Лабораторная работа №4

Реализация приложения по распознаванию номеров домов

Набор изображений из *Google Street View* с изображениями номеров домов, содержащий 10 классов, соответствующих цифрам от 0 до 9.

- 73257 изображений цифр в обучающей выборке;
- 26032 изображения цифр в тестовой выборке;
- 531131 изображения, которые можно использовать как дополнение к обучающей выборке;
- В двух форматах:
  - Оригинальные изображения с выделенными цифрами;
  - Изображения размером 32×32, содержащие одну цифру;
- Данные первого формата можно скачать по ссылкам:
  - http://ufldl.stanford.edu/housenumbers/train.tar.gz (http://ufldl.stanford.edu/housenumbers/train.tar.gz) (обучающая выборка);
  - http://ufldl.stanford.edu/housenumbers/test.tar.gz (http://ufldl.stanford.edu/housenumbers/test.tar.gz) (тестовая выборка);
  - http://ufldl.stanford.edu/housenumbers/extra.tar.gz (http://ufldl.stanford.edu/housenumbers/extra.tar.gz) (дополнительные данные);
- Данные второго формата можно скачать по ссылкам:
  - http://ufldl.stanford.edu/housenumbers/train_32x32.mat (http://ufldl.stanford.edu/housenumbers/train_32x32.mat) (обучающая выборка);
  - http://ufldl.stanford.edu/housenumbers/test_32x32.mat (http://ufldl.stanford.edu/housenumbers/test_32x32.mat) (тестовая выборка);
  - http://ufldl.stanford.edu/housenumbers/extra_32x32.mat (http://ufldl.stanford.edu/housenumbers/extra_32x32.mat) (дополнительные данные);
- Описание данных на английском языке доступно по ссылке:
  - http://ufldl.stanford.edu/housenumbers/ (http://ufldl.stanford.edu/housenumbers/)

Задание 1

Реализуйте глубокую нейронную сеть (полносвязную или сверточную) и обучите ее на синтетических данных (например, наборы *MNIST* (http://yann.lecun.com/exdb/mnist/ (http://yann.lecun.com/exdb/mnist/)) или *notMNIST*).

Ознакомьтесь с имеющимися работами по данной тематике: англоязычная статья (http://static.googleusercontent.com/media/research.google.com/en//pubs/archive/42241.pdf (http://static.googleusercontent.com/media/research.google.com/en//pubs/archive/42241.pdf)), видео на *YouTube* (https://www.youtube.com/watch?v=vGPI_JvLoN0) (https://www.youtube.com/watch?v=vGPI_JvLoN0)).

Используем архитектуру *LeNet-5* и обучим сеть сначала на данных из набора *MNIST*.

In [0]:

```
import warnings

warnings.filterwarnings('ignore')
```

In [2]:

```
from google.colab import drive

drive.mount('/content/drive', force_remount = True)
```

```
Mounted at /content/drive
```

In [0]:

```
! pip install tensorflow-gpu --pre --quiet
```

In [0]:

```
import tensorflow as tf
from tensorflow import keras

# To fix memory leak: https://github.com/tensorflow/tensorflow/issues/33009

tf.compat.v1.disable_eager_execution()
```

In [0]:

```
import numpy as np
```

In [0]:

```
from tensorflow.keras.datasets import mnist

(x_train, y_train), (x_test, y_test) = mnist.load_data()
```

In [0]:

```
x_train = tf.keras.utils.normalize(x_train, axis = 1)
x_test = tf.keras.utils.normalize(x_test, axis = 1)
```

In [0]:

```
x_train = x_train[..., np.newaxis]
x_test = x_test[..., np.newaxis]
```

In [9]:

```
from tensorflow.keras.utils import to_categorical

y_train, y_test = to_categorical(y_train), to_categorical(y_test)

y_train.shape
```

Out[9]:

```
(60000, 10)
```

In [0]:

```
IMAGE_DIM_0, IMAGE_DIM_1 = x_train.shape[1], x_train.shape[2]
```

In [0]:

```
CLASSES_N = y_train.shape[1]
```

In [12]:

```
x_train.shape, x_test.shape
```

Out[12]:

```
((60000, 28, 28, 1), (10000, 28, 28, 1))
```

In [13]:

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import AveragePooling2D, Conv2D, Dense, Flatten

model = tf.keras.Sequential()

model.add(Conv2D(6, kernel_size = (5, 5), strides = (1, 1),
                 activation = 'tanh', padding = 'same',
                 input_shape = (IMAGE_DIM_0, IMAGE_DIM_1, 1)))
model.add(AveragePooling2D(pool_size = (2, 2), strides = (2, 2),
                           padding = 'valid'))
model.add(Conv2D(16, kernel_size = (5, 5), strides = (1, 1),
                 activation = 'tanh', padding = 'valid'))
model.add(AveragePooling2D(pool_size = (2, 2), strides = (2, 2),
                           padding = 'valid'))
model.add(Flatten())
model.add(Dense(120, activation = 'tanh'))
model.add(Dense(84, activation = 'tanh'))
model.add(Dense(CLASSES_N, activation = 'softmax'))
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/py
thon/ops/resource_variable_ops.py:1666: calling BaseResourceVariable.__init_
_ (from tensorflow.python.ops.resource_variable_ops) with constraint is depr
ecated and will be removed in a future version.
Instructions for updating:
If using Keras pass *_constraint arguments to layers.
```

In [0]:

```
# 'sparse_categorical_crossentropy' gave NAN loss

model.compile(optimizer = 'adam',
              loss = 'categorical_crossentropy',
              metrics = ['categorical_accuracy'])
```

In [15]:

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d (Conv2D)              (None, 28, 28, 6)         156       
_________________________________________________________________
average_pooling2d (AveragePo (None, 14, 14, 6)         0         
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 10, 10, 16)        2416      
_________________________________________________________________
average_pooling2d_1 (Average (None, 5, 5, 16)          0         
_________________________________________________________________
flatten (Flatten)            (None, 400)               0         
_________________________________________________________________
dense (Dense)                (None, 120)               48120     
_________________________________________________________________
dense_1 (Dense)              (None, 84)                10164     
_________________________________________________________________
dense_2 (Dense)              (None, 10)                850       
=================================================================
Total params: 61,706
Trainable params: 61,706
Non-trainable params: 0
_________________________________________________________________
```

In [0]:

```
EPOCHS_N = 20
```

In [0]:

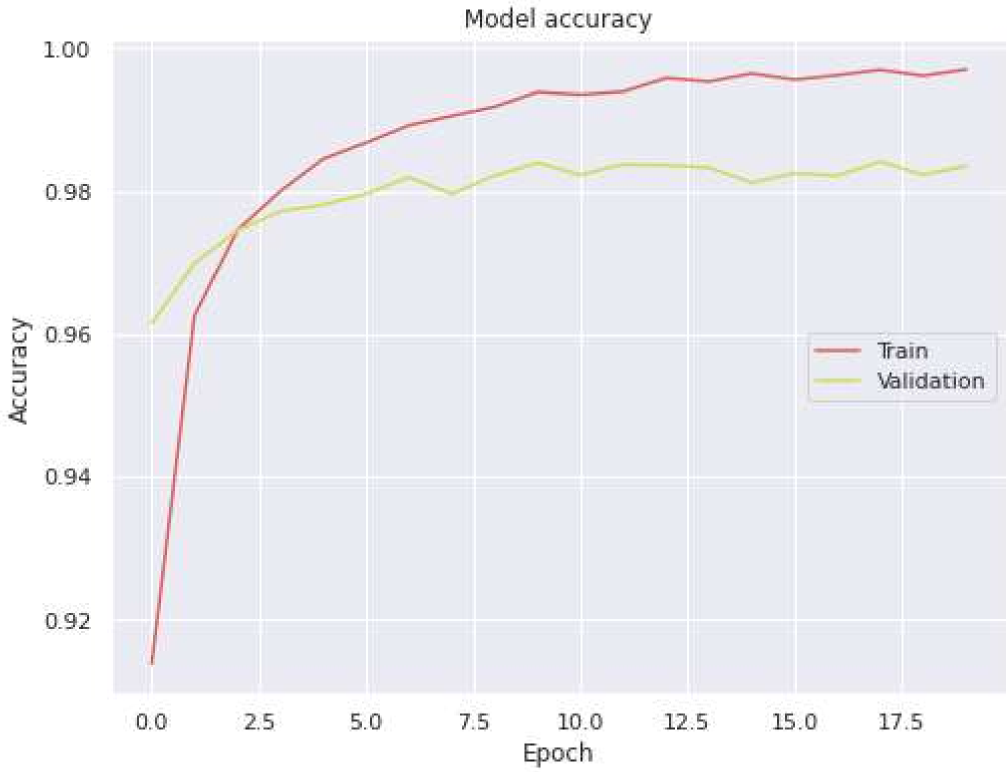
```
history = model.fit(x = x_train, y = y_train, validation_split = 0.15,
                    epochs = EPOCHS_N, verbose = 0)
```

In [0]:

```
%matplotlib inline

import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib import rcParams

rcParams['figure.figsize'] = 8, 6

sns.set()
sns.set_palette(sns.color_palette('hls'))

def plot_accuracy(_history,
                  _train_acc_name = 'accuracy',
                  _val_acc_name = 'val_accuracy'):

    plt.plot(_history.history[_train_acc_name])
    plt.plot(_history.history[_val_acc_name])

    plt.title('Model accuracy')

    plt.ylabel('Accuracy')
    plt.xlabel('Epoch')

    plt.legend(['Train', 'Validation'], loc = 'right')

    plt.show()

def plot_loss(_history,
              _train_loss_name = 'loss',
              _val_loss_name = 'val_loss'):

    plt.plot(_history.history[_train_loss_name])
    plt.plot(_history.history[_val_loss_name])

    plt.title('Model loss')

    plt.ylabel('Loss')
    plt.xlabel('Epoch')

    plt.legend(['Train', 'Validation'], loc = 'right')

    plt.show()
```

