

School of Computer Science and Engineering J Component report

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TITLE

Honeybee Sub-Species and Health Classification Using Deep Learning

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Last but not the least, we are grateful to all our fellow classmates and our friends for the suggestions and support given to us throughout the completion of our project.

ABSTRACT

Up to one third of the global food production depends on the pollination of honeybees which makes them an important role in the ecosystem. We need to have healthy honeybees in order to make best use out of it. While many indications of hive strength and health are visible on the inside of the hive, frequent check-ups on the hive are time-consuming and disruptive to the bee's workflow and hive in general. By investigating the bees that leave the hive, we can gain a more complete understanding of the hive itself. For example, an unhealthy hive infected with varroa mites will have bees with deformed wings or mites on their backs. These characteristics can be observed without opening the hive.

To enhance the process of apiculture, we will be using CNN model to detect the health of the honeybees. Along with that we will be using the same CNN model to detect the Sub-Species. After completion of the training, we will be testing our model using validation data through various plots.

INTRODUCTION

Honey is being widely used in our everyday life. It has high impact on our health and resolves many health-related issues such as healing wounds, indigestion, sore throat, and cough. It is also used as an ingredient in most of the FMCG goods such as food and beverages, cosmetics and many more.

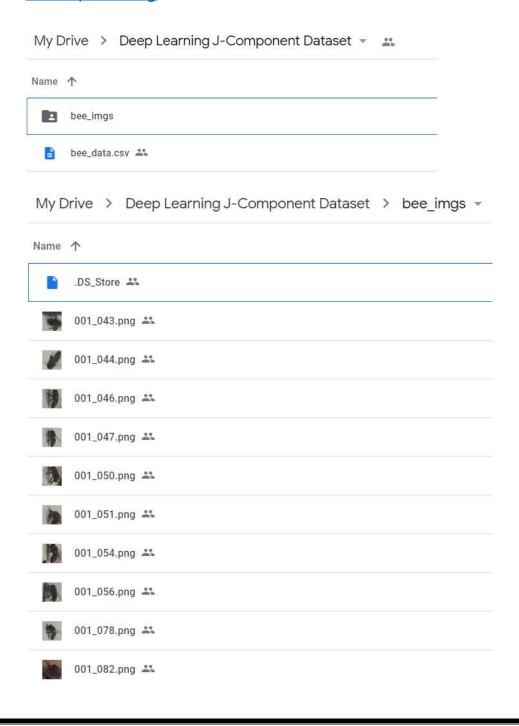
The current world is meeting with high demands of honey, due to which there is a lack of honey production. In order to improve honey production, nomadic beekeepers move their hives according to the floral blossom. The remoteness of the apiaries can make it harder for them to keep control over the hives and to intervene on time in case of illness or other stressors that affect bee health.

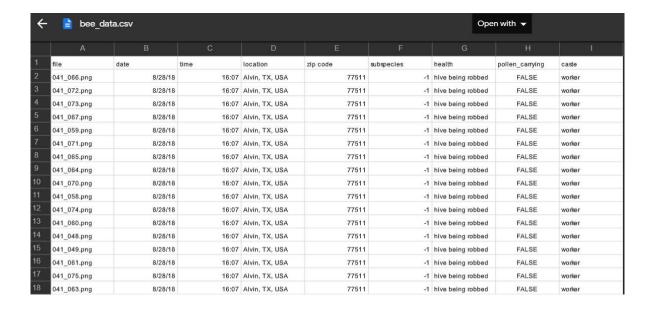
Bees may be small, but they play an enormous part in supporting biodiversity and maintaining natural ecosystems. They produce honey and are essential for pollinating fruit trees and crops, contributing to crop yields. Many beekeepers move their hives according to the blooming periods of flowers in the area. For them, keeping track of the remote hives can be a time consuming and costly venture.

4. ABOUT THE DATASET

The Dataset we had referred with the help of Kaggle platform and National Geography. It consists of 5100+ images and its annotations such as location, date, time, sub-species and health condition which is in the form of .CSV

https://drive.google.com/drive/folders/1q_ZfDWVJCgs8sDc5gRybNc908I7D_ICG?usp=sharing





5. OBJECTIVE/PROBLEM STATEMENT

In the present world there is a huge demand of honey, due to which there is a lack of honey production. In order to improve honey production, nomadic beekeepers move their hives according to the floral blossom. The remoteness of the apiaries can make it harder for them to keep control over the hives and to intervene on time in case of illness or other stressors that affect bee health. To avoid that complexity, we will be proposing a CNN architecture that helps in classifying subspecies and health status.

6. 1. PROPOSED ARCHITECTURE FOR BEE SUB-SPECIES CLASSIFICATION

Bees are classified based on Sub-Species. These are:

- 1. **Carniolan honeybee:** It's a sub-species of a western honeybee and a native to Slovenia.
- 2. **Italian honeybee:** It's a sub-species of a western honeybee and a native to Italy.
- 3. **Russian honeybee:** It's a sub-species that originates in the Primorsky region of Russia.
- 4. **VSH Italian honeybee:** It's a trait of honeybee that enables a colony to survive without mite controls. Its originations are from Italy.
- 5. **Western honeybee:** It's a European honeybee that consists of 7-12 species worldwide.

