

UNIVERSITAT POLITÈCNICA DE CATALUNYA

MACHINE LEARNING II

Image Classification Using Kernels

Authors:

Benjamí Parellada
Sígrid Vila



UNIVERSITAT POLITÈCNICA DE CATALUNYA
BARCELONATECH

Facultat d'Informàtica de Barcelona

FIB

Fall Semester 2021/2022

CONTENTS

1	Introduction	2
2	Previous work	3
3	Methodology	4
3.1	Images	4
3.2	Preprocessing	4
3.3	Feature Extraction	5
3.4	Models	6
3.4.1	K-Nearest Neighbours	6
3.4.2	Support Vector Machine	7
3.4.3	Convulational Neural Networks	9
3.5	Experimentation	10
4	Case study	11
5	Results	11
5.1	Kernalized SVM	12
5.2	Overall best model	13
5.3	Discussion of the results	14
6	Conclusion	14
7	Future Work	15
8	References	17

1 INTRODUCTION

Image recognition is the part of computer vision which uses machine learning to identify and detect objects or features in a digital visual formats, such as image or video. The main application of image recognition is the classification and detection of objects, patterns, or properties of objects, in digital images. With a wide array of applications such as image retrieval, facial recognition, computer aided design, robotics, and surveillance.

A fundamental element of computer vision and image recognition is the extraction of features from images. There are many types of features such as edges, corners, blobs, moments, etc. Most features, such as edges and corners, are local features. Local features are useful for object detection because they are highly invariant to affine transformations, such as rotation and scaling. Other features, such as blobs, moments, etc., are useful for object recognition, as we hope similar objects maintain their form.

In this project, we build and test models for the multinomial task of classifying images using kernel methods. Concretely, we extract various features from the images and using Support Vector Machines (SVM) as a classifier we determine how accurate the classification is with each representation. The focus of this project is to study and delve deeper into kernels, as such we use different kernels in order to solve the proposed problem and implement the log kernel from Boughorbel et al. [1], the generalized histogram intersection kernel from Boughorbel et al. [2] and mixture kernels from [9].

To test the effectiveness of the SVM with the different kernels, we have used a subset of the COREL database for content based image retrieval [8]. The results from the various kernelized SVM are contrasted with state of the art convolutional neural networks (CNN) and a simpler models such as logistic regression.

The results returned from the implemented kernels are not as good as the ones presented in the literature. In fact, none of our results are as good as the presented literature using the SVM, this is probably due to the fact that we have used images-classes that are a bit harder to distinguish using color histograms since some classes share a very similar color distribution profile.

The remainder of the paper is organized as follows. Section 2 presents the previous state of the art work done in relation to solving this problem. Section 4 presents the COREL database and the subset of images we are using to test our algorithms. Section 3 presents the mathematical background needed to understand the corresponding design done, and the kernels used. Section 5 presents the results with the approach presented. Finally, Section 6 draws the conclusions of the paper.

2 PREVIOUS WORK

While image retrieval and recognition has been recently dominated by Neural Networks, with accuracies of over 90% this year with CoAtNet-3 [3] and ViT-G/14 [10], the performance seems to be reaching a stand-still and the computational resources and number of parameters needed is staggering. Hence, simpler models with similar performances are always welcome.

Kernel based methods such as KSVM have been studied in many contexts. The main computational advantage of kernel-based methods is that they do not require explicit feature mapping or feature engineering and are able to implicitly capture the inherent structure of the input space, allowing them to achieve superior generalization performance. Despite its success, however, the performance of a kernel-based classifier depends crucially on the selection of an appropriate kernel function. A large collection of kernel functions are available, each with their own strengths and weaknesses.

In 2005, Boughorbel published various works on image recognition using KSVM, our particular interests comes from Conditionally Positive Definite Kernels [1] in which a rigorous comparison was made on the performance of different kernels on the task of image classification with KSVM’s. Using a dataset of six classes of one hundred images in RGB, he extracted the color histograms of each image and used SVM with different kernels in order to predict the classes. The particular kernels used were Radial Basis Function (RBF), Laplace, Power, and they introduced a new conditionally positive definite kernel they named Log.

The use of color histograms brings the question to compare histograms adequately. There are many metrics to compare distributions of histograms [5]. The group of Boughorbel at the same year, also presented a new kernel, based on histogram intersection (GHI) for image retrieval with good results [2].