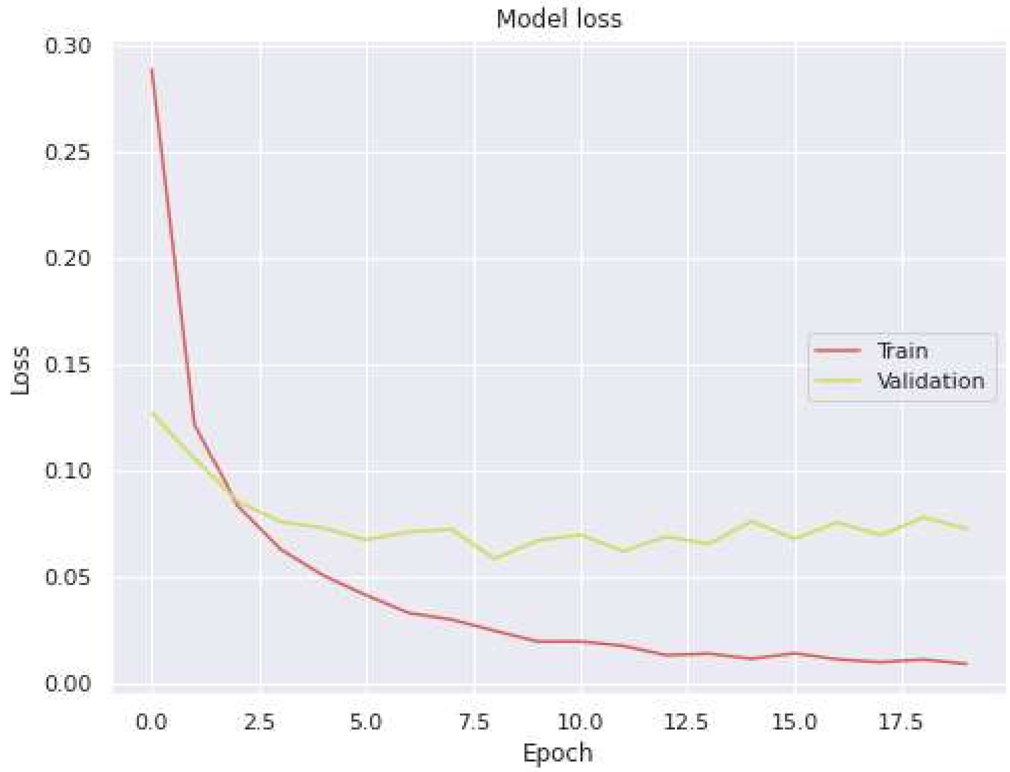
In [19]:

```
plot_accuracy(history, 'categorical_accuracy', 'val_categorical_accuracy')
```



In [20]:

```
plot_loss(history)
```



In [21]:

```
results = model.evaluate(x_test, y_test)

print('Test loss, test accuracy:', results)
```

```
Test loss, test accuracy: [0.05852550842055716, 0.9841]
```

Удалось достичь отличного результата — точность распознавания на тестовой выборке составила 98%.

Задание 2

После уточнения модели на синтетических данных попробуйте обучить ее на реальных данных (набор *Google Street View*). Что изменилось в модели?

Одна цифра

In [0]:

```
DS_URL_FOLDER = 'http://ufldl.stanford.edu/housenumbers/'

FIRST_DS_EXT = '.tar.gz'
SECOND_DS_EXT = '_32x32.mat'

TRAIN_DS_NAME = 'train'
TEST_DS_NAME = 'test'
EXTRA_DS_NAME = 'extra'
```

In [0]:

```
from urllib.request import urlretrieve
import tarfile
import os

def load_file(_url_folder, _name, _ext, _key, _local_ext = ''):

    file_url_ = _url_folder + _name + _ext

    local_file_name_ = _name + '_' + _key + _local_ext

    urlretrieve(file_url_, local_file_name_)

    return local_file_name_

def tar_gz_to_dir(_url_folder, _name, _ext, _key):

    local_file_name_ = load_file(_url_folder, _name, _ext, _key, _ext)

    dir_name_ = _name + '_' + _key

    with tarfile.open(local_file_name_, 'r:gz') as tar_:
        tar_.extractall(dir_name_)

    os.remove(local_file_name_)

    return dir_name_
```

In [0]:

```
second_ds_train_file = load_file(DS_URL_FOLDER, TRAIN_DS_NAME, SECOND_DS_EXT,
                                 'second')
second_ds_test_file = load_file(DS_URL_FOLDER, TEST_DS_NAME, SECOND_DS_EXT,
                                'second')
second_ds_extra_file = load_file(DS_URL_FOLDER, EXTRA_DS_NAME, SECOND_DS_EXT,
                                 'second')
```

In [0]:

```
from scipy import io

second_ds_train = io.loadmat(second_ds_train_file)
second_ds_test = io.loadmat(second_ds_test_file)
second_ds_extra = io.loadmat(second_ds_extra_file)
```

In [26]:

```
X_second_ds_train = np.moveaxis(second_ds_train['X'], -1, 0)
X_second_ds_test = np.moveaxis(second_ds_test['X'], -1, 0)
X_second_ds_extra = np.moveaxis(second_ds_extra['X'], -1, 0)

y_second_ds_train = second_ds_train['y']
y_second_ds_test = second_ds_test['y']
y_second_ds_extra = second_ds_extra['y']

print(X_second_ds_train.shape, y_second_ds_train.shape)
print(X_second_ds_test.shape, y_second_ds_test.shape)
print(X_second_ds_extra.shape, y_second_ds_extra.shape)
```

```
(73257, 32, 32, 3) (73257, 1)
(26032, 32, 32, 3) (26032, 1)
(531131, 32, 32, 3) (531131, 1)
```

In [0]:

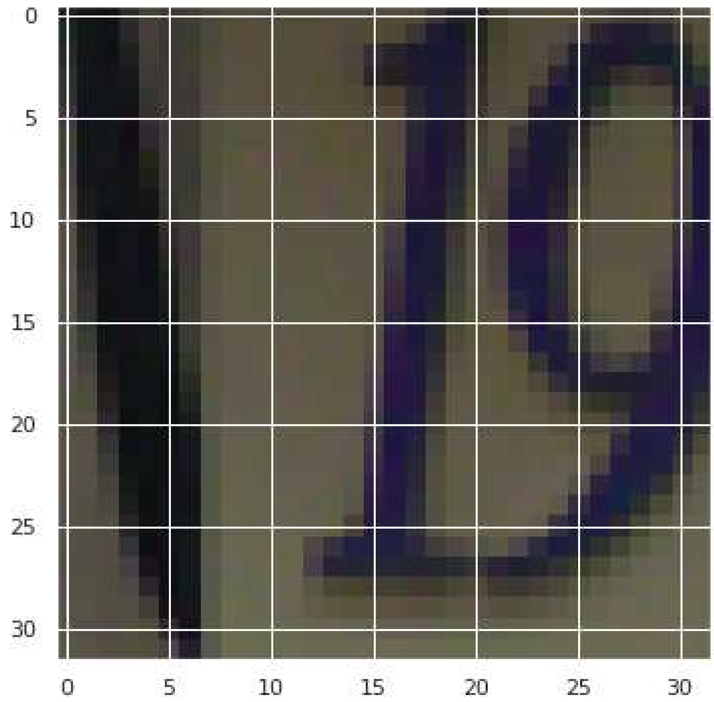
```
%matplotlib inline

import matplotlib.pyplot as plt
```

In [0]:

```
import seaborn as sns

from matplotlib import rcParams

rcParams['figure.figsize'] = 8, 6

sns.set()

sns.set_palette(sns.color_palette('hls'))
```

In [29]:

```
plt.imshow(X_second_ds_train[0])

plt.show()
```



In [0]:

```
IMAGE_DIM_0_2 = X_second_ds_train.shape[-3]
IMAGE_DIM_1_2 = X_second_ds_train.shape[-2]
IMAGE_DIM_2_2 = X_second_ds_train.shape[-1]
```

In [0]:

```
y_second_ds_train_cat = to_categorical(y_second_ds_train)
y_second_ds_test_cat = to_categorical(y_second_ds_test)
```

In [0]:

```
CLASSES_N_2 = y_second_ds_train_cat.shape[1]
```

In [0]:

```
model_2 = tf.keras.Sequential()

model_2.add(Conv2D(6, kernel_size = (5, 5), strides = (1, 1),
                   activation = 'tanh', padding = 'same',
                   input_shape = (IMAGE_DIM_0_2, IMAGE_DIM_1_2, IMAGE_DIM_2_2)))
model_2.add(AveragePooling2D(pool_size = (2, 2), strides = (2, 2),
                             padding = 'valid'))
model_2.add(Conv2D(16, kernel_size = (5, 5), strides = (1, 1),
                   activation = 'tanh', padding = 'valid'))
model_2.add(AveragePooling2D(pool_size = (2, 2), strides = (2, 2),
                             padding = 'valid'))
model_2.add(Flatten())
model_2.add(Dense(120, activation = 'tanh'))
model_2.add(Dense(84, activation = 'tanh'))
model_2.add(Dense(CLASSES_N_2, activation = 'softmax'))
```