We will be building an architecture that helps in classifying these subspecies. The architecture can be seen in the below Figure (1).

Layer	filters	kernel size	Stride	Padding	Size of Feature map	Activation Function
Input					100 x 100 x3	
Conv1	12	3	-	same	100 x 100 x 6	Relu
MaxPool1	-	-	2	-	50 x 50 x 6	-
Conv2	12	3	-	same	50 x 50 x 12	Relu
MaxPool2	-	-	2	-	25 x 25 x 12	-
Conv3	12	3	-	same	25 x 25 x 12	Relu
MaxPool3	-	-	2	-	12 x 12 x 12	-
Conv4	12	3	-	same	12 x 12 x 12	Relu
MaxPool4	1-1	-	2	-	6 x 6 x 12	-
Conv5	12	3	-	same	6 x 6 x 12	Relu
MaxPool5	-	-	2	-	3 x 3 x 12	-
Flatten	-	-	-	-	(None ,108)	-
Dense	-	-	=	-	(None ,7)	Softmax

Figure (1)

Our proposed CNN for sub-species classification is a customized architecture consisting of five convolution layers and five max pool layers with some hyperparameters mentioned. Convolution operations are performed to obtain reduced size. Pooling is done so that we will be able to do upsampling or downsampling. We use a flatten layer to get the output in a column vector which will be useful for triggering to the next fully connected layers. There is one fully connected layer in our architecture and some hyperparameters are also mentioned for that.

6. 2. PROPOSED ARCHITECTURE FOR BEE HEALTH CLASSIFICATION

Bees are classified based on health. These are:

- 1. **Healthy:** These honeybees that are not suffering from any disease.
- 2. **Varrora mites:** These are tiny red brown external parasites of honeybees.
- 3. **Ant problems:** These ants colonize the honey and decreases the bee morale to fight against it.
- 4. **Hive being robbed:** It refers to bee killing bees.
- 5. **Missing queen:** Absence of queen decreases the bee morale.

We will be building an architecture that helps in classifying these bees based on health. The architecture can be seen in the below Figure (2).

Layer	filters	kernel size	Stride	Padding	Size of Feature map	Activation Function
Input					100 x 100 x3	
Conv1	12	3	-	same	100 x 100 x 6	Relu
MaxPool1	-	-	2	-	50 x 50 x 6	-
Conv2	12	3	-	same	50 x 50 x 12	Relu
MaxPool2	-	1.7	2	-	25 x 25 x 12	-
Conv3	12	3	7-2	same	25 x 25 x 12	Relu
MaxPool3	-	-	2	-	12 x 12 x 12	-
Conv4	12	3	-	same	12 x 12 x 12	Relu
MaxPool4	-	-	2	-	6 x 6 x 12	-
Conv5	12	3	-	same	6 x 6 x 12	Relu
MaxPool5	-	-	2	-	3 x 3 x 12	-
Flatten	-	-	-	-	(None ,108)	
Dense	-	-	-	-	(None ,7)	Softmax

Figure (2)

Our proposed CNN for bee health classification is a customized architecture consisting of five convolution layers and five max pool layers with some hyperparameters mentioned. Convloution operations are performed to obtain reduced size. Pooling is done so that we will be able to do upsampling or downsampling. We use a flatten layer to get the output in a column vector which will be useful for triggering to the next fully connected layers. There is one fully connected layer in our architecture and some hyperparameters are also mentioned for that.

7. CODE SCREENSHOTS

Honey Bee Sub-Species and Health Classification using Deep Learning

Imports

```
In [ ]: # Libraries
          import pandas as pd
          import numpy as np
          import sys
          import os
          import random
          from pathlib import Path
          # Image processing
          import imageio
          import skimage
import skimage.io
import skimage.transform
          import matplotlib.pyplot as plt
          import seaborn as sns
          # ML
          import scipy
          from sklearn.model_selection import train_test_split
          from sklearn import metrics
          from keras import optimizers
          from keras.models import Sequential
from keras.layers import Dense, Conv2D, Flatten, MaxPool2D, Dropout, BatchNormalization, Leak
          from keras.preprocessing.image import ImageDataGenerator
          from keras.callbacks import ModelCheckpoint, Callback, EarlyStopping, ReduceLROnPlateau
from keras.utils import to_categorical
          import tensorflow
          np.random.seed(42)
          tensorflow.set_random_seed(42)
          # Global variables
          img_folder='../input/bee_imgs/bee_imgs/'
img_width=100
          img_height=100
          img_channels=3
          Using TensorFlow backend.
```

Reading Bee data

	datetime	file	location	zip code	subspecies	health	pollen_carrying	caste
0	2018-08-28 16:07:00	041_066.png	Alvin, TX, USA	77511	-1	hive being robbed	False	worker
1	2018-08-28 16:07:00	041_072.png	Alvin, TX, USA	77511	-1	hive being robbed	False	worker
2	2018-08-28 16:07:00	041_073.png	Alvin, TX, USA	77511	-1	hive being robbed	False	worker
3	2018-08-28 16:07:00	041_067.png	Alvin, TX, USA	77511	-1	hive being robbed	False	worker
4	2018-08-28 16:07:00	041_059.png	Alvin, TX, USA	77511	-1	hive being robbed	False	worker

