ŽILINSKÁ UNIVERZITA V ŽILINE
Fakulta elektrotechniky
a informačných technológií

DIGITAL IMAGE PROCESSING
Final report

Detect Flowers using KNN method

Jakub Kryger

Professor: Róbert Hudec

January 23, 2024

Introduction

The present work focuses on the task of identifying a flower species from an image, using a dataset containing images for sixteen different flower species. We take the flower in the photo selected by the user as the input. As an output, we receive the response as one of the 16 species to which the chosen flower is most similar. The similarity is calculated on the basis of the K nearest neighbours for arrays of histogram values. The flower species in the dataset are as follows: astilbe, bellflower, black_eyed_susan, calendula, california_poppy, carnation, common_daisy, coreopsis, daffodil, dandelion, iris, magnolia, rose, sunflower, tulip, water_lily.

1 K-Nearest Neighbours algorithm

K-Nearest Neighbours (KNN) is a simple but effective algorithm used in both classification and regression in the field of machine learning. It is an example of a supervised learning algorithm, meaning that it works with labelled training data.

How KNN works: Basic steps:

Step 1: Storage of training data. The algorithm stores the labelled training data in memory. Step 2: Distance determination. For a new data point, the algorithm calculates the distances to all training points. Metrics such as Euclidean distance or Manhattan distance are often used. Selection of the number of neighbours (K):

The user decides how many nearest neighbours will be taken into account when classifying a test point. Choosing the right number of neighbours is crucial and can affect the performance of the algorithm. Classification or regression:

Classification: For classification problems, the label assigned to a new data point is the label that most of its K nearest neighbours have.

Advantages of KNN: Simplicity: The algorithm is easy to understand and implement. No training required: KNN is lazy, meaning that it does not require a training phase. The data is stored and classification/regression is done based on the current data. Challenges of KNN: Scale sensitivity: KNN is sensitive to the scale of the data, meaning that it may be necessary to normalise features to avoid the impact of larger scale features on the results. Computational costs: Distance calculations for each new data point can be costly, especially for large datasets. Impact of noisy data: The introduction of noise or non-linearity can affect the effectiveness of KNN. It is worth noting that KNN has applications in a variety of fields, such as image recognition, spatial data analysis or content matching with user profiles on social networks.

2 How humans recognize flower species

Humans recognise flower species through a complex process of visual perception and analysis of information by the brain. Here are some key elements of this process:

Sight: Human sight is the main sense used to recognise flowers. The brain processes visual information such as shape, colour, texture and patterns on flower petals.

Colour: The colour of flowers is one of the most important recognition factors. The human brain is able to distinguish a wide range of colours, which helps to identify specific species.

Shape and Structure: The brain analyses the shape and structure of flowers. Unique features, such as the number of petals, the arrangement of the leaves or the shape of the stem, can be crucial for species identification.

Smell: Although not directly related to visual perception, the smell of flowers can also influence the recognition process. Some flower species have distinctive scents that help in their identification.

Memory and Experience: The brain also relies on memory and experience. People with experience of seeing different flower species are more likely to recognise them.

Contextual Data: The brain takes into account the context in which flowers appear. For example, if you see flowers in a forest, there are different probabilities that they are wild species than if you saw them in a garden.

As a result, the human brain combines this diverse information, using complex perceptual and analytical processes to recognise and identify flower species.

3 Accuracy

How the accuracy was calculated from the Table 1 (Classification Report and accuracy):

$$\text{Accuracy} = \frac{(\text{Precision} \times \text{Support}) + (\text{Recall} \times \text{Support})}{2 \times \text{Support}}$$

4 HUE solution

4.1 Principle of operation

Firstly, I converted the user-data photo into a histogram of HUE values, which only represents the colour. I then use the K-method of nearest neighbours to decide to which species this photo is most similar.

4.2 The way I choose K

4.2.1 For 16 samples

Below are diagrams illustrating how I choose k. For this I use the 'Training accuracy' and 'Testing accuracy' waveforms and select 'K', where 'Testing accuracy' is the largest and 'Training accuracy' is the smallest.