In [0]:

```
model_2.compile(optimizer = 'adam',
                loss = 'categorical_crossentropy',
                metrics = ['categorical_accuracy'])
```

In [35]:

```
model_2.summary()
```

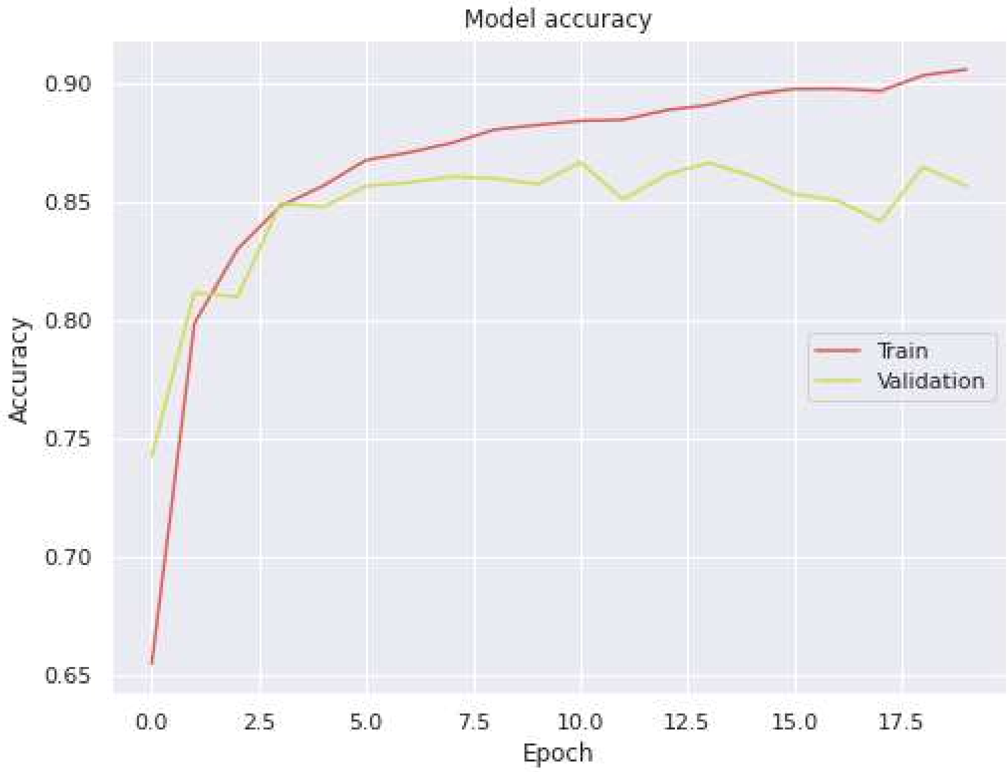
```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_2 (Conv2D)            (None, 32, 32, 6)         456       
_________________________________________________________________
average_pooling2d_2 (Average (None, 16, 16, 6)         0         
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 12, 12, 16)        2416      
_________________________________________________________________
average_pooling2d_3 (Average (None, 6, 6, 16)          0         
_________________________________________________________________
flatten_1 (Flatten)          (None, 576)               0         
_________________________________________________________________
dense_3 (Dense)              (None, 120)               69240     
_________________________________________________________________
dense_4 (Dense)              (None, 84)                10164     
_________________________________________________________________
dense_5 (Dense)              (None, 11)                935       
=================================================================
Total params: 83,211
Trainable params: 83,211
Non-trainable params: 0
_________________________________________________________________
```

In [0]:

```
history_2 = model_2.fit(x = X_second_ds_train, y = y_second_ds_train_cat,
                        validation_split = 0.15, epochs = EPOCHS_N, verbose = 0)
```

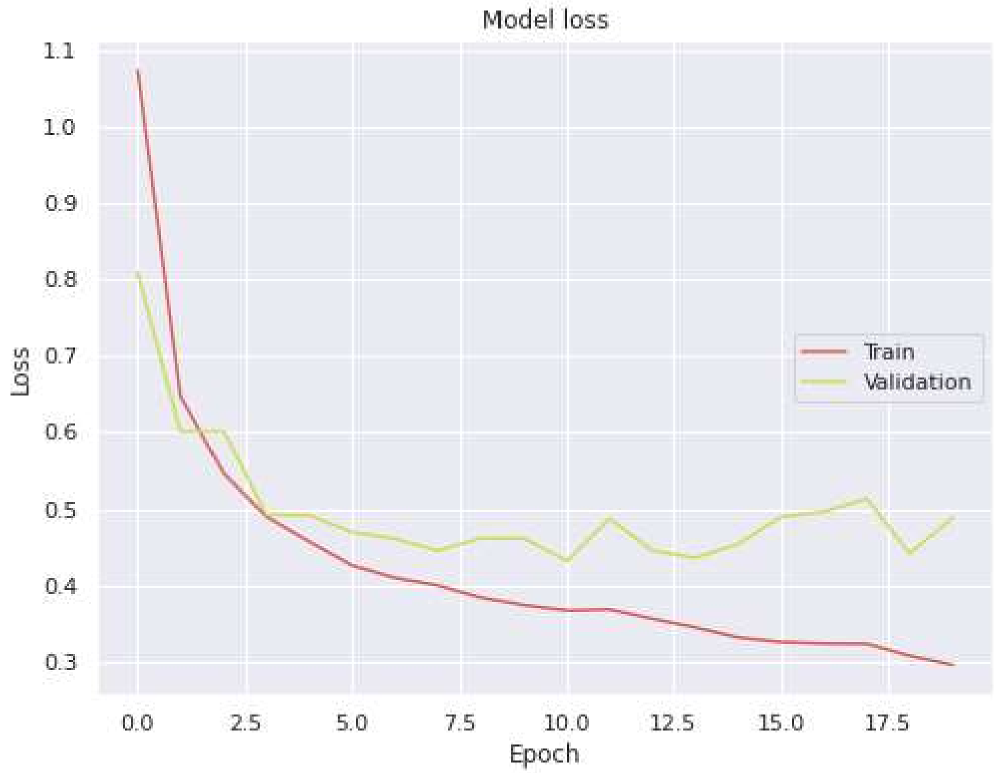
In [37]:

```
plot_accuracy(history_2, 'categorical_accuracy', 'val_categorical_accuracy')
```



In [38]:

```
plot_loss(history_2)
```



In [39]:

```
results = model_2.evaluate(X_second_ds_test, y_second_ds_test_cat)

print('Test loss, test accuracy:', results)
```

```
Test loss, test accuracy: [0.5583448587804025, 0.8333973]
```

Здесь в модели изменилось то, что добавился ещё один класс — *нет цифры*.

Эти данные более сложны для распознавания, что повлияло на результат — точность распознавания на тестовой выборке составила 83%.

Несколько цифр

Загрузим первый датасет — реальные изображения с несколькими цифрами и рамками границ.

In [0]:

```
from imageio import imread
import pandas as pd

def image_to_array(_image):
    try:
        array_ = imread(_image)

        return True, array_
    except:
        return False, None

def dir_to_dataframe(_dir_path):

    data_ = []

    files_ = sorted(os.listdir(_dir_path))

    for f in files_:
        file_path_ = os.path.join(_dir_path, f)

        can_read_, im = image_to_array(file_path_)

        if can_read_:
            data_.append(im)

    dataframe_ = pd.DataFrame()

    dataframe_['data'] = np.array(data_)

    return dataframe_
```

In [0]:

```
PROCESS = False
```

In [0]:

```
if PROCESS:
    first_ds_train_dir = tar_gz_to_dir(
        DS_URL_FOLDER, TRAIN_DS_NAME, FIRST_DS_EXT, 'first')
    first_ds_test_dir = tar_gz_to_dir(
        DS_URL_FOLDER, TEST_DS_NAME, FIRST_DS_EXT, 'first')
```

In [0]:

```
if PROCESS:
    first_ds_train_subdir = os.path.join(first_ds_train_dir, 'train')
    first_ds_test_subdir = os.path.join(first_ds_test_dir, 'test')
```

In [0]:

```
if PROCESS:
    first_ds_train_images_df = dir_to_dataframe(first_ds_train_subdir)
    first_ds_test_images_df = dir_to_dataframe(first_ds_test_subdir)
```

In [0]:

```
import h5py

if PROCESS:
    first_ds_train_boxes_mat = h5py.File(
        os.path.join(first_ds_train_subdir, 'digitStruct.mat'), 'r')
    first_ds_test_boxes_mat = h5py.File(
        os.path.join(first_ds_test_subdir, 'digitStruct.mat'), 'r')
```

In [0]:

```
import numpy as np
import pickle
import h5py

def mat_to_pickle(_mat_path, _key):

    f = h5py.File(_mat_path, 'r')

    metadata = {}

    metadata['height'] = []
    metadata['label'] = []
    metadata['left'] = []
    metadata['top'] = []
    metadata['width'] = []

    def print_attrs(name, obj):

        vals = []

        if obj.shape[0] == 1:
            vals.append(int(obj[0][0]))
        else:
            for k in range(obj.shape[0]):

                vals.append(int(f[obj[k][0]][0][0]))

        metadata[name].append(vals)

    for item in f['/digitStruct/bbox']:

        f[item[0]].visititems(print_attrs)

    with open('{}.pickle'.format((_key)),'wb') as pf:

        pickle.dump(metadata, pf, pickle.HIGHEST_PROTOCOL)
```