Kernel	CV Error	Test Error
RBF	24.38 ± 0.54	24.33 ± 1.06
Laplace	23.50 ± 0.82	24.66 ± 0.89
Power	21.88 ± 0.15	21.44 ± 2.16
Log	21.77 ± 0.20	21.12 ± 1.70
GHI	21.11 ± 1.29	20.33 ± 1.70

Table 1: Summary of the results presented by Boughorbel et al. in [1, 2] using the COREL Database.

More recently, mixture models have proven to be quite useful in modeling complex densities and very flexible, as using a small number of components, one can model very

complex distributions. Tian et al. [9] have applied kernel mixture models on image classification and achieved higher classification accuracy than conventional SVM with any single kernels.

3 METHODOLOGY

In this section we shall describe the implementation of the algorithm that shall detect and classify images from a subset of classes. The pipeline that our computer vision system is represented in Figure 1. Concretely, from an input image, there is a Preprocessing applied, after which we extract global features for each class. These local features are fed to a machine learning model which will predict the class of the input image. Following, we explain step by step each of the points in the diagram to explain the overall classifier.

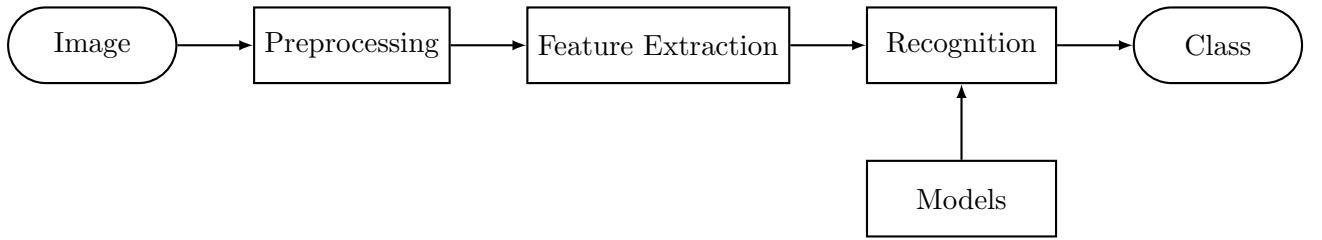


Figure 1: Flux diagram of our image classification system.

3.1 IMAGES

Before we can start any sort of processing or modeling, we need images to build our discriminant model which will classify the input images. These images are split into 2 parts: training and validation. The images used in the training set represent 90% of the images we have and will be used to construct the machine learning models. Once these models have been tuned, we process in the same way the images from the validation set to get unbiased generalized error of the classifier.

The specific information on the image database used is described in section 4.

3.2 PREPROCESSING

Independent if the image is train or validation, they all will have to follow the same processing. In the case of this project, the processing is minimal, we only test different color spaces and color normalization.

- **RGB**: the default 3D space most images are in. We can transform the image into the chromatic representation in order to normalize the space:

$$r = \frac{R}{R + G + B} \quad g = \frac{G}{R + G + B} \quad b = \frac{B}{R + G + B}$$

Since $r + g + b = 1$, we can eliminate one dimension by using this transformation, there is also a benefit that we are invariant to different levels of illumination in the image.

There are other representations of color, such as HSV and CIELAB which have their benefits. In HSV, the Hue component represents the chrome directly, which is ideal for working on image classes that are very reliant on color. However, there are some downsides to this representation, the Hue is cyclic as such 0° and 360° represent the same color, and you either map it to polar coordinates or use some programming hack to make them the same. Moreover, the Hue value of black can be random and we do not have invariance towards illumination.

The CIELAB, is also a 3D space where the main benefit is that changes of color represent a uniform change, however, while the values of a^* and b^* tend to be around [-128, 127] there is no guarantee and the computation from RGB to $L^*a^*b^*$ is quite costly.

Evaluating the costs of each of these color spaces, the easiest representation seems to be the RGB color space with the chromatic normalization. We have the benefit of reducing by one dimension the image while maintaining all the relevant information.

3.3 FEATURE EXTRACTION

After reading and processing the images, we need to extract features from them. At first, we tried to flatten each image and compare pixel by pixel, however this approach lent a myriad of problems. First, the computational complexity of this approach was unfeasible just by flattening one RGB image of 320×320 would produce 307200 features. Second, not all images are 320×320 , as such we had to pad these images and center them correctly. Third, it is not translation, nor rotational invariant, just one shift of one pixel to each row of the image would make our classifier fail. Hence, the need for better descriptors was needed.