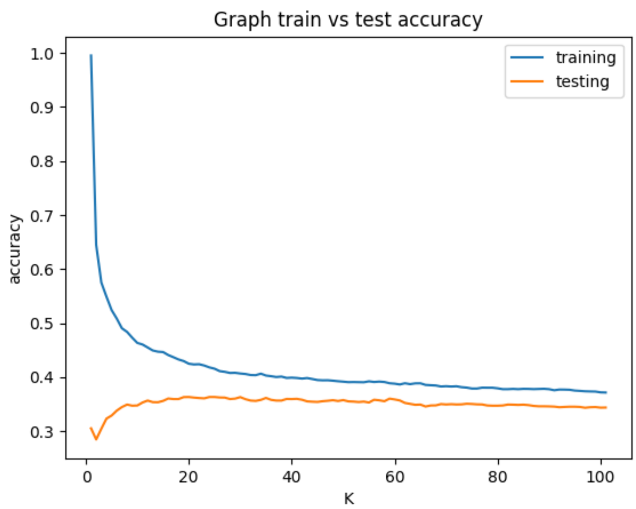

Figure 1: Graph of training and testing accuracy for 16 samples

Table 1: Classification Report and accuracy for K=59

Class	Precision	Recall	F1-Score	Support
astilbe	0.26	0.24	0.25	226
bellflower	0.43	0.13	0.20	253
black_eyed_susan	0.25	0.39	0.30	302
calendula	0.30	0.30	0.30	293
california_poppy	0.23	0.12	0.16	322
carnation	0.32	0.34	0.33	288
common_daisy	0.31	0.40	0.35	306
coreopsis	0.23	0.27	0.25	297
daffodil	0.37	0.35	0.36	321
dandelion	0.25	0.19	0.22	297
iris	0.57	0.59	0.58	321
magnolia	0.33	0.38	0.35	316
rose	0.36	0.22	0.27	293
sunflower	0.33	0.48	0.39	286
tulip	0.30	0.32	0.31	300
water_lily	1.00	0.96	0.98	301
Accuracy			**0.36**	4722
Macro Avg	0.36	0.36	0.35	4722
Weighted Avg	0.37	0.36	0.35	4722

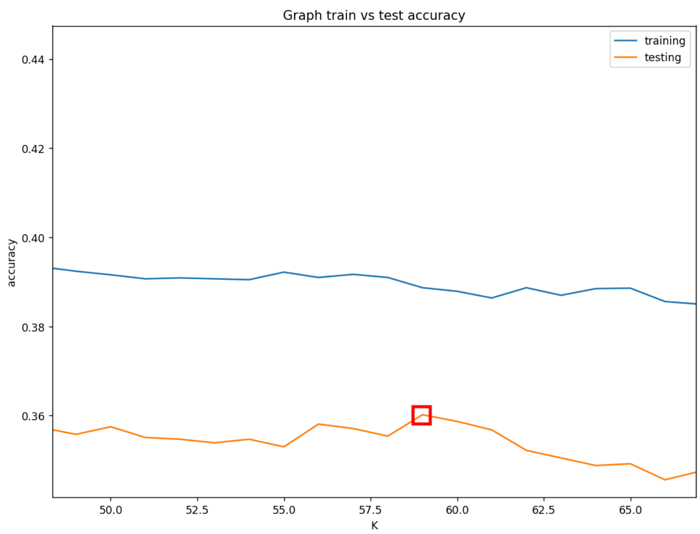

Figure 2: How I chose K = 59

5 Ycbcr solution

5.1 Principle of operation

The principle is very similar except that I use a different colour representation - YCbCr.

YCbCr, which stands for Luminance (Y), Chrominance Blue (Cb), and Chrominance Red (Cr), is a color space commonly used in video compression and broadcasting. It separates the brightness information (luminance) from the color information (chrominance) in an image or video.

5.2 Sampling and quantification of the histogram

Since we have two histograms: Chrominance Blue and Chrominance Red. I formulated the table of histogram values as a combination of 2 tables side by side to use the same computation method as in HUE example, as following:

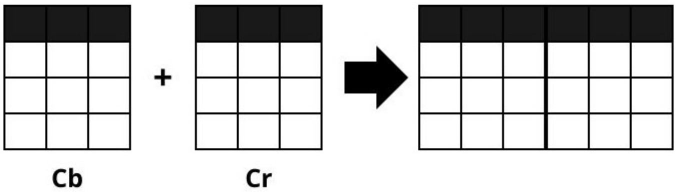

Figure 3: Combining histograms

I converted each histogram into 32 samples. So my histogram table has 64 columns.

5.3 The way I choose K

Below are diagrams illustrating how I choose k. The method is the same as above.