In [0]:

```
if PROCESS:
    mat_to_pickle(
        os.path.join(first_ds_train_subdir, 'digitStruct.mat'), 'train_bbox')
    mat_to_pickle(
        os.path.join(first_ds_test_subdir, 'digitStruct.mat'), 'test_bbox')
```

In [0]:

```
if PROCESS:
    train_bbox_data = np.load('train_bbox.pickle', allow_pickle = True)
    test_bbox_data = np.load('test_bbox.pickle', allow_pickle = True)
```

In [0]:

```
if PROCESS:
    plt.imshow(first_ds_train_images_df['data'][0])

    plt.show()
```

In [0]:

```
MAX_DIGITS = 6
```

In [0]:

```python
def to_full_df(_ds_images_df, _bbox_data):

    LENGTH = len(_bbox_data['height'])

    BBOX_SHAPE_TUPLE = (LENGTH, MAX_DIGITS)

    bbox_heights = np.zeros(BBOX_SHAPE_TUPLE)
    bbox_labels = np.zeros(BBOX_SHAPE_TUPLE)
    bbox_lefts = np.zeros(BBOX_SHAPE_TUPLE)
    bbox_tops = np.zeros(BBOX_SHAPE_TUPLE)
    bbox_widths = np.zeros(BBOX_SHAPE_TUPLE)

    for i in range(LENGTH):

        j = 0

        l = len(_bbox_data['height'][i])

        while j < l:

            bbox_heights[i][j] = _bbox_data['height'][i][j]
            bbox_labels[i][j] = _bbox_data['label'][i][j]
            bbox_lefts[i][j] = _bbox_data['left'][i][j]
            bbox_tops[i][j] = _bbox_data['top'][i][j]
            bbox_widths[i][j] = _bbox_data['width'][i][j]

            j = j + 1

    data_dict_ = {
        'data': _ds_images_df['data'],

        'height_0': bbox_heights[:, 0],
        'label_0': bbox_labels[:, 0],
        'left_0': bbox_lefts[:, 0],
        'top_0': bbox_tops[:, 0],
        'width_0': bbox_widths[:, 0],

        'height_1': bbox_heights[:, 1],
        'label_1': bbox_labels[:, 1],
        'left_1': bbox_lefts[:, 1],
        'top_1': bbox_tops[:, 1],
        'width_1': bbox_widths[:, 1],

        'height_2': bbox_heights[:, 2],
        'label_2': bbox_labels[:, 2],
        'left_2': bbox_lefts[:, 2],
        'top_2': bbox_tops[:, 2],
        'width_2': bbox_widths[:, 2],

        'height_3': bbox_heights[:, 3],
        'label_3': bbox_labels[:, 3],
        'left_3': bbox_lefts[:, 3],
        'top_3': bbox_tops[:, 3],
        'width_3': bbox_widths[:, 3],

        'height_4': bbox_heights[:, 4],
        'label_4': bbox_labels[:, 4],
        'left_4': bbox_lefts[:, 4],
        'top_4': bbox_tops[:, 4],
```

```
        'width_4': bbox_widths[:, 4],

        'height_5': bbox_heights[:, 5],
        'label_5': bbox_labels[:, 5],
        'left_5': bbox_lefts[:, 5],
        'top_5': bbox_tops[:, 5],
        'width_5': bbox_widths[:, 5],
    }

    full_ds_ = pd.DataFrame(data_dict_,
                            columns = [
                                'data',

                                'height_0',
                                'label_0',
                                'left_0',
                                'top_0',
                                'width_0',

                                'height_1',
                                'label_1',
                                'left_1',
                                'top_1',
                                'width_1',

                                'height_2',
                                'label_2',
                                'left_2',
                                'top_2',
                                'width_2',

                                'height_3',
                                'label_3',
                                'left_3',
                                'top_3',
                                'width_3',

                                'height_4',
                                'label_4',
                                'left_4',
                                'top_4',
                                'width_4',

                                'height_5',
                                'label_5',
                                'left_5',
                                'top_5',
                                'width_5',
                                ])

    return full_ds_
```

In [0]:

```
if PROCESS:
    first_ds_train_full_df = to_full_df(
        first_ds_train_images_df, train_bbox_data)
    first_ds_test_full_df = to_full_df(
        first_ds_test_images_df, test_bbox_data)
```

In [0]:

```
def no_more_than_two_digits(_full_df):

    _2_digits_df = _full_df[_full_df['height_2'] == 0.0].reset_index()

    _2_digits_df = _2_digits_df.drop(columns = [
                                                'height_2',
                                                'label_2',
                                                'left_2',
                                                'top_2',
                                                'width_2',

                                                'height_3',
                                                'label_3',
                                                'left_3',
                                                'top_3',
                                                'width_3',

                                                'height_4',
                                                'label_4',
                                                'left_4',
                                                'top_4',
                                                'width_4',

                                                'height_5',
                                                'label_5',
                                                'left_5',
                                                'top_5',
                                                'width_5'
                                                ])

    return _2_digits_df
```

In [0]:

```
if PROCESS:
    first_ds_train_2_digits_df = no_more_than_two_digits(
        first_ds_train_full_df)
    first_ds_test_2_digits_df = no_more_than_two_digits(
        first_ds_test_full_df)
```

In [0]:

```
from math import ceil

def get_image_central_square(_image):

    dim_0 = _image.shape[0]
    dim_1 = _image.shape[1]

    if dim_0 == 0 or dim_1 == 0:

        print(_image.shape)

    cutoff_ = ceil(abs(dim_0 - dim_1) / 2)

    if dim_0 > dim_1:
        cut_image_ = _image[cutoff_:-cutoff_,
                            :,
                            :]
    elif dim_0 < dim_1:
        cut_image_ = _image[:,
                            cutoff_:-cutoff_,
                            :]
    else:
        cut_image_ = _image[:,
                            :,
                            :]

    return cut_image_
```

In [0]:

```
NEW_IMAGE_DIM = 50
```

In [0]:

```
import cv2

def resize_image(_image, _dim_0 = NEW_IMAGE_DIM, _dim_1 = NEW_IMAGE_DIM):

    try:
        resized_ = cv2.resize(_image, dsize = (_dim_0, _dim_1),
                              interpolation = cv2.INTER_CUBIC)
    except:
        print(_image.shape)

    return resized_
```

In [0]:

```
def process_image(_image):

    squared_ = get_image_central_square(_image)

    resized_ = resize_image(squared_)

    return resized_
```

In [0]:

```
def get_digits_n_from_row(_row):

    if _row['height_1'] != 0.0:
        return 2

    if _row['height_0'] != 0.0:
        return 1

    return 0
```

In [0]:

```
def to_new_format_dataframe(_dataframe):

    df_copy_ = _dataframe.copy()

    rrrr = df_copy_.apply(lambda row: process_image(row['data']), axis = 1)

    df_copy_.drop(columns = ['data'])

    df_copy_['data'] = rrrr

    nnnn = df_copy_.apply(lambda row: get_digits_n_from_row(row), axis = 1)

    df_copy_['digits_n'] = nnnn

    df_copy_['digit_0'] = df_copy_['label_0'].astype(int)
    df_copy_['digit_1'] = df_copy_['label_1'].astype(int)

    df_copy_ = df_copy_.drop(columns = [
                                    'height_0',
                                    'label_0',
                                    'left_0',
                                    'top_0',
                                    'width_0',

                                    'height_1',
                                    'label_1',
                                    'left_1',
                                    'top_1',
                                    'width_1'
                                   ])

    return df_copy_
```

In [0]:

```
if PROCESS:
    train_resized_df = to_new_format_dataframe(first_ds_train_2_digits_df)
    test_resized_df = to_new_format_dataframe(first_ds_test_2_digits_df)
```

In [0]:

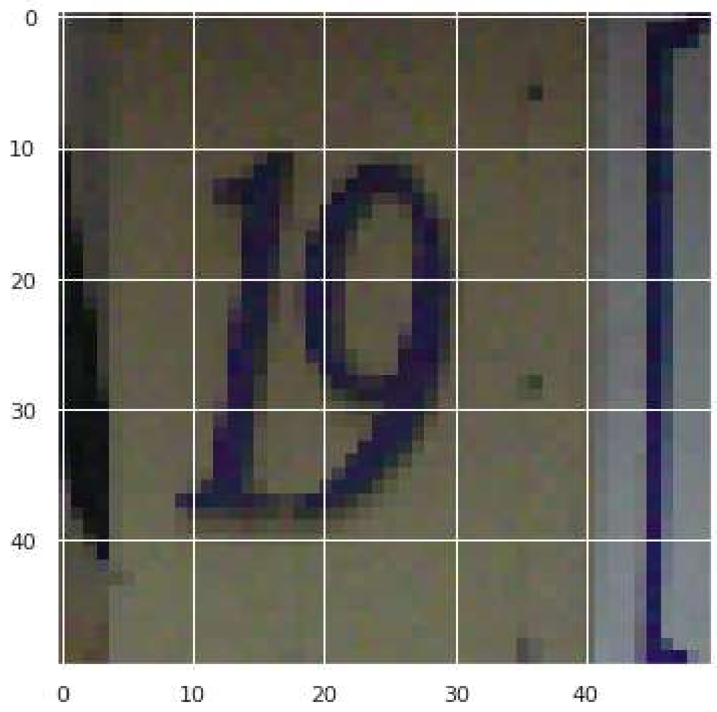
```
if PROCESS:
    train_resized_df.to_pickle(
        '/content/drive/My Drive/Colab Files/mo-2/multidigit_train.pkl')
    test_resized_df.to_pickle(
        '/content/drive/My Drive/Colab Files/mo-2/multidigit_test.pkl')
```