The main descriptor used is the color histograms, which is basically the distribution of colors in each of the dimensions in the color space. So, since we normalized the RGB color space, the corresponding color histogram for an image will be a two vectors, each representing a component, i.e. r and g . Here we see the benefit of this color representation, with HSV or CIELAB, we would have needed to use three vectors to

represent each of the components of the color space, however using normalization in RGB there is one color that can be linearly computed from the other two.

We decided to use color histograms for two reasons: the first was that in [1, 2, 9], they used it as a global feature. Secondly, there is usually a relationship between color and the object represented. Especially in our database, for example elephants are mostly gray, beaches mostly blue, etc. Hence, using color histograms as global features describing the image will produce descriptors that are invariant to geometric transformations.

While this approach has quite a few benefits, we have to be careful when we define the number of bins in the histograms. We want them to be the same for each image, and one would be quick to set 256 or 64 as they did in [1, 2]. However, fixing the number of bins does not guarantee that the bins match between histograms, as such two very different color distributions could have the same number of counts in their histogram due to the bins not representing the same values. The correct way to proceed is to homogeneously map all the input space into a fix number of bins. We also tested with histogram equalization which is a technique for adjusting image intensities to enhance contrast, however the results were worse than not using it.

Summarizing, for each image we concatenate the counts of the two normalized color histograms by homogeneously mapping $[0, 1]$ into 128 bins. We also add the mean and standard deviation of each color component and, of course, the appropriate label into a matrix.

3.4 MODELS

With the feature descriptors obtained from the images described in the previous section, we train a model that will be used to recognize the different classes that can appear in the image. Since we have more than one class, we have to use multi-class classifiers.

3.4.1 K-NEAREST NEIGHBOURS

K-Nearest Neighbors (KNN) is an instance-based learning method which does not attempt to construct a general internal model, but simply stores instances of the training data. Classification is computed from a simple majority vote of the K nearest neighbors of each point.

As we are using color histograms as descriptors, we are comparing normalized values against each other. As such, we are just comparing distances between the histograms which should be in Euclidean Space. Hence, we can use KNN without worry.

We have one hyperparameter to tune: K , which is the number of neighbors that will

vote on each instance. We test with wide array of odd values using cross-validation. We particularly use odd-values since it is impossible to have a tie when voting.

3.4.2 SUPPORT VECTOR MACHINE

The objective of Support Vector Machine (SVM) is to find a hyperplane in an N-dimensional space that distinctly classifies the data points.

The SVM can be reduced to a quadratic minimization problem:

$$W(\boldsymbol{\alpha}) = - \sum_{i=1}^l \alpha_i + \frac{1}{2} \sum_{i,j=1}^l \alpha_i \alpha_j y_i y_j K(\mathbf{x}_i, \mathbf{x}_j)$$

with respect to Khun-Tucker coefficients $\boldsymbol{\alpha}$, under que equilibirum constraint:

$$\sum_{i=1}^l \alpha_i y_i = 0$$

As long as $K(\mathbf{x}_i, \mathbf{x}_j)$ is conditionally positive definite, the $W(\boldsymbol{\alpha})$ is convex with respect to $\boldsymbol{\alpha}$, therefore the minimization is achieved at a unique minimum.

This addition allows to modify the classic SVM which performs linear classification, to efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

The kernels we tested are:

- **Linear** is the simplest of all kernel functions. It would equate to the classic SVM without kernel, the main inconvenient is that we need numerical data as input.

$$K_L(\mathbf{x}, \mathbf{x}') = \langle \mathbf{x}, \mathbf{x}' \rangle$$

- **Gaussian Radial Basis Function** (RBF) or Gaussian kernel. A general purpose kernel typically used when no prior knowledge is available about the data.

$$K_{RBF}(\mathbf{x}, \mathbf{x}') = \exp(-\sigma \|\mathbf{x} - \mathbf{x}'\|^2)$$

Intuitively, the σ parameter defines how far the influence of a single training example reaches, with low values meaning ‘far’ and high values meaning ‘close’. The gamma parameters can be seen as the inverse of the radius of influence of samples selected by the model as support vectors.