Performing EDA

(i) Distribution of bees by categories

```
In []: f, ax = plt.subplots(nrows=2, ncols=2, figsize=(12,8))

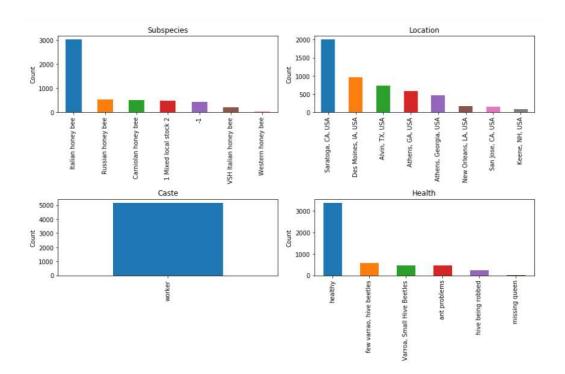
bees.subspecies.value_counts().plot(kind='bar', ax=ax[0, 0])
    ax[0,0].set_ylabel('Count')
    ax[0,0].set_title('Subspecies')

bees.location.value_counts().plot(kind='bar', ax=ax[0, 1])
    ax[0,1].set_title('Location')
    ax[0,1].set_ylabel('Count')

bees.caste.value_counts().plot(kind='bar', ax=ax[1, 0])
    ax[1,0].set_title('Caste')
    ax[1,0].set_ylabel('Count')

bees.health.value_counts().plot(kind='bar', ax=ax[1,1])
    ax[1,1].set_title('Health')
    ax[1,1].set_ylabel('Count')

f.subplots_adjust(hspace=0.7)
f.tight_layout()
plt.show()
```



Bees images

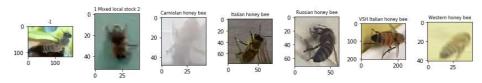
Subspecies of Bee

```
In []: # Selecting first subspecies titles
subspecies = bees['subspecies'].cat.categories
f, ax = plt.subplots(nrows=1,ncols=subspecies.size, figsize=(12,3))
i=0

# We will try to draw the first found bee of given subspecies
for s in subspecies:
    if s == 'healthy': continue
    file=img_folder + bees[bees['subspecies']==s].iloc[0]['file']
    im=imageio.imread(file)
    ax[i].imshow(im, resample=True)
    ax[i].set_title(s, fontsize=8)
    i+=1

plt.suptitle("Subspecies of Bee")
plt.tight_layout()
plt.show()
```

Subspecies of Bee



Healthy Bees

```
In []: ncols = 5
healthy = bees[bees['health'] == 'healthy'].sample(ncols)

f, ax = plt.subplots(nrows=1,ncols=ncols, figsize=(12,3))

for i in range(0,5):
    file = img_folder + healthy.iloc[i]['file']
    ax[i].imshow(imageio.imread(file))

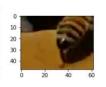
plt.suptitle("Healthy Bees")
plt.tight_layout()
plt.show()
```









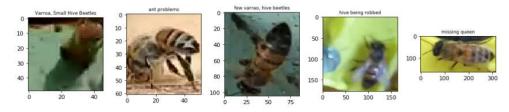


Sick Bees

```
In []: health_cats = bees['health'].cat.categories
    f, ax = plt.subplots(1, health_cats.size-1, figsize=(12,4))
    i=0
    for c in health_cats:
        if c == 'healthy': continue
        bee = bees[bees['health'] == c].sample(1).iloc[0]
        ax[i].imshow(imageio.imread(img_folder + bee['file']))
        ax[i].set_title(bee['health'], fontsize=8)
        i += 1

plt.suptitle("Sick Bees")
    plt.tight_layout()
    plt.show()
```

Sick Bees



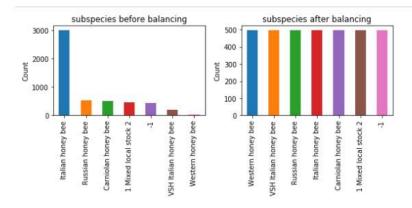
Bee subspecies classification

Preprocessing includes data balancing and augmentation. Then we'll be ready to train CNN.