In [0]:

```
train_multidigit_df = pd.read_pickle(
    '/content/drive/My Drive/Colab Files/mo-2/multidigit_train.pkl')
test_multidigit_df = pd.read_pickle(
    '/content/drive/My Drive/Colab Files/mo-2/multidigit_test.pkl')
```

In [64]:

```
plt.imshow(train_multidigit_df['data'][0])

plt.show()
```



In [65]:

```
print('digits_n:', train_multidigit_df['digits_n'][0], '\t',
      'digit_0:', train_multidigit_df['digit_0'][0], '\t',
      'digit_1:', train_multidigit_df['digit_1'][0])
```

```
digits_n: 2	digit_0: 1	digit_1: 9
```

In [0]:

```
inputs = keras.Input(shape = (NEW_IMAGE_DIM, NEW_IMAGE_DIM, IMAGE_DIM_2_2))
```

In [0]:

```
from tensorflow.keras.layers import Dropout, MaxPooling2D

l_d_0_0 = Conv2D(16, kernel_size = (5, 5), strides = (1, 1),
                activation = 'relu', padding = 'same')(inputs)
l_d_0_1 = MaxPooling2D(pool_size = (2, 2), strides = 2,
                            padding = 'valid')(l_d_0_0)
l_d_0_2 = Dropout(0.2)(l_d_0_0)

l_d_1_0 = Conv2D(32, kernel_size = (5, 5), strides = (1, 1),
                activation = 'relu', padding = 'same')(l_d_0_2)
l_d_1_1 = MaxPooling2D(pool_size = (2, 2), strides = 1,
                            padding = 'valid')(l_d_1_0)
l_d_1_2 = Dropout(0.2)(l_d_1_0)

l_d_2_0 = Conv2D(64, kernel_size = (5, 5), strides = (1, 1),
                activation = 'relu', padding = 'same')(l_d_1_2)
l_d_2_1 = MaxPooling2D(pool_size = (2, 2), strides = 2,
                            padding = 'valid')(l_d_2_0)
l_d_2_2 = Dropout(0.2)(l_d_2_0)

l_fl_0 = Flatten()(l_d_2_2)
l_dense_0 = Dense(2400, activation = 'relu')(l_fl_0)

output_common = Dense(1200, activation = 'relu')(l_dense_0)

digits_n_output = Dense(2, activation = 'softmax', name = 'digits_n')(output_common)
digit_0_output = Dense(10, activation = 'softmax', name = 'digit_0')(output_common)
digit_1_output = Dense(11, activation = 'softmax', name = 'digit_1')(output_common)
```

In [0]:

```
def digits_n_loss(n_logits, n_labels):
    return tf.reduce_mean(
        tf.compat.v1.losses.softmax_cross_entropy(n_logits, n_labels))

def digit_0_loss(digit_0_logits, digit_0_labels):
    return tf.reduce_mean(
        tf.compat.v1.losses.softmax_cross_entropy(digit_0_logits, digit_0_labels))

def digit_1_loss(digit_1_logits, digit_1_labels):
    return tf.reduce_mean(
        tf.compat.v1.losses.softmax_cross_entropy(digit_1_logits, digit_1_labels))

losses = {
    'digits_n': digits_n_loss,
    'digit_0': digit_0_loss,
    'digit_1': digit_1_loss
}

loss_weights = {
    'digits_n': 1.0,
    'digit_0': 1.0,
    'digit_1': 1.0
}
```

In [0]:

```
model_3 = keras.Model(inputs = inputs,
                      outputs = [
                                 digits_n_output,
                                 digit_0_output,
                                 digit_1_output])
```

In [70]:

```
model_3.summary()
```

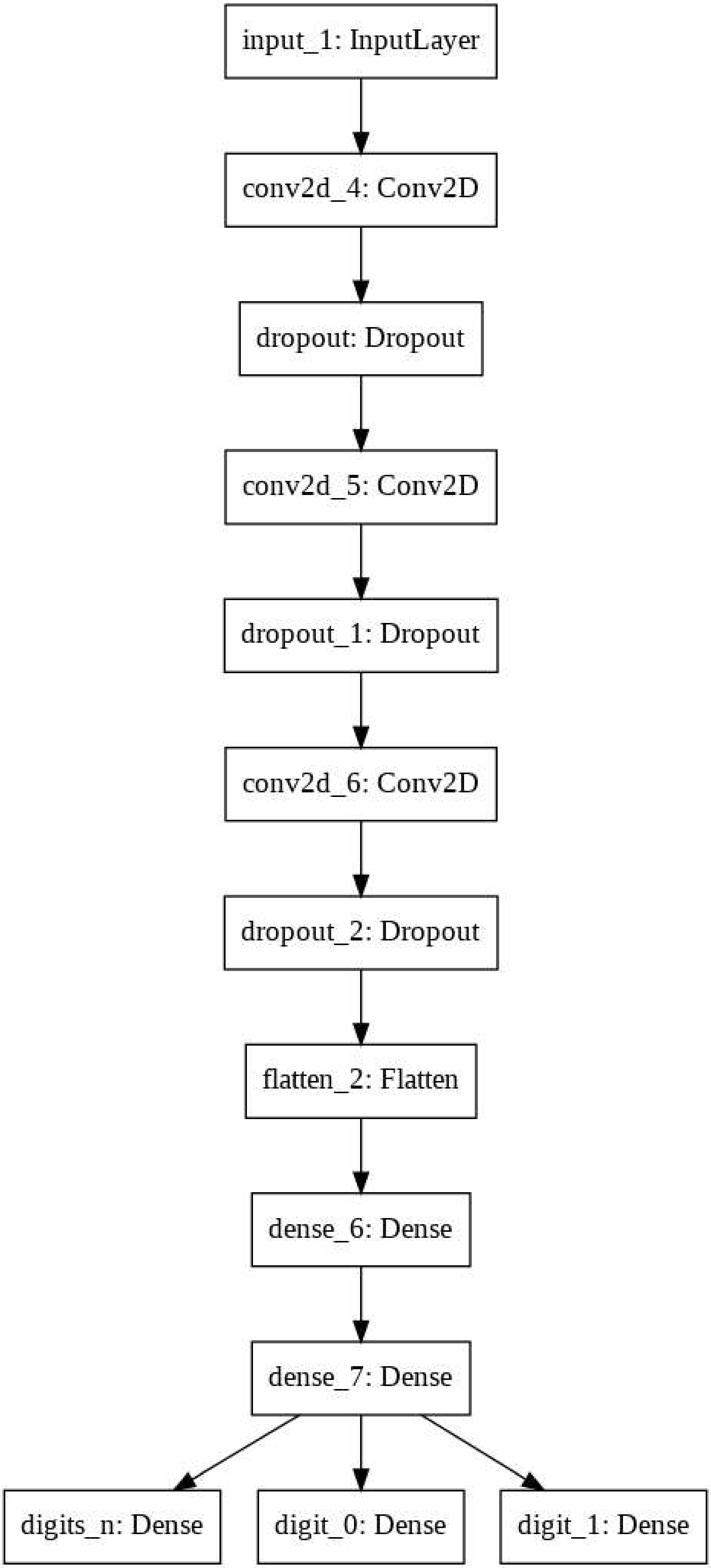
```
Model: "model"
____________________________________________________________________________
______________________
Layer (type)                    Output Shape          Param #     Connected t
o
============================================================================
=====================
input_1 (InputLayer)            [(None, 50, 50, 3)]   0

____________________________________________________________________________
______________________
conv2d_4 (Conv2D)               (None, 50, 50, 16)    1216        input_1[0]
[0]
____________________________________________________________________________
______________________
dropout (Dropout)               (None, 50, 50, 16)    0           conv2d_4[0]
[0]
____________________________________________________________________________
______________________
conv2d_5 (Conv2D)               (None, 50, 50, 32)    12832       dropout[0]
[0]
____________________________________________________________________________
______________________
dropout_1 (Dropout)             (None, 50, 50, 32)    0           conv2d_5[0]
[0]
____________________________________________________________________________
______________________
conv2d_6 (Conv2D)               (None, 50, 50, 64)    51264       dropout_1
[0][0]
____________________________________________________________________________
______________________
dropout_2 (Dropout)             (None, 50, 50, 64)    0           conv2d_6[0]
[0]
____________________________________________________________________________
______________________
flatten_2 (Flatten)             (None, 160000)        0           dropout_2
[0][0]
____________________________________________________________________________
______________________
dense_6 (Dense)                 (None, 2400)          384002400   flatten_2
[0][0]
____________________________________________________________________________
______________________
dense_7 (Dense)                 (None, 1200)          2881200     dense_6[0]
[0]
____________________________________________________________________________
______________________
digits_n (Dense)                (None, 2)             2402        dense_7[0]
[0]
____________________________________________________________________________
______________________
digit_0 (Dense)                 (None, 10)            12010       dense_7[0]
[0]
____________________________________________________________________________
______________________
digit_1 (Dense)                 (None, 11)            13211       dense_7[0]
[0]
============================================================================
```

```
======================
Total params: 386,976,535
Trainable params: 386,976,535
Non-trainable params: 0
```

In [71]:

```
keras.utils.plot_model(model_3, 'multidigit.png')
```

Out[71]:


input_1: InputLayer
conv2d_4: Conv2D
dropout: Dropout
conv2d_5: Conv2D
dropout_1: Dropout
conv2d_6: Conv2D
dropout_2: Dropout
flatten_2: Flatten
dense_6: Dense
dense_7: Dense
digits_n: Dense
digit_0: Dense
digit_1: Dense