Increasing σ leads to a better fit to training data (danger of ending up overfitting), and decreasing σ (towards zero) leads to a worse fit to training data (danger of ending up underfitting)

- **Laplace radial basis kernel** very similar to the classical Gaussian RBF, a general purpose kernel and used when no further prior knowledge is available.

$$K_{LRBF}(\mathbf{x}, \mathbf{x}') = \exp(-\sigma \|\mathbf{x} - \mathbf{x}'\|)$$

- **Polynomial** represents the similarity between two vectors. Not only does it take into consideration the similarity in one dimension, but in multiple. It basically counts the interaction between characteristics.

$$K_P(\mathbf{x}, \mathbf{x}') = (\theta \langle \mathbf{x}, \mathbf{x}' + c \rangle)^p$$

The p should be a positive integer, θ represents the scale of the interaction and c an offset. With $\theta = -1$ and $c = 0$ this can lead to a scale invariant SVM classifier. It is quite useful in image classification.

- **Logarithmic** kernel as presented by Boughorbel et al. [1]. A conditionally positive kernel, with one parameter p .

$$K_{Log}(\mathbf{x}, \mathbf{x}') = -\log(1 + \|\mathbf{x} - \mathbf{x}'\|^\beta)$$

- **Generalized Intersection Histogram** kernel as presented by Boughorbel et al. [2]. A conditionally positive kernel, with one parameter p .

$$K_{GHI}(\mathbf{x}, \mathbf{x}') = \sum_{i=1}^m \min\{|x_i|^\beta, |x'_i|^\beta\}$$

- **Mixture** kernels, take use of the property that the sum of kernels is kernel. As such, we can define kernels by adjusting the weight of each kernel. Being K_1 and K_2 kernels we can define a mixture kernel as:

$$K_{Mix}(\mathbf{x}, \mathbf{x}') = \lambda K_1(\mathbf{x}, \mathbf{x}') + (1 - \lambda) K_2(\mathbf{x}, \mathbf{x}')$$

As such, we define the following kernels, the first one and the idea to produce these kernels comes from [9].

$$\begin{aligned} K_{RBF-P}(\mathbf{x}, \mathbf{x}') &= \lambda K_{RBF}(\mathbf{x}, \mathbf{x}') + (1 - \lambda) K_P(\mathbf{x}, \mathbf{x}') \\ K_{RBF-Log}(\mathbf{x}, \mathbf{x}') &= \lambda K_{RBF}(\mathbf{x}, \mathbf{x}') + (1 - \lambda) K_{Log}(\mathbf{x}, \mathbf{x}') \end{aligned}$$

$$\begin{aligned}
K_{Log-P}(\mathbf{x}, \mathbf{x}') &= \lambda K_{Log}(\mathbf{x}, \mathbf{x}') + (1 - \lambda) K_P(\mathbf{x}, \mathbf{x}') \\
K_{RBF-GIH}(\mathbf{x}, \mathbf{x}') &= \lambda K_{RBF}(\mathbf{x}, \mathbf{x}') + (1 - \lambda) K_{GIH}(\mathbf{x}, \mathbf{x}') \\
K_{Log-GIH}(\mathbf{x}, \mathbf{x}') &= \lambda K_{Log}(\mathbf{x}, \mathbf{x}') + (1 - \lambda) K_{GIH}(\mathbf{x}, \mathbf{x}') \\
K_{GIH-P}(\mathbf{x}, \mathbf{x}') &= \lambda K_{GIH}(\mathbf{x}, \mathbf{x}') + (1 - \lambda) K_P(\mathbf{x}, \mathbf{x}')
\end{aligned}$$

The SVM is formulated for binary classification, in our case, a classification problems which include more than two classes we opt for a one-against-one method. This method constructs $\binom{k}{2}$ classifiers where each one is trained on data from the two respective classes. Prediction is done by voting where each classifier gives a prediction and the class which is predicted more often wins, similar to KNN.

Finally, other than the parameters from each kernel, the SVM used in classification uses one hyperparameter C . C behaves as a regularization parameter in the SVM and trades off correct classification of training examples against maximization of the decision function's margin. For larger values of C , a smaller margin will be accepted if the decision function is better at classifying all training points correctly. A lower C will encourage a larger margin, therefore a simpler decision function, at the cost of training accuracy.

3.4.3 CONVULATIONAL NEURAL NETWORKS

For the the purpose of this project, we create a Convulational Neural Networks (CNN) similar to the VGG-16 [7], the following is a description of the blocks used

1. **Convulational Blocks** which consists of a padding layer to ensure we can stride over the edges, a convolutional layer of stride 3 and a rectification (ReLU) non-linearity activation function, and finally a max pooling layer.
2. **Flatten** which flattens a matrix to a 1-Dimensional vector.
3. **Dropout** which randomly zeroes some of the elements of the input tensor to reduce overfitting.
4. **Fully connected layers** which consist of densely connected layers with a ReLU or a log soft-max for the final layer.