(i) Data preprocessing for Bee subspecies

- Balancing samples by subspecies

```
In [ ]: # The same split-balance will be used in 2 places: subspecies and health CNN.
         def split_balance(bees, field_name):
             # Splitting to train and test before balancing
             train_bees, test_bees = train_test_split(bees, random_state=24)
             # Splitting train to train and validation datasets
             # Validation for use during learning
             train_bees, val_bees = train_test_split(train_bees, test_size=0.1, random_state=24)
             #Balance by subspecies to train_bees_bal_ss dataset
             # Number of samples in each category
             ncat_bal = int(len(train_bees)/train_bees[field_name].cat.categories.size)
             train_bees_bal = train_bees.groupby(field_name, as_index=False).apply(lambda g: g.sampl
         e(ncat_bal, replace=True)).reset_index(drop=True)
             return(train_bees_bal, val_bees, test_bees)
         def plot_balanced(train_bees, train_bees_bal, field_name):
             # Plot before and after balancing
             f, axs = plt.subplots(1,2, figsize=(8,4))
             # Before
             ax = train_bees[field_name].value_counts().plot(kind='bar', ax=axs[0])
             ax.set_title('%s before balancing' % field_name)
             ax.set_ylabel('Count')
             # After
            ax = train_bees_bal[field_name].value_counts().plot(kind='bar', ax=axs[1])
ax.set_title('%s after balancing' % field_name)
             ax.set_ylabel('Count')
             plt.tight_layout()
             plt.show()
         # Split/balance and plotting the result
         train_bees_bal, val_bees, test_bees = split_balance(bees, 'subspecies')
         plot_balanced(bees, train_bees_bal, 'subspecies')
         # Using balanced dataset as main
         train_bees = train_bees_bal
```



- Preparing features

We prepare train bees dataset to load them and use ImageDataGenerator to randomly shift/rotate/zoom.

```
In [ ]: def prepare2train(train_bees, val_bees, test_bees, field_name):
            train_X = np.stack(train_bees['file'].apply(read_img))
            train_y = pd.get_dummies(train_bees[field_name], drop_first=False)
             # Validation during training data to calc val_loss metric
            val_X = np.stack(val_bees['file'].apply(read_img))
            val_y = pd.get_dummies(val_bees[field_name], drop_first=False)
            test_X = np.stack(test_bees['file'].apply(read_img))
            test_y = pd.get_dummies(test_bees[field_name], drop_first=False)
            # Data augmentation - rotate, zoom and shift input images.
            generator = ImageDataGenerator(
                     featurewise_center=False,
                     samplewise_center=False,
                     featurewise_std_normalization=False,
                    samplewise_std_normalization=False,
                    zca_whitening=False,
                    rotation_range=180,
                    zoom_range = 0.1,
                    width_shift_range=0.2,
                    height_shift_range=0.2,
                    horizontal_flip=True,
                    vertical_flip=True)
            generator.fit(train_X)
            return (generator, train_X, val_X, test_X, train_y, val_y, test_y)
        # Call image preparation and one hot encoding
        generator, train_X, val_X, test_X, train_y, val_y, test_y = prepare2train(train_bees, val_be
        es, test_bees, 'subspecies')
        /opt/conda/lib/python3.6/site-packages/skimage/transform/_warps.py:110: UserWarning: Anti-ali
        asing will be enabled by default in skimage 0.15 to avoid aliasing artifacts when down-sampli
        ng images
          warn("Anti-aliasing will be enabled by default in skimage 0.15 to "
```

Train Bee Subspecies CNN

```
In [ ]: # We'll stop training if no improvement after some epochs
        earlystopper1 = EarlyStopping(monitor='loss', patience=10, verbose=1)
        # Save the best model during the traning
        checkpointer1 = ModelCheckpoint('best_model1.h5'
                                         , monitor='val_acc'
                                         ,verbose=1
                                         , save_best_only=True
                                        , save_weights_only=True)
        # Build CNN model
        model1=Sequential()
        model1.add(Conv2D(6, kernel_size=3, input_shape=(img_width, img_height,3), activation='relu'
        , padding='same'))
        model1.add(MaxPool2D(2))
        model1.add(Conv2D(12, kernel_size=3, activation='relu', padding='same'))
        model1.add(MaxPool2D(2))
        model1.add(Flatten())
        model1.add(Dense(train_y.columns.size, activation='softmax'))
        model1.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
        training1 = model1.fit_generator(generator.flow(train_X,train_y, batch_size=60)
                                ,epochs=65
                                 ,validation_data=[val_X, val_y]
                                 ,steps_per_epoch=65
                                 ,callbacks=[earlystopper1, checkpointer1])
        # Get the best saved weights
        model1.load_weights('best_model1.h5')
```