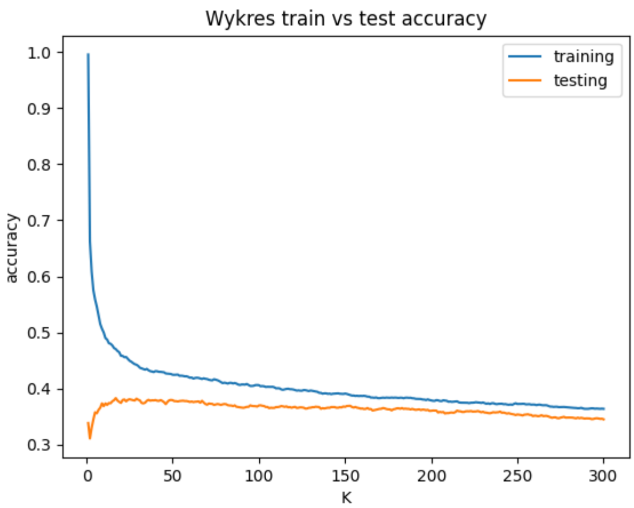

Figure 4: Graph of training and testing accuracy

Table 2: Classification Report and accuracy for K=17

Class	Precision	Recall	F1-Score	Support
astilbe	0.29	0.28	0.28	226
bellflower	0.24	0.18	0.21	253
black_eyed_susan	0.29	0.53	0.38	302
calendula	0.46	0.28	0.35	293
california_poppy	0.26	0.20	0.22	322
carnation	0.33	0.33	0.33	288
common_daisy	0.27	0.43	0.34	306
coreopsis	0.30	0.25	0.27	297
daffodil	0.37	0.31	0.34	321
dandelion	0.27	0.18	0.22	297
iris	0.56	0.52	0.54	321
magnolia	0.36	0.47	0.41	316
rose	0.34	0.26	0.30	293
sunflower	0.42	0.47	0.44	286
tulip	0.38	0.38	0.38	300
water_lily	1.00	0.99	0.99	301
Accuracy			0.38	4722
Macro Avg	0.38	0.38	0.37	4722
Weighted Avg	0.39	0.38	0.38	4722

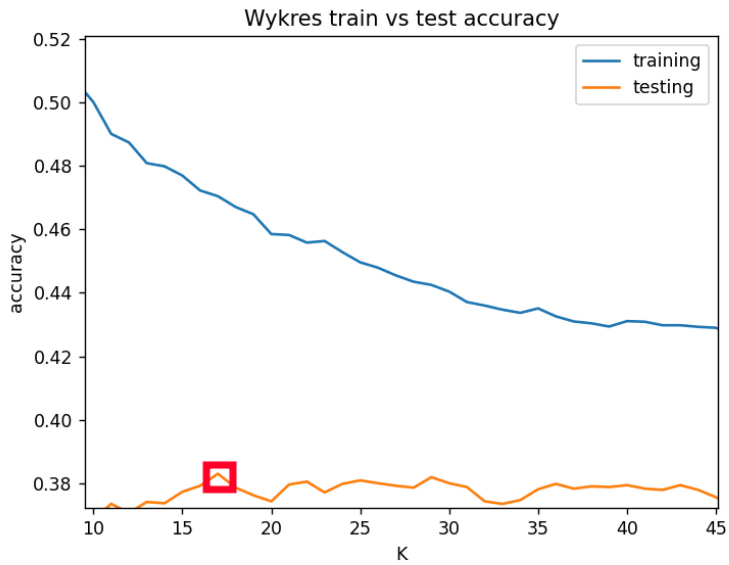

Figure 5: How I chose K = 17

6 Explanation program flow

The program can be divided into two parts, the first part is preparation and the second part is the actual launch of the program. In the first part, first we prepare a python program that will create a csv file containing data from histograms of all photos in the training set. Then we use the histograms.csv file in diagramcsv_and_report.py to select the appropriate k value. Then we use the histograms.csv file in the diagramcsv_and_report.py program to create a csv file needed to prepare a chart from which we can read the best K parameter and to create a classification report table to check the quality of the algorithm.

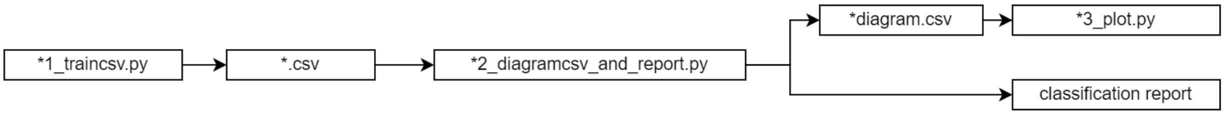

Figure 6: program structure - preparation part

In the second part, the program is running with the interface. The input is a previously created table with histograms as a training set and a photo indicated by the user as a test. The output of the KubasProgram gives us the most common flower and the accuracy of the selection. These two values: flower species and accuracy are placed in the GUI.