We combine four blocks of 1), after which we flatten the image 2), and apply dropout 3), after the network has been flattened, we 2 densly connected layers 4) with the second one being a log soft-max. All this is trained for 30 epochs in which we use the negative log likelihood loss which is useful for multi-class classification problems.

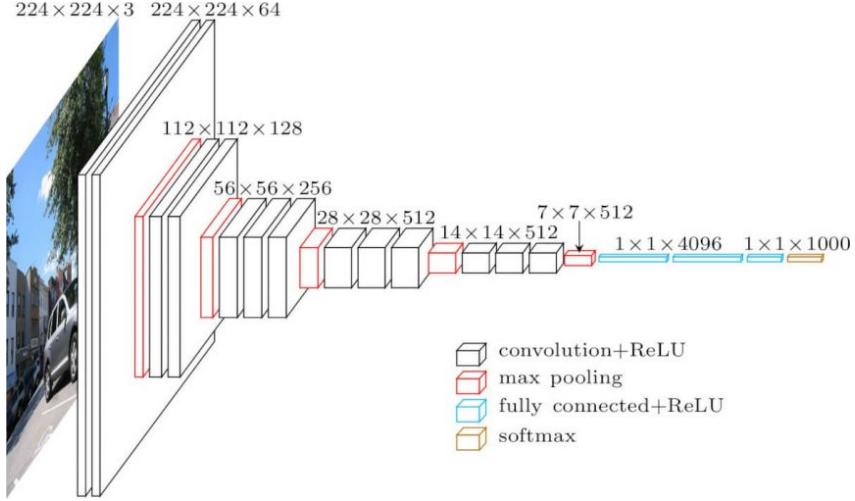


Figure 2: Summary of the architecture of the VGG-16 architecture, which is similar to ours. Image from [neurohive, 2018](#).

3.5 EXPERIMENTATION

The objective of this work is to recognize what appears in an image from a subset of possible classes. To this end, we shall try the different models used on the preprocessed and features extracted from the images. The images are partitioned into train and test. For the KNN and SVM models we use 5-fold cross validation in order to find the best hyperparameters. Once the parameters are tuned, we use cross validation with the training partition in order to return a valid unbiased generalization error and we use the validation set to return an unbiased generalization error of a sample the model has never seen. For the CNN, the procedure is similar, however we are training and evaluating it on every epoch.

KNN	$k \in \{3, 5, 7, 9, 13, 15, 17, 21, 35, 51\}$
SVM	$C \in \{0.001, 0.01, 0.1, 1, 10, 100, 1000\}$
RBF	$\sigma \in \{0.001, 0.01, 0.1, 1, 10, 100, 1000\}$
P	$p \in \{2, 3, 4, 5\}$
Log/GHI	$\beta \in \{0.1, 0.2, 0.25, 0.3, 0.4, 0.7, 0.9\}$
Mix	$\lambda \in \{0.2, 0.4, 0.5, 0.6, 0.8\}$

Table 2: Different hyperparameters tuned and the ranges checked.

Take into consideration, that for the mixed kernels, we only tune the mix λ parameter, taking the best hyperparameters for the different individual kernels.

4 CASE STUDY

In order to apply the work described above we use the COREL database [8]. However, for the scope of this project, the entire database would be impossible to train and compute, since it contains 10800 which can be divided into 80 different classes, e.g., autumn, aviation, bus, castle, cloud, dog, elephant, primates, ship, tiger, train, waterfall, etc.

The original papers from Bougħorbel [1] used 6 distinct classes: castle, sun rises, grasses, mountains, birds and waterfalls. To validate the results in the paper, we decide to use 10 different classes that are not the same as the presented in it. The classes we use are: beaches, bus, dinosaurs, elephants, flowers, foods, horses, monuments, mountains and snow, and people in villages in Africa. A sample of the images used can be found in Figure 3. Each class contains 100 RGB images, 90 will form the training set and the 10 remaining the validation set.



Figure 3: Each row in each block represents one of the 10 classes used for the experiments. Left block: beaches, buses, dinosaurs, elephants, flowers; right block: food, horses, monuments, mountains, people in Africa.