Train Bee Subspecies CNN

Epoch 8/65

Epoch 10/65

s: 0.7801 - val_acc: 0.6804

s: 0.7610 - val_acc: 0.6778

Epoch 00008: val_acc did not improve from 0.68041

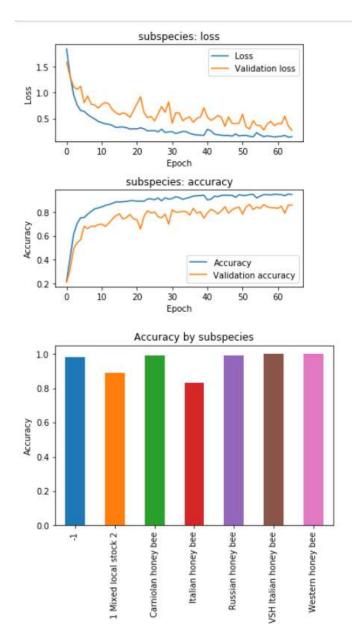
Epoch 00009: val_acc did not improve from 0.68041

```
In [ ]: # We'll stop training if no improvement after some epochs
      earlystopper1 = EarlyStopping(monitor='loss', patience=10, verbose=1)
       # Save the best model during the traning
      checkpointer1 = ModelCheckpoint('best_model1.h5'
                                ,monitor='val_acc'
                                ,verbose=1
                                , save_best_only=True
                                , save_weights_only=True)
      # Build CNN model
      model1=Sequential()
      model1.add(Conv2D(6, kernel_size=3, input_shape=(img_width, img_height,3), activation='relu'
       , padding='same')
      model1.add(MaxPool2D(2))
      model1.add(Conv2D(12, kernel_size=3, activation='relu', padding='same'))
      model1.add(MaxPool2D(2))
      model1.add(Flatten())
      model1.add(Dense(train_y.columns.size, activation='softmax'))
      model1.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
      training1 = model1.fit_generator(generator.flow(train_X, train_y, batch_size=60)
                          , epochs=65
                          ,validation_data=[val_X, val_y]
                          ,steps_per_epoch=65
                          ,callbacks=[earlystopper1, checkpointer1])
      # Get the best saved weights
      model1.load_weights('best_model1.h5')
      Epoch 1/65
      65/65 [============ ] - 13s 200ms/step - loss: 1.8389 - acc: 0.2246 - val_lo
      ss: 1.5899 - val_acc: 0.2113
      Epoch 00001: val_acc improved from -inf to 0.21134, saving model to best_model1.h5
      Epoch 2/65
      s: 1.3108 - val_acc: 0.3170
      Epoch 00002: val_acc improved from 0.21134 to 0.31701, saving model to best_model1.h5
      Epoch 3/65
      s: 1.1133 - val_acc: 0.4923
      Epoch 00003: val_acc improved from 0.31701 to 0.49227, saving model to best_model1.h5
      s: 1.0656 - val acc: 0.5412
      Epoch 00004: val_acc improved from 0.49227 to 0.54124, saving model to best_model1.h5
      Epoch 5/65
      s: 1.1208 - val_acc: 0.5670
      Epoch 00005: val_acc improved from 0.54124 to 0.56701, saving model to best_model1.h5
      Epoch 6/65
      s: 0.8074 - val_acc: 0.6804
      Epoch 00006: val_acc improved from 0.56701 to 0.68041, saving model to best_model1.h5
      Epoch 7/65
                65/65 [===
      s: 0.9344 - val_acc: 0.6598
      Epoch 00007: val_acc did not improve from 0.68041
```

```
Epoch 00063: val_acc did not improve from 0.86340
       Epoch 64/65
       s: 0.3607 - val_acc: 0.8582
       Epoch 00064: val_acc did not improve from 0.86340
       s: 0.2764 - val_acc: 0.8557
       Epoch 00065: val_acc did not improve from 0.86340
In [ ]: model1.summary()
                              Output Shape
                                                    Param #
       Layer (type)
       conv2d_1 (Conv2D)
                              (None, 100, 100, 6)
                                                    168
       max_pooling2d_1 (MaxPooling2 (None, 50, 50, 6)
                                                    0
       conv2d_2 (Conv2D)
                               (None, 50, 50, 12)
                                                    660
       max_pooling2d_2 (MaxPooling2 (None, 25, 25, 12)
                                                    0
       conv2d_3 (Conv2D)
                              (None, 25, 25, 12)
                                                    1308
       max_pooling2d_3 (MaxPooling2 (None, 12, 12, 12)
       conv2d 4 (Conv2D)
                              (None, 12, 12, 12)
                                                    1308
       max_pooling2d_4 (MaxPooling2 (None, 6, 6, 12)
                                                    0
       conv2d_5 (Conv2D)
                               (None, 6, 6, 12)
                                                    1308
       max_pooling2d_5 (MaxPooling2 (None, 3, 3, 12)
                                                    0
       flatten_1 (Flatten)
                               (None, 108)
                                                    0
       dense_1 (Dense)
                               (None, 7)
                                                    763
       Total params: 5,515
       Trainable params: 5,515
       Non-trainable params: 0
```

4.3 Evaluate bee subspecies detection model

```
In [ ]: def eval_model(training, model, test_X, test_y, field_name):
               # Trained model analysis and evaluation
               f, ax = plt.subplots(2,1, figsize=(5,5))
               ax[0].plot(training.history['loss'], label="Loss")
ax[0].plot(training.history['val_loss'], label="Validation loss")
ax[0].set_title('%s: loss' % field_name)
ax[0].set_xlabel('Fpoch')
               ax[0].set_ylabel('Loss')
ax[0].legend()
               ax[1].plot(training1.history['acc'], label="Accuracy")
ax[1].plot(training1.history['val_acc'], label="Validation accuracy")
ax[1].set_title('%s: accuracy' % field_name)
               ax[1].set_xlabel('Epoch')
               ax[1].set_ylabel('Accuracy')
               ax[1].legend()
               plt.tight_layout()
plt.show()
               # Accuracy by subspecies
               test_pred = model.predict(test_X)
               acc_by_subspecies = np.logical_and((test_pred > 0.5), test_y).sum()/test_y.sum()
               acc_by_subspecies.plot(kind='bar', title='Accuracy by %s' % field_name)
               plt.ylabel('Accuracy')
               plt.show()
               # Printing metrics
               print("Classification report")
               test_pred = np.argmax(test_pred, axis=1)
               test_truth = np.argmax(test_y.values, axis=1)
               print(metrics.classification_report(test_truth, test_pred, target_names=test_y.columns))
               # Loss function and accuracy
               test_res = model.evaluate(test_X, test_y.values, verbose=0)
               print('Loss function: %s, accuracy:' % test_res[0], test_res[1])
          # Call evaluation function
          eval_model(training1, model1, test_X, test_y, 'subspecies')
```