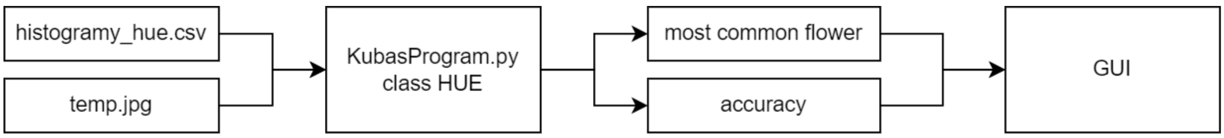

Figure 7: program structure - GUI part

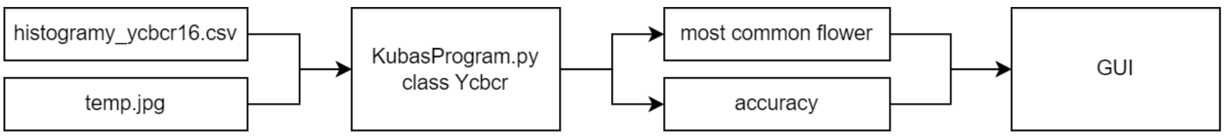

Figure 8: program structure - GUI part

7 Graphical user interface

The programme interface is as follows:

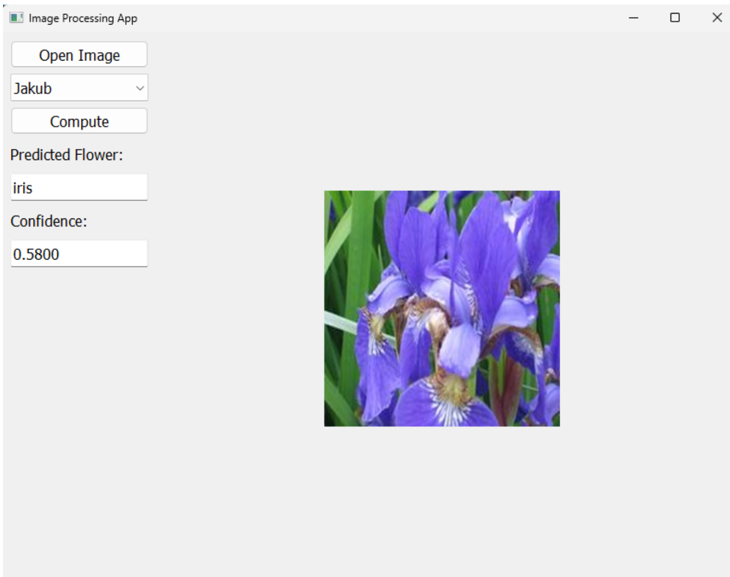

Figure 9: program interface

Functions of the various buttons:

- Open image: The user can select a picture of a flower
- Jakub: choice of algorithm where Jakub means using the HUE color space and Jakub Ycbcr means using YCbCr color space
- Compute: a button for the program to perform calculations and an indication of the recognized species
- Predicted flower: recognized flower species
- Confidence: solution accuracy based on the classification report

In the graphical user interface, there is the HUE method with a histogram divided into 16 samples and the YCbCr method with a histogram divided into 32 samples, making 64 samples (because we have separate histograms for Chrominance Blue and Chrominance Red.

8 Improving the model

It is possible to improve the model by changing the resolution of the photos because we are only looking at the colours and not the shape anyway. This can help the programme to run faster

Another idea is to add a function that limits the influence of the colour green on the result of the calculation, as green plant parts such as stems and leaves are not helpful in distinguishing flower species by colour. What we want to focus on is the colour of the petals.

9 Conclusions

Identifying flowers by using only colours is not the best method for recognising species. This is because different species often have the same colours and the histogram of the photograph looks similar. A human can recognise the species of flower when the picture is in greyscale, because the flower species are usually distinguished by the shape of the petals, leaves and stem.

As can be seen from the above comparison, the YCbCr colour representation has a slightly higher accuracy (0,38)than the HUE representation. In addition, the method was compared with a hue histogram divided into 16 and 256 samples and the accuracy is 0.36 and 0.37 accordingly.