5 RESULTS

We computed first the average validation error using 5-fold cross validation for the different hyperparameters explained in section 3 on the test data to obtain the best hyperparameters for each kernel and SVM combination and the number of neighbors that vote, K , on the KNN.

Since this project is more focused on studying kernels, we present the full table of the different results that the kernalized SVM has achieved in order to draw a comparison

	0.001	0.01	0.1	0.5	1	2	10
rbfdot	0.001000	0.001000	0.001000	0.001000	0.001000	0.001000	0.001000
polydot	3.000000	3.000000	4.000000	5.000000	3.000000	2.000000	3.000000
logdot	5.000000	5.000000	3.000000	2.000000	2.000000	5.000000	3.000000
gihdot	2.000000	2.000000	2.000000	2.000000	2.000000	2.000000	2.000000
laplacedot	0.010000	10.000000	0.010000	0.010000	0.010000	0.010000	0.010000
mix_rbf_dot_polydot	0.800000	0.600000	0.500000	0.500000	0.800000	0.200000	0.400000
mix_rbf_dot_logdot	0.600000	0.200000	0.200000	0.800000	0.800000	0.200000	0.800000
mix_log_dot_polydot	0.600000	0.500000	0.200000	0.200000	0.500000	0.200000	0.500000
mix_rbf_dot_gihdot	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
mix_log_dot_gihdot	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
mix_poly_dot_gihdot	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

between the kernels on our specific problems. Once we have decided which of these combinations of hyperparameter and kernel is the best for the SVM, we choose the one that returns the least validation error and compare it with the CNN and KNN.

5.1 KERNELIZED SVM

After cross validating to find the best hyperparameter for each value of C , we compute the validation error using these parameters.

Kernel	0.001	0.01	0.1	0.5	1	2	10
K_L	0.3033	0.3211	0.3056	0.3389	0.3311	0.3167	0.3322
K_{GRBF}	0.9267	0.9178	0.6189	0.4011	0.3056	0.2944	0.3011
K_{LRBF}	0.9289	0.9022	0.5822	0.3222	0.3044	0.2789	0.2556
K_P	0.2856	0.2933	0.2956	0.3067	0.2889	0.2933	0.2978
K_{Log}	0.9278	0.6789	0.3311	0.3956	0.3911	0.3900	0.4200
K_{GIH}	0.3533	0.4256	0.4178	0.3922	0.4556	0.4011	0.4144
K_{RBF-P}	0.4211	0.3867	0.3822	0.3767	0.4011	0.3856	0.3911
$K_{RBF-Log}$	0.9222	0.7367	0.3411	0.3244	0.3933	0.4156	0.4111
K_{Log-P}	0.3989	0.4056	0.4100	0.4100	0.3867	0.4022	0.3400

Table 3: Validation error for different kernels and values of C

We see the best performing ones are pretty much all the Linears, Polynomials and the Mix 1 and Mix 3. Specially, the polynomial kernel.

The following table presents the winning kernel hyperparameters:

Just like in the cross-validation error, the kernels with the best validation error are the polynomials and now it's a bit more clear. Nevertheless, the results are very tight to conclude that one is better than the other to perform image classification.

To show a bit more how the kernels have performed, these are the confusion matrices for

Kernel	0.001	0.01	0.1	0.5	1	2	10
K_L	0.2400	0.2400	0.2600	0.2600	0.2600	0.2600	0.2600
K_{GRBF}	0.4900	0.4900	0.4900	0.3300	0.2900	0.2700	0.2800
K_{LRBF}	0.2500	0.2500	0.2600	0.2900	0.2500	0.2700	0.2500
K_P	0.3600	0.3500	0.2900	0.4000	0.4000	0.4100	0.4100
K_{Log}	0.2800	0.3700	0.4200	0.4000	0.4100	0.4200	0.4200
K_{GIH}	0.3600	0.3200	0.3600	0.2900	0.2600	0.2400	0.2400
K_{RBF-P}	0.3000	0.3100	0.3400	0.3700	0.3400	0.3900	0.3300
$K_{RBF-Log}$	0.3600	0.3400	0.3400	0.3200	0.3800	0.4400	0.3900
K_{Log-P}	0.3800	0.3700	0.3000	0.3900	0.3500	0.3800	0.3300

Table 4: Test error for different kernels and values of C

the best kernels:

Pred/Ref	Beach	Bus	Dino	Eleph	Flwr	Food	Hors	Monu	Moun	Peop
Beaches	4	1	-	-	-	1	-	2	2	-
Bus	-	8	-	-	-	-	-	1	1	-
Dinosaurs	-	-	10	-	-	-	-	-	-	-
Elephants	1	1	-	6	-	-	1	1	-	-
Flowers	-	-	-	-	9	1	-	-	-	-
Foods	-	1	-	-	-	8	-	-	1	-
Horses	-	-	-	1	-	-	9	-	-	-
Monuments	-	-	-	-	-	-	-	8	1	1
Mountains	3	1	-	1	-	-	-	-	5	-
People	-	-	-	-	-	1	-	1	-	8

Table 5: Confusion matrix for the multiclass SVM with a Polynomial kernel of degree 3.

We can see that the kernels distinguish very well the buses, dinosaurs and people living in Africa. However, it has difficulties distinguishing well enough the beaches or the foods. For the rest of categories, the classification is pretty accurate. Beaches and mountains get confused, and it is pretty clear why, the colors are very similar between both of these classes as we can see in Figure 3.

5.2 OVERALL BEST MODEL

Once we have seen which SVM and kernel combination returns the best result, we compare this method with more state of the art approaches such as CNN. The results of our application can be found here:

Model	Train Error	Test Error
KNN	0.3767	0.3100
SVM	0.2856	0.2500
CNN	0.1690	0.1800

Table 6: Summary of the results using the methodology presented on the COREL Database. For the SVM the hyperparameters were set was set at $C = 0.001$ and a polynomial kernel with degree 3; for the KNN the best K achieved in cross validation was $K = 9$.

5.3 DISCUSSION OF THE RESULTS

We can see similar performances for the Linear and Poly kernel, which are the best ones followed by the Mix1 and Mix3 and then the Mix2, the Log and the Laplace kernels. Finally, the worst one is the RBF kernel.

In comparison to the results obtained by the papers [1, 2, 9], they obtained their best results using the Log kernel and the Power kernel. Taking into account that we used some other kernels, our results for the Log are far worse than the ones from the paper. However, we obtained very similar results with the Linear and Poly kernels.

6 CONCLUSION

In this paper we have presented a methodology to solve an image classification problem exploring and testing many different kernels and some of the state of the art methods. To this end, we created a subset of images from the COREL [8] database whcih amounted to 10 distinct classes.

From these images, various preprocessing techniques have been tested, such as histogram equalization, changing the color space to HSV, CIELAB and chromatic normalization; however, the only relevant preprocessing ended up being RGB normalization to reduce the number of features of the dataset.

From this preprocessed images, we feature extract color histograms in order to distinguish the different classes. These descriptors have the property of being invariant to geometric transformations. Thanks the the properties color histograms bring us, along with the nature of the problem, has brought us to believe that these descriptors are pretty adequate to determine the presence of different categories in the images.

Once the color histograms have been obtained, the dataset is split into train and test to construct machine learning models. The proposed models are: K-nearest neighbors

(KNN), kernalized support vector machines (KSVM), and convolutional neural networks (CNN). The CNN, do not need the feature extraction described earlier, and will be trained and tested on the images directly. Once the models have been trained, we validate the results on a test dataset partition.

For the KNN and SVM, we search which hyperparameters are the best for each model. The main focus of this paper was exploring kernel methods, as such an extensive search and development of kernels has been proposed. The best kernels, in contrast to the literature read, have been polynomial kernels with degree 3.

Looking at the results, we believe that SVM can be comparable result to CNN in simple image classification problems. The results presented here are not comparable to the immense neural networks presented in recent state of the art implementations of this problem, such as the ones presented in [3] and [10], which have millions of parameters. However, compared to a not so fine-tuned neural network, kernalized SVM and CNN seem comparable with the support vector machine being better in some cases.

Without doubt, we have learned a lot about the difficulties of creating a pattern matching computer vision model, from which color space to choose, to the selection of feature extraction and preprocessing, to selecting which models are the best, to selecting and researching different kernels to used. It is a laborious work that requires both human and machine time in order to develop a correct experimentation technique to present valid results, as we have done here.

7 FUTURE WORK

There are some limitations in our paper and places we wish to further this research.