Classification report				
8	precision	recall	f1-score	support
-1	0.83	0.98	0.90	108
1 Mixed local stock 2	0.49	0.89	0.63	102
Carniolan honey bee	0.97	0.99	0.98	147
Italian honey bee	0.98	0.83	0.90	754
Russian honey bee	0.98	0.99	0.99	124
VSH Italian honey bee	0.90	1.00	0.95	54
Western honey bee	1.00	1.00	1.00	4
micro avg	0.89	0.89	0.89	1293
macro avg	0.88	0.96	0.91	1293
weighted avg	0.93	0.89	0.90	1293

Loss function: 0.24511571190473375, accuracy: 0.8917246713992338

2. CNN model for Bee health classification

Data preprocessing for Bee health classification

- Balance Bees by health

```
In [ ]: # Split/balance and plot the result
          train_bees_bal, val_bees, test_bees = split_balance(bees, 'health')
          plot_balanced(train_bees, train_bees_bal, 'health')
          # we will use balanced dataset as main
          train_bees_bal = train_bees
                        health before balancing
                                                                    health after balancing
                                                         600
             2000
                                                         400
           B 1000
                                                         200
                                                                          healthy
                                                                                beetles
                                     hive beetles
                                                                                           Hive Beetles
                          Hive
                                                                                hive
                                                                                      ant
                                     varrao,
                               hive
                          Varroa,
```

Features augmentation and labels one hot encoding for Health CNN

```
In [ ]: # Call image preparation and one hot encoding from Bee subspecies section
generator, train_X, val_X, test_X, train_y, val_y, test_y = prepare2train(train_bees, val_be
es, test_bees, 'health')

/opt/conda/lib/python3.6/site-packages/skimage/transform/_warps.py:110: UserWarning: Anti-ali
asing will be enabled by default in skimage 0.15 to avoid aliasing artifacts when down-sampli
ng images.
warn("Anti-aliasing will be enabled by default in skimage 0.15 to "
```

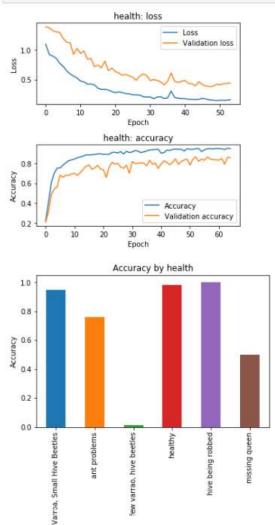
5.2 Train Bee health CNN

```
In [ ]: # We'll stop training if no improvement after some epochs
        earlystopper2 = EarlyStopping(monitor='val_acc', patience=10, verbose=1)
        # Save the best model during the traning
        checkpointer2 = ModelCheckpoint('best_model2.h5'
                                         , monitor='val_acc'
                                         ,verbose=1
                                          , save_best_only=True
                                         , save_weights_only=True)
        # Build CNN model
        model2=Sequential()
        model2.add(Conv2D(6, kernel_size=3, input_shape=(img_width, img_height,3), activation='relu'
         , padding='same'))
        model2.add(MaxPool2D(2))
        model2.add(Conv2D(12, kernel_size=3, activation='relu', padding='same'))
        model2.add(MaxPool2D(2))
        model2.add(Conv2D(4, kernel_size=3, activation='relu', padding='same'))
        model2.add(MaxPool2D(2))
        model2.add(Conv2D(6, kernel_size=3, activation='relu', padding='same'))
        model2.add(MaxPool2D(2))
        model2.add(Conv2D(12, kernel_size=3, activation='relu', padding='same'))
        model2.add(MaxPool2D(2))
        model2.add(Flatten())
        model2.add(Dense(train_y.columns.size, activation='softmax'))
        model2.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
        # Train
        training2 = model2.fit_generator(generator.flow(train_X,train_y, batch_size=60))
                                 ,epochs=65
                                 ,validation_data=[val_X, val_y]
                                 ,steps_per_epoch=65
,callbacks=[earlystopper2, checkpointer2])
        # Get the best saved weights
        model2.load_weights('best_model2.h5')
```

```
Epoch 1/65
s: 1.3882 - val_acc: 0.6443
Epoch 00001: val_acc improved from -inf to 0.64433, saving model to best_model2.h5
Epoch 2/65
s: 1.3701 - val_acc: 0.6443
Epoch 00002: val acc did not improve from 0.64433
Epoch 3/65
s: 1.3242 - val_acc: 0.6418
Epoch 00003: val_acc did not improve from 0.64433
s: 1.2994 - val_acc: 0.5825
Epoch 00004: val_acc did not improve from 0.64433
Epoch 5/65
s: 1.2929 - val_acc: 0.5593
Epoch 00005: val_acc did not improve from 0.64433
Epoch 6/65
s: 1.1892 - val_acc: 0.6211
Epoch 00006: val_acc did not improve from 0.64433
Epoch 7/65
s: 1.1270 - val_acc: 0.6340
Epoch 00007: val_acc did not improve from 0.64433
Epoch 8/65
s: 1.1191 - val_acc: 0.6392
Epoch 00008: val_acc did not improve from 0.64433
Epoch 9/65
s: 0.9237 - val_acc: 0.6881
Epoch 00009: val_acc improved from 0.64433 to 0.68814, saving model to best_model2.h5
Epoch 10/65
s: 1.0235 - val_acc: 0.6521
Epoch 00010: val_acc did not improve from 0.68814
Epoch 11/65
s: 0.9378 - val acc: 0.6701
Epoch 00047: val_acc did not improve from 0.84021
Epoch 48/65
s: 0.3808 - val acc: 0.8351
Epoch 00048: val_acc did not improve from 0.84021
Epoch 49/65
s: 0.3853 - val_acc: 0.8325
Epoch 00049: val_acc did not improve from 0.84021
Epoch 50/65
s: 0.4218 - val_acc: 0.8299
Epoch 00050: val_acc did not improve from 0.84021
s: 0.4100 - val_acc: 0.8299
Epoch 00051: val_acc did not improve from 0.84021
Epoch 52/65
s: 0.4304 - val_acc: 0.8325
Epoch 00052: val_acc did not improve from 0.84021
Epoch 53/65
65/65 [============================ - 8s 126ms/step - loss: 0.1540 - acc: 0.9444 - val_los
s: 0.4353 - val_acc: 0.8273
Epoch 00053: val_acc did not improve from 0.84021
Enoch 54/65
s: 0.4434 - val_acc: 0.8273
Epoch 00054: val_acc did not improve from 0.84021
Epoch 00054: early stopping
```