In [0]:

```
X_multidigit = tf.keras.utils.normalize(np.asarray(list(train_multidigit_df['data'])), axis

y_n_multidigit = (to_categorical(train_multidigit_df['digits_n']
                                 .astype('category')
                                 .cat.codes.astype('int32')))
y_d_0_multidigit = (to_categorical(train_multidigit_df['digit_0']
                                   .astype('category')
                                   .cat.codes.astype('int32')))
y_d_1_multidigit = (to_categorical(train_multidigit_df['digit_1']
                                   .astype('category')
                                   .cat.codes.astype('int32')))

y_multidigit = [
                y_n_multidigit,
                y_d_0_multidigit,
                y_d_1_multidigit
               ]
```

In [0]:

```
model_3.compile(optimizer = 'adam',
                loss = losses, loss_weights = loss_weights,
                metrics = ['categorical_accuracy'])
```

In [74]:

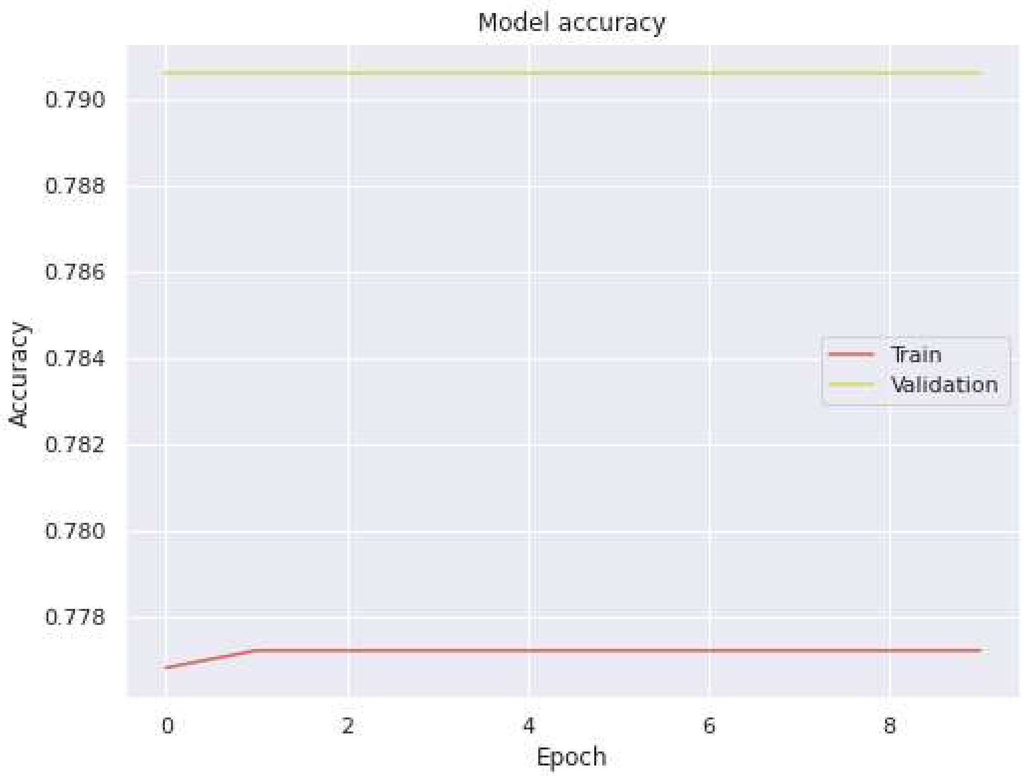
```
history_3 = model_3.fit(x = X_multidigit,
                        y = y_multidigit,
                        epochs = 10,
                        validation_split = 0.15)
```

```
Train on 19776 samples, validate on 3491 samples
Epoch 1/10
19776/19776 [==============================] - 42s 2ms/sample - loss: 5.1188
- digits_n_loss: 0.5362 - digit_0_loss: 2.2618 - digit_1_loss: 2.3208 - digi
ts_n_categorical_accuracy: 0.7768 - digit_0_categorical_accuracy: 0.1993 - d
igit_1_categorical_accuracy: 0.2216 - val_loss: 5.1304 - val_digits_n_loss:
0.5209 - val_digit_0_loss: 2.2729 - val_digit_1_loss: 2.3354 - val_digits_n_
categorical_accuracy: 0.7906 - val_digit_0_categorical_accuracy: 0.1871 - va
l_digit_1_categorical_accuracy: 0.2094
Epoch 2/10
19776/19776 [==============================] - 42s 2ms/sample - loss: 5.1175
- digits_n_loss: 0.5361 - digit_0_loss: 2.2612 - digit_1_loss: 2.3203 - digi
ts_n_categorical_accuracy: 0.7772 - digit_0_categorical_accuracy: 0.2000 - d
igit_1_categorical_accuracy: 0.2228 - val_loss: 5.1304 - val_digits_n_loss:
0.5209 - val_digit_0_loss: 2.2729 - val_digit_1_loss: 2.3354 - val_digits_n_
categorical_accuracy: 0.7906 - val_digit_0_categorical_accuracy: 0.1871 - va
l_digit_1_categorical_accuracy: 0.2094
Epoch 3/10
19776/19776 [==============================] - 42s 2ms/sample - loss: 5.1175
- digits_n_loss: 0.5361 - digit_0_loss: 2.2612 - digit_1_loss: 2.3203 - digi
ts_n_categorical_accuracy: 0.7772 - digit_0_categorical_accuracy: 0.2000 - d
igit_1_categorical_accuracy: 0.2228 - val_loss: 5.1304 - val_digits_n_loss:
0.5209 - val_digit_0_loss: 2.2729 - val_digit_1_loss: 2.3354 - val_digits_n_
categorical_accuracy: 0.7906 - val_digit_0_categorical_accuracy: 0.1871 - va
l_digit_1_categorical_accuracy: 0.2094
Epoch 4/10
19776/19776 [==============================] - 42s 2ms/sample - loss: 5.1175
- digits_n_loss: 0.5361 - digit_0_loss: 2.2612 - digit_1_loss: 2.3203 - digi
ts_n_categorical_accuracy: 0.7772 - digit_0_categorical_accuracy: 0.2000 - d
igit_1_categorical_accuracy: 0.2228 - val_loss: 5.1304 - val_digits_n_loss:
0.5237 - val_digit_0_loss: 2.2674 - val_digit_1_loss: 2.3326 - val_digits_n_
categorical_accuracy: 0.7906 - val_digit_0_categorical_accuracy: 0.1871 - va
l_digit_1_categorical_accuracy: 0.2094
Epoch 5/10
19776/19776 [==============================] - 42s 2ms/sample - loss: 5.1175
- digits_n_loss: 0.5361 - digit_0_loss: 2.2612 - digit_1_loss: 2.3203 - digi
ts_n_categorical_accuracy: 0.7772 - digit_0_categorical_accuracy: 0.2000 - d
igit_1_categorical_accuracy: 0.2228 - val_loss: 5.1304 - val_digits_n_loss:
0.5237 - val_digit_0_loss: 2.2756 - val_digit_1_loss: 2.3326 - val_digits_n_
categorical_accuracy: 0.7906 - val_digit_0_categorical_accuracy: 0.1871 - va
l_digit_1_categorical_accuracy: 0.2094
Epoch 6/10
19776/19776 [==============================] - 42s 2ms/sample - loss: 5.1175
- digits_n_loss: 0.5361 - digit_0_loss: 2.2612 - digit_1_loss: 2.3203 - digi
ts_n_categorical_accuracy: 0.7772 - digit_0_categorical_accuracy: 0.2000 - d
igit_1_categorical_accuracy: 0.2228 - val_loss: 5.1304 - val_digits_n_loss:
0.5292 - val_digit_0_loss: 2.2756 - val_digit_1_loss: 2.3271 - val_digits_n_
categorical_accuracy: 0.7906 - val_digit_0_categorical_accuracy: 0.1871 - va
l_digit_1_categorical_accuracy: 0.2094
Epoch 7/10
19776/19776 [==============================] - 42s 2ms/sample - loss: 5.1175
- digits_n_loss: 0.5361 - digit_0_loss: 2.2612 - digit_1_loss: 2.3203 - digi
ts_n_categorical_accuracy: 0.7772 - digit_0_categorical_accuracy: 0.2000 - d
igit_1_categorical_accuracy: 0.2228 - val_loss: 5.1304 - val_digits_n_loss:
```

```
0.5209 - val_digit_0_loss: 2.2756 - val_digit_1_loss: 2.3354 - val_digits_n_
categorical_accuracy: 0.7906 - val_digit_0_categorical_accuracy: 0.1871 - va
l_digit_1_categorical_accuracy: 0.2094
Epoch 8/10
19776/19776 [==============================] - 42s 2ms/sample - loss: 5.1175
- digits_n_loss: 0.5361 - digit_0_loss: 2.2612 - digit_1_loss: 2.3203 - digi
ts_n_categorical_accuracy: 0.7772 - digit_0_categorical_accuracy: 0.2000 - d
igit_1_categorical_accuracy: 0.2228 - val_loss: 5.1304 - val_digits_n_loss:
0.5237 - val_digit_0_loss: 2.2756 - val_digit_1_loss: 2.3326 - val_digits_n_
categorical_accuracy: 0.7906 - val_digit_0_categorical_accuracy: 0.1871 - va
l_digit_1_categorical_accuracy: 0.2094
Epoch 9/10
19776/19776 [==============================] - 42s 2ms/sample - loss: 5.1175
- digits_n_loss: 0.5361 - digit_0_loss: 2.2612 - digit_1_loss: 2.3203 - digi
ts_n_categorical_accuracy: 0.7772 - digit_0_categorical_accuracy: 0.2000 - d
igit_1_categorical_accuracy: 0.2228 - val_loss: 5.1304 - val_digits_n_loss:
0.5209 - val_digit_0_loss: 2.2756 - val_digit_1_loss: 2.3354 - val_digits_n_
categorical_accuracy: 0.7906 - val_digit_0_categorical_accuracy: 0.1871 - va
l_digit_1_categorical_accuracy: 0.2094
Epoch 10/10
19776/19776 [==============================] - 42s 2ms/sample - loss: 5.1175
- digits_n_loss: 0.5361 - digit_0_loss: 2.2612 - digit_1_loss: 2.3203 - digi
ts_n_categorical_accuracy: 0.7772 - digit_0_categorical_accuracy: 0.2000 - d
igit_1_categorical_accuracy: 0.2228 - val_loss: 5.1304 - val_digits_n_loss:
0.5237 - val_digit_0_loss: 2.2756 - val_digit_1_loss: 2.3326 - val_digits_n_
categorical_accuracy: 0.7906 - val_digit_0_categorical_accuracy: 0.1871 - va
l_digit_1_categorical_accuracy: 0.2094
```

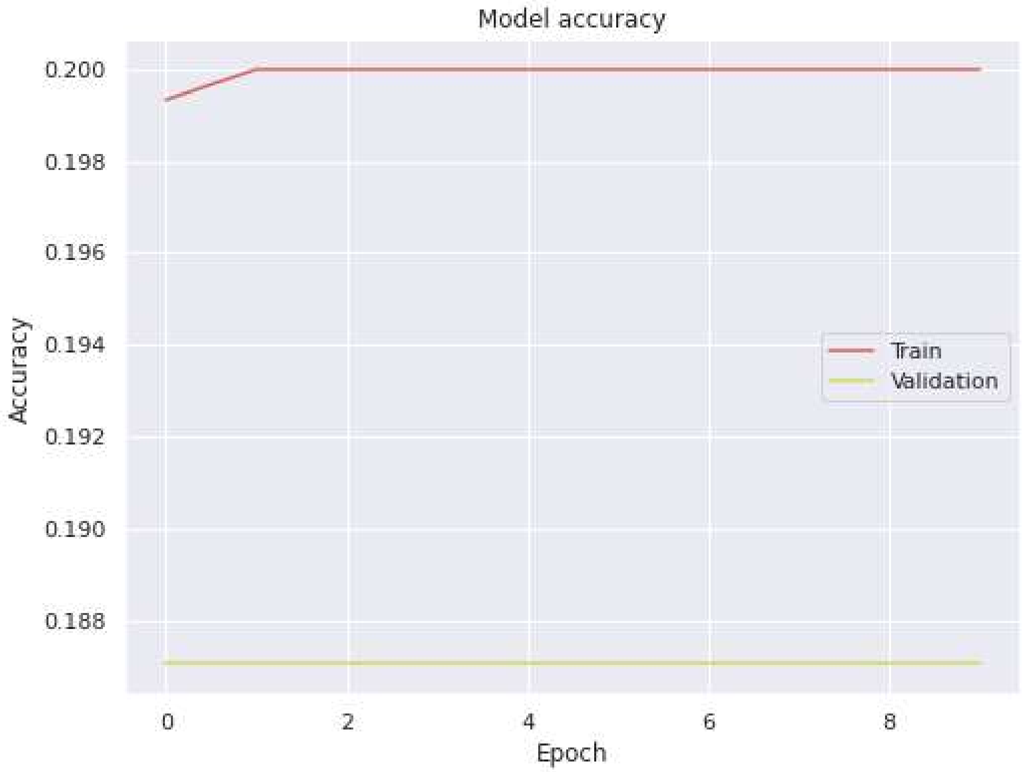
In [75]:

```
plot_accuracy(history_3, 'digits_n_categorical_accuracy', 'val_digits_n_categorical_accurac
```



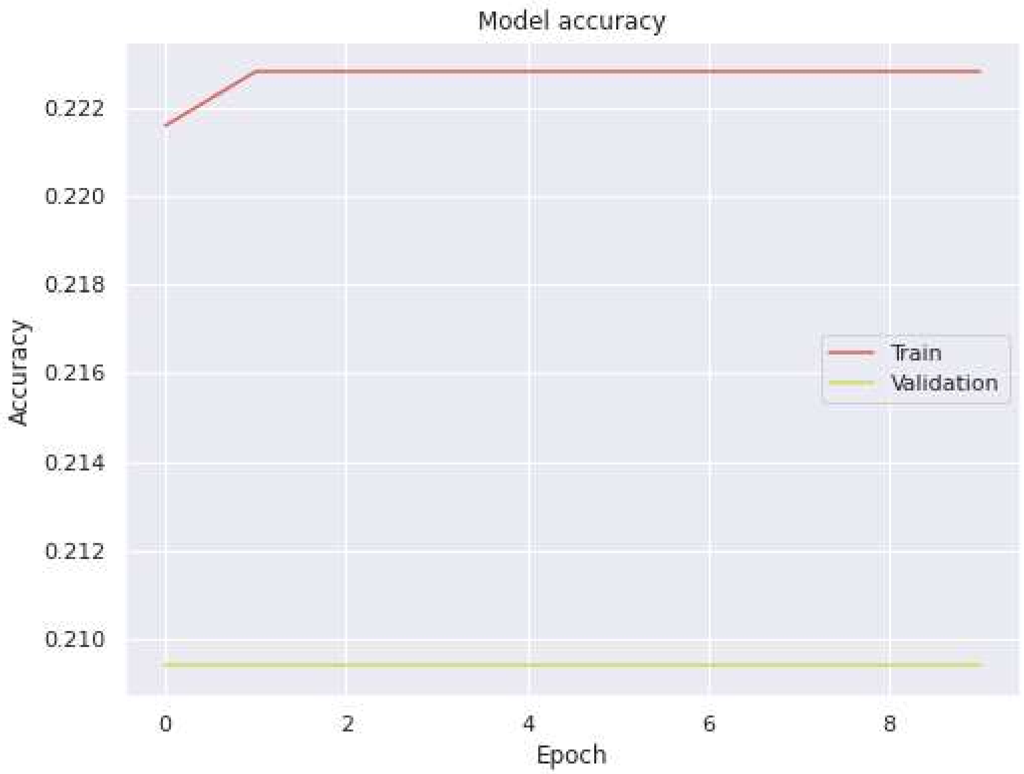
In [76]:

```
plot_accuracy(history_3, 'digit_0_categorical_accuracy', 'val_digit_0_categorical_accuracy'
```



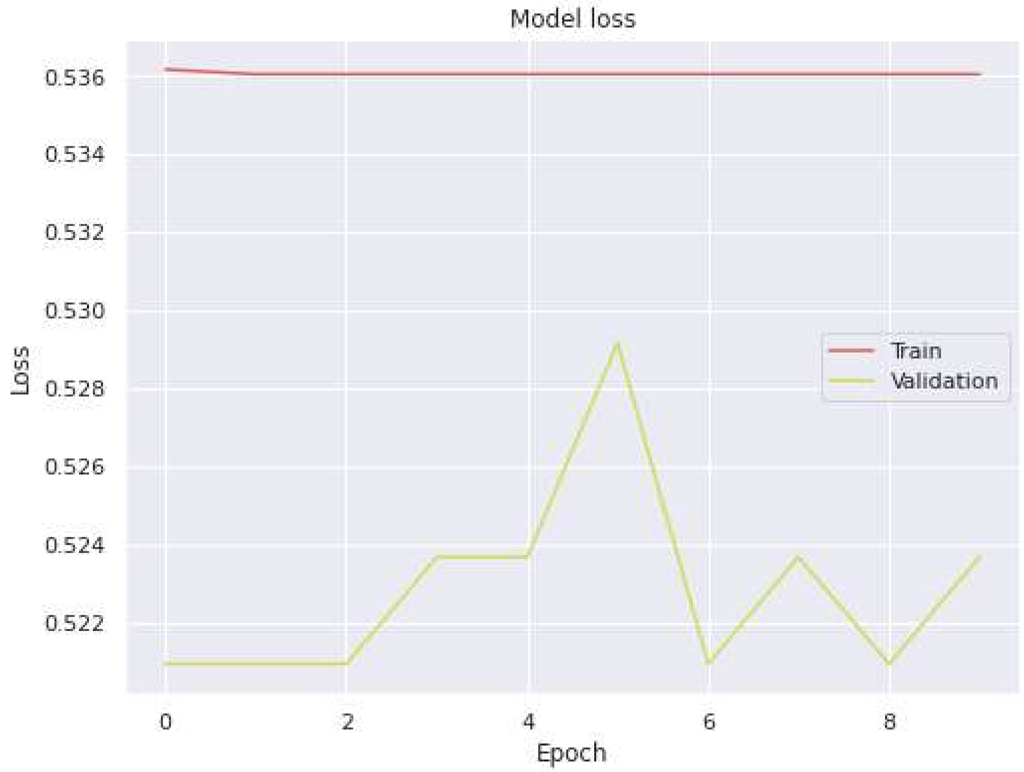
In [77]:

```
plot_accuracy(history_3, 'digit_1_categorical_accuracy', 'val_digit_1_categorical_accuracy'
```