- Color spaces: we briefly tested with other color spaces such as HSV and CIELAB, which in principal have good properties, however the results given in intermediate results were not as good. While the proposed color space in section 3 was invariant to illumination and 2D, we found no literature talking how to achieve the same properties using HSV and CIELAB. However, a formal comparison between the different color spaces could have been produced, even if it was 2D color histograms versus 3D.
- Feature extraction: while color histograms seemed to work pretty well, there surges problems when class have similar colors, as we saw in the confusion matrix. Hence, it makes sense to search for other features from the images to correctly classify whenever images have similar color distributions. At first we tried a few, the mo-

ments of the histogram, contours, etc. however since one of the kernels was based on histogram comparison, we decided to just use the color histograms.

- Kernalized distance metrics: while reading [5], the results seemed obvious that the Earth Movers Distance (EMD) seems to work very well on image retrieval problems in comparing histogram distributions. Being a metric, it should be easy to propose a kernel from this distance, and they did in [4]. We tried implementing it, however, while there are some implementations in R the original algorithm is in $O(n^3 \log n)$, which makes it unfeasible to train with various hyperparameters in the given time frame. While there are approximations in linear time [6], we feel it is out of the scope of this project to research and implement it.
- Tuning hyperparameter: while competent with the tuning grid, it surprised us that the main literature [1, 2, 9] did not mention specifically what hyperparameters worked best for them. There are still some improvements to be made in the tuning of kernels, such as the power kernel and mixture kernels. For the power kernel, we decided to fix the scale (θ) to 1 and the offset (c) to 0 in order to simplify both our code and the grid search. For the mixture kernels, we used the best hyperparameters found for both models independently and tested the mixing coefficient (λ). We are assuming the best hyperparameters for each independent kernel will be the best for the mixture, however this assumption might not be accurate as there might exist interaction between the hyperparameters.

Finally, combinations of more than 2 kernels could be tested in the same manner, or using mixtures of mixtures. However, the complexity of these models might not achieve better results than simply the original kernels, as what happened in our results in section 5.

- Images without a class: while the images we tested with all belong to a class, in real world applications this assumption does not need to hold. Hence, future work should be done to test the presented models with images they have never seen which belong to no class. Currently, the way the model is implemented, it returns the probabilities of belonging to each class and it assigns the image to the one with the highest probability. In order to take into consideration images that do not have a class, a probability threshold could be set in order to discriminate if the image belongs to the subset of images viewed or is a new class not belonging to the subset of known classes.

Future work could be done in searching and setting this threshold which would probably require another machine learning model which would minimize the number of miss-classifications. The framework is quite similar to the one presented in our code, however since the literature presented only took into consideration the classes

used, and this would strive the project away from studying kernels, we have decided against implementing it.

8 REFERENCES

- [1] Sabri Boughorbel, J-P Tarel, and Nozha Boujemaa. “Conditionally positive definite kernels for svm based image recognition”. In: *2005 IEEE International Conference on Multimedia and Expo*. IEEE. 2005, pp. 113–116.
- [2] Sabri Boughorbel, J-P Tarel, and Nozha Boujemaa. “Generalized histogram intersection kernel for image recognition”. In: *IEEE International Conference on Image Processing 2005*. Vol. 3. IEEE. 2005, pp. III–161.
- [3] Zihang Dai et al. “CoAtNet: Marrying Convolution and Attention for All Data Sizes”. In: *arXiv preprint arXiv:2106.04803* (2021).
- [4] Yulia Dodonova et al. “Kernel classification of connectomes based on earth mover’s distance between graph spectra”. In: *arXiv preprint arXiv:1611.08812* (2016).
- [5] Yossi Rubner, Carlo Tomasi, and Leonidas J Guibas. “The earth mover’s distance as a metric for image retrieval”. In: *International journal of computer vision* 40.2 (2000), pp. 99–121.
- [6] Sameer Shirdhonkar and David W Jacobs. “Approximate earth mover’s distance in linear time”. In: *2008 IEEE Conference on Computer Vision and Pattern Recognition*. IEEE. 2008, pp. 1–8.
- [7] Karen Simonyan and Andrew Zisserman. “Very deep convolutional networks for large-scale image recognition”. In: *arXiv preprint arXiv:1409.1556* (2014).
- [8] D Tao. *The corel database for content based image retrieval*. 2009.
- [9] Dongping Tian, Xiaofei Zhao, and Zhongzhi Shi. “Support vector machine with mixture of kernels for image classification”. In: *International Conference on Intelligent Information Processing*. Springer. 2012, pp. 68–76.
- [10] Xiaohua Zhai et al. “Scaling vision transformers”. In: *arXiv preprint arXiv:2106.04560* (2021).