5.3 Evaluate Bee health classification model

In []: # Call evaluation with charts
 eval_model(training2, model2, test_X, test_y, 'health')



Classification report				
	precision	recall	f1-score	support
Varroa, Small Hive Beetles	0.48	0.96	0.64	102
ant problems	0.94	0.76	0.84	117
few varrao, hive beetles	0.44	0.03	0.05	139
healthy	0.94	0.99	0.96	866
hive being robbed	0.90	1.00	0.95	61
missing queen	0.67	0.50	0.57	8
micro avg	0.86	0.86	0.86	1293
macro avg	0.73	0.71	0.67	1293
weighted avg	0.85	0.86	0.83	1293

Loss function: 0.37857956102165435, accuracy: 0.8600154679501969

6. Visualization of Conv2D layers

```
In [ ]: # Now we will be looking how our models process images. Our models contains Conv2D layers wi th kernels inside.
            # We are going to convolve a sample image through kernels and see how does it look before an
            # Function for Conv2D layers visualization:
In [ ]: # Common function for visualization of kernels
            def visualize_layer_kernels(img, conv_layer, title):
                 # Extracting kernels from given layer
                 weights1 = conv_layer.get_weights()
                 kernels = weights1[0]
                 kernels_num = kernels.shape[3]
                 # Each row contains 3 images: kernel, input image, output image
f, ax = plt.subplots(kernels_num, 3, figsize=(7, kernels_num*2))
                 for i in range(0, kernels_num):
                      \label{lem:kernels} $$ \ker[i][0].imshow((kernel * 255).astype(np.uint8), vmin=0, vmax=255) $$ ax[i][0].set_title("Kernel %d" % i, fontsize = 9) $$
                      # Getting and draw sample image from test data
ax[i][1].imshow((img * 255).astype(np.uint8), vmin=0, vmax=255)
ax[i][1].set_title("Before", fontsize=8)
                       # Filtered image - apply convolution
                      img_filt = scipy.ndimage.filters.convolve(img, kernel)
ax[i][2].imshow((img_filt * 255).astype(np.uint8), vmin=0, vmax=255)
ax[i][2].set_title("After", fontsize=8)
                 plt.suptitle(title)
                 plt.tight_layout()
                 plt.subplots_adjust(top=0.93)
                 plt.show()
```

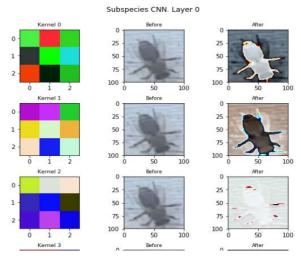
Visualizing convolutions in Bee subspecies CNN

