Recognition of Handwritten Music Symbols using Meta-features Obtained from Weak Classifiers based on Nearest Neighbor

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Abstract: The classification of musical symbols is an important step for Optical Music Recognition systems. However, little progress has been made so far in the recognition of handwritten notation. This paper considers a scheme that combines ideas from ensemble classifiers and dissimilarity space to improve the classification of handwritten musical symbols. Several sets of features are extracted from the input. Instead of combining them, each set of features is used to train a weak classifier that gives a confidence for each possible category of the task based on distance-based probability estimation. These confidences are not combined directly but used to build a new set of features called Confidence Matrix, which eventually feeds a final classifier. Our work demonstrates that using this set of features as input to the classifiers significantly improves the classification results of handwritten music symbols with respect to other features directly retrieved from the image.

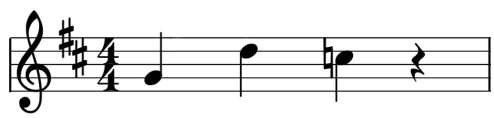
1 INTRODUCTION

Composing music with pen and paper is still a common procedure for most musicians. Nevertheless, digital versions of music scores offer a great deal of advantages with respect to the physical ones. For instance, issues related to the storage, distribution, preservation, and reproduction of the information are straightforwardly solved in the digital domain. Also, having such music information encoded in a structured format opens the possibility of applying computational music tools for tasks such as content-based music searches, musicological analysis or organization in digital libraries, among others.

In order to take advantage of the aforementioned processes, handwritten scores need to be transcribed onto a digital version. Most commonly, this is done by hand using some kind of software for music score edition. Unfortunately, the process can be very tedious since the complexity of music notation inevitably leads to burdensome and uncomfortable interfaces based on *drag and drop* actions with the mouse.

An effortless alternative for the user to obtain the digital version of a handwritten music composition is to resort to an Optical Music Recognition (OMR) system (Bainbridge and Bell, 2001). These systems import a scanned version of the music sheet and try to automatically export the information to some type of machine-readable format such as *MusicXML*, *MIDI* or *MEI* (see Fig. 1).

(a) Example of input score for an OMR system



(b) Symbolic representation of the input score

Figure 1: The task of Optical Music Recognition (OMR) is to analyze an image containing a music score to export its musical content into some machine-readable format.

Given the particularities of music notation, an OMR system usually follows a segmentation-based approach: isolated symbols are initially detected and, then, classified. The process starts with a preprocessing stage, which focuses on providing robustness to the system by means of binarization and deskewing. Then, a process for the detection and removal of staff lines takes place. Although these lines are necessary

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for human readability, they complicate the segmentation of musical symbols. Given that, the more accurate this process, the better the detection of musical symbols, much research effort has been devoted to this process, which can be considered nowadays as a research topic by itself (Dalitz et al., 2008). After this stage, symbol detection is performed by searching the remaining meaningful objects of the score. Finally, once single pieces of the score have been isolated, a hypothesis about the type of each one is emitted in the classification stage. A comprehensive experimentation was carried out by Rebelo et al. (Rebelo et al., 2010), which presented a comparative study on different algorithms for the classification of musical symbols.

Unfortunately, the classification of music symbols is still far from achieving accurate results, especially for handwritten scores (Rebelo et al., 2012). The great variability in the manner of writing the musical symbols is the main difficulty to overcome, similarly to the field of handwritten text recognition (Romero et al., 2012). Thus, there is still a need for developing algorithms that can provide a more accurate classification of handwritten music symbols.

This work presents the classification of isolated handwritten music symbols by means of meta-features extracted from the decisions of weak classifiers, each of which focuses on different features of the input. This strategy has been proven to be very accurate in the context of shape recognition (Rico-Juan and Calvo-Zaragoