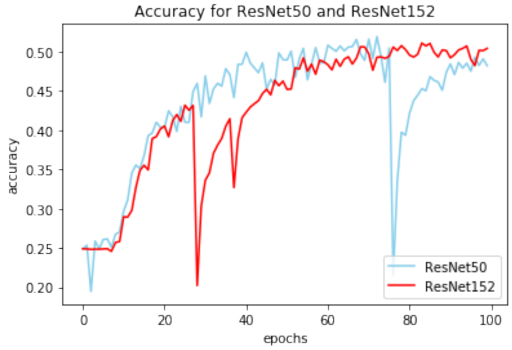
In [24]:
```
models_2 = [adjust_model(models.resnet50()), adjust_model(models.resnet152())]
optimizers_2 = [optim.SGD(models_2[i].parameters(), lr=0.1, momentum=0.9) for i in rang
names = ['ResNet50', 'ResNet152']
```

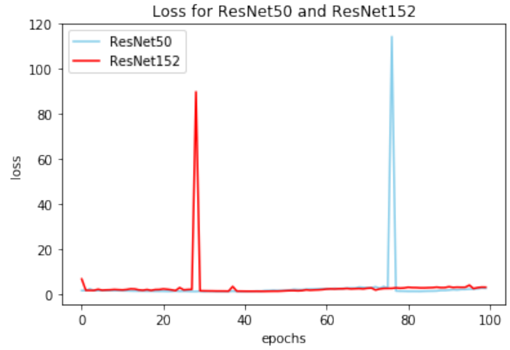
In [ ]:
```
for i in range(len(names)):
    accuracy, loss = train_model(models_2[i], criterion, optimizers_2[i], train_loader,
    torch.save(accuracy, names[i] + '_0.1_accuracy.pt')
    torch.save(loss, names[i] + '_0.1_loss.pt')
    torch.save(models_2[i], names[i] + '_0.1_model.pt')
```

ResNet50 and ResNet152 showed worse results compared to ResNet18: resulting accuracy was 48.3.79% and 49.75% for ResNet50 and ResNet152 respectivly.

In [26]:
```
resnet50_152_accuracy = [torch.load("../input/fer2013-results/results/ResNet50_0.1_accu
                         torch.load("../input/fer2013-results/results/ResNet152_0.1_accuracy.pt")]

resne50_152_loss = [torch.load("../input/fer2013-results/results/ResNet50_0.1_loss.pt")
                    torch.load("../input/fer2013-results/results/ResNet152_0.1_loss.pt")]
```

In [27]:
```
title1 = 'Accuracy for ResNet50 and ResNet152'
title2 = 'Loss for ResNet50 and ResNet152'
make_plots(resnet50_152_accuracy, resne50_152_loss, title1, title2, names)
```





In [28]:
```
print_acc_loss_results('Model', names, resnet50_152_accuracy, resne50_152_loss)
```

```
Min losses:
Model ResNet50: Loss 1.40201 at the epoch # 31
Model ResNet152: Loss 1.47128 at the epoch # 46

Resulting accuracies:
Model ResNet50: Accuracy 48.30
Model ResNet152: Accuracy 49.75

Accuracies at minimal loss epoch:
Model ResNet50: Accuracy 46.92 at the epoch # 31
Model ResNet152: Accuracy 45.21 at the epoch # 46
```

6.5 Testing best model on Test dataset

ResNet18 with learning rate 0.1 showed best results on validation dataset. Therefore it was chosen as our final model and will be tested with test dataset

```
In [29]: test_loader = make_dataloader(testing_data, 100, False)
         model_best = torch.load('../input/fer2013-results/results/ResNet18_lr_0.1_model.pt')
         acc, losses = eval_model(model_best, test_loader, criterion)
```

```
In [30]: print('Test accuracy: ' + str(acc*100))
```

```
Test accuracy: 58.59893825319078
```

The test accuracy of ResNet18 model trained with 0.1 learing rate on FER2013 dataset is **58.6%**.

7 Conclusion

Recognizing facial expressions from images is not trivial and a simple linear model is not sufficient. We have tried different model types and received quite good results with CNN models. However, the best result we got with the ResNet18 model. In the end we had 58.6% accuracy on the test data (which is by now published including the labels, since the kaggle competition has long ended). This might not be good enough to be used in production, but a very good start.