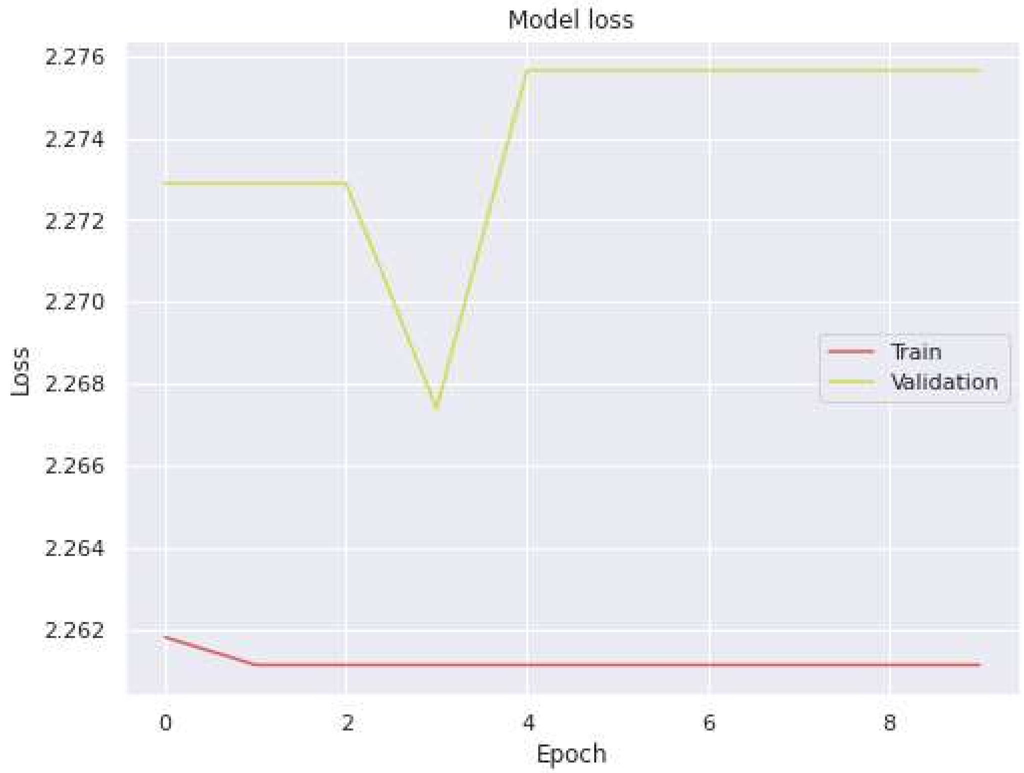
In [78]:

```
plot_loss(history_3, 'digits_n_loss', 'val_digits_n_loss')
```



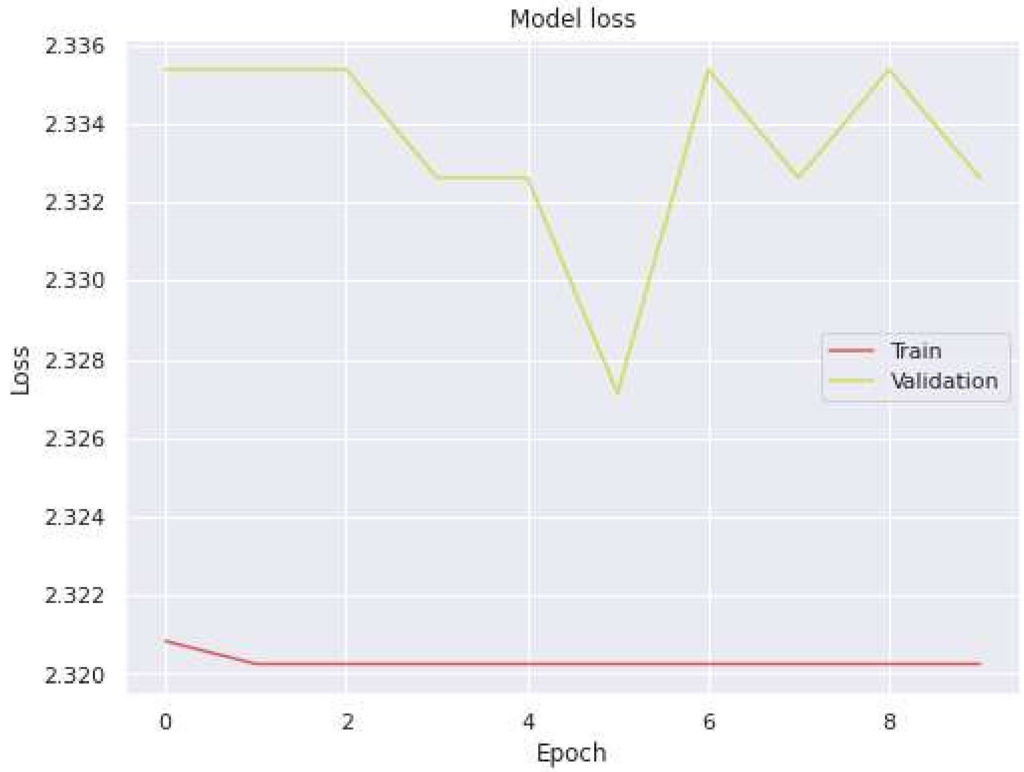
In [79]:

```
plot_loss(history_3, 'digit_0_loss', 'val_digit_0_loss')
```



In [80]:

```
plot_loss(history_3, 'digit_1_loss', 'val_digit_1_loss')
```



In [0]:

```
X_test_multidigit = tf.keras.utils.normalize(
    np.asarray(list(test_multidigit_df['data'])), axis = 1)

y_n_test_multidigit = (to_categorical(test_multidigit_df['digits_n']
                                 .astype('category')
                                 .cat.codes.astype('int32')))
y_d_0_test_multidigit = (to_categorical(test_multidigit_df['digit_0']
                                   .astype('category')
                                   .cat.codes.astype('int32')))
y_d_1_test_multidigit = (to_categorical(test_multidigit_df['digit_1']
                                   .astype('category')
                                   .cat.codes.astype('int32')))

y_test_multidigit = [
                     y_n_test_multidigit,
                     y_d_0_test_multidigit,
                     y_d_1_test_multidigit
                    ]
```

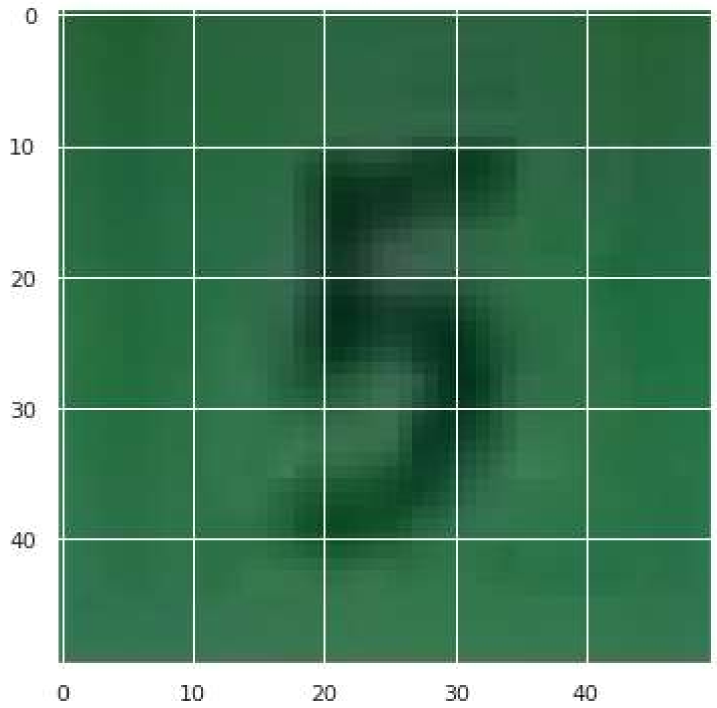
In [82]:

```
results_3 = model_3.evaluate(X_test_multidigit, y_test_multidigit)

for i, k in enumerate(history_3.history.keys()):
    if i < len(results_3):
        print(k, '\t', results_3[i])
```

```
loss	 5.093077011154151
digits_n_loss	 0.5423692
digit_0_loss	 2.236772
digit_1_loss	 2.3139274
digits_n_categorical_accuracy	 0.7709198
digit_0_categorical_accuracy	 0.22437494
digit_1_categorical_accuracy	 0.22908017
```

In [83]:

```
plt.imshow(test_multidigit_df['data'][0])

plt.show()
```



In [84]:

```
prediction_3 = model_3.predict(np.asarray([test_multidigit_df['data'][0]]))

print('digits_n:', prediction_3[0].squeeze(), '\n',
      'digit_0:', prediction_3[1].squeeze(), '\n',
      'digit_1:', prediction_3[2].squeeze())
```

```
digits_n: [0. 1.]
 digit_0: [1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 digit_1: [1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
```

Задание 3

Сделайте множество снимков изображений номеров домов с помощью смартфона на ОС *Android*. Также можно использовать библиотеки *OpenCV*, *Simple CV* или *Pygame* для обработки изображений с общедоступных камер видеонаблюдения (например, https://www.earthcam.com/) (https://www.earthcam.com/)).

В качестве примера использования библиотеки *TensorFlow* на смартфоне можете воспользоваться демонстрационным приложением от *Google* (https://github.com/tensorflow/tensorflow/tree/master/tensorflow/examples/android) (https://github.com/tensorflow/tensorflow/tree/master/tensorflow/examples/android)).

Задание 4

Реализуйте приложение для ОС *Android*, которое может распознавать цифры в номерах домов, используя разработанный ранее классификатор. Какова доля правильных классификаций?