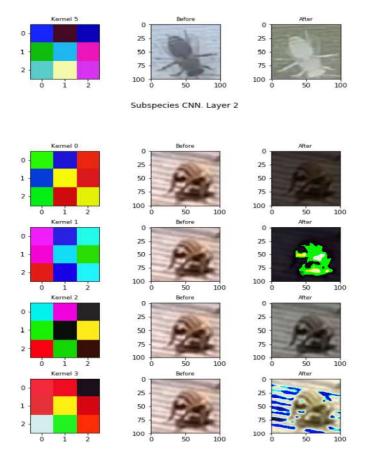
```
In []: # Taking a sample image to visualize convolution
    idx = random.randint(0,len(test_X)-1)
    img = test_X[idx,:,:,:]

# Taking 1st convolutional layer and we will look at it's filters
    conv1 = model1.layers[0]
    img = visualize_layer_kernels(img, conv1, "Subspecies CNN. Layer 0")

# Taking sample image to visualize convolution
    idx = random.randint(0,len(test_y)-1)
    img = test_X[idx,:,:,:]

# Taking another convolutional layer and lwe will ook at it's filters
    conv2 = model1.layers[2]
    res = visualize_layer_kernels(img, conv2, "Subspecies CNN. Layer 2")
```





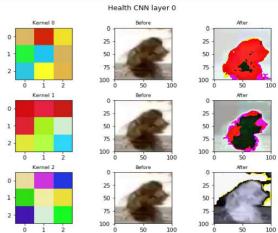
Visualizing convolutions in Bee health CNN

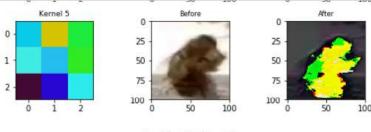
```
In []: # Take sample image to visualize convolution
idx = random.randint(0,len(test_X)-1)
img = test_X[idx,:,:,:]

# Taking 1st convolutional layer and look at it's filters
conv1 = model2.layers[0]
visualize_layer_kernels(img, conv1, "Health CNN layer 0")

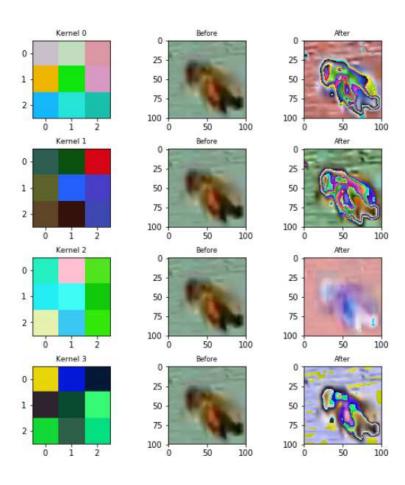
# Taking sample image to visualize convolutoin
idx = random.randint(0,len(test_X)-1)
img = test_X[idx,:,:,:]

# Taking another convolutional layer and look at it's filters
conv2 = model2.layers[2]
visualize_layer_kernels(img, conv2, "Health CNN layer 2")
```





Health CNN layer 2



8. RESULTS AND CONCLUSION

• Bee Sub-Species Classification Report -

Classification report				
	precision	recal1	f1-score	support
-1	0.83	0.98	0.90	108
1 Mixed local stock 2	0.49	0.89	0.63	102
Carniolan honey bee	0.97	0.99	0.98	147
Italian honey bee	0.98	0.83	0.90	754
Russian honey bee	0.98	0.99	0.99	124
VSH Italian honey bee	0.90	1.00	0.95	54
Western honey bee	1.00	1.00	1.00	4
micro avg	0.89	0.89	0.89	1293
macro avg	0.88	0.96	0.91	1293
weighted avg	0.93	0.89	0.90	1293

Loss function: 0.24511571190473375, accuracy: 0.8917246713992338

The above report talks about various classification metrics such as **precision, recall, f1-score,** and **support**. And after considering all these metrics into consideration, we can say that our model performs well, with an accuracy score of 0.891 for Bee Sub-Species Classification.

• Bee Health Classification Report -

	precision	recall	f1-score	support
Varroa, Small Hive Beetles	0.51	0.95	0.66	102
ant problems	0.86	0.79	0.83	117
few varrao, hive beetles	0.82	0.19	0.31	139
healthy	0.95	0.97	0.96	866
hive being robbed	0.91	0.98	0.94	61
missing queen	1.00	0.88	0.93	8
micro avg	0.87	0.87	0.87	1293
macro avg	0.84	0.80	0.77	1293
weighted avg	0.89	0.87	0.85	1293

Loss function: 0.34877999666257137, accuracy: 0.8708430008194932

The above report talks about various classification metrics such as **precision, recall, f1-score,** and **support**. And after considering all these metrics into consideration, we can say that our model performs well, with an accuracy score of 0.870 for Bee Health Classification.

- CNN Model for Bee Sub-Species Classification: 0.891 (89.1%)
- CNN Model for Bee Health Classification: 0.870 (87.0%)

9. REFERENCES

https://www.analyticsvidhya.com/blog/2018/12/guide-convolutional-neural-network-cnn/

https://medium.com/analytics-vidhya/cnn-32fbc1706a89

 $\frac{https://towardsdatascience.com/the-5-classification-evaluation-metrics-you-must-know-aa97784ff226}{know-aa97784ff226}$

https://www.osbeehives.com/blogs/beekeeping-blog/types-of-honey-bee-and-their-traits

https://www.nationalgeographic.com/animals/invertebrates/facts/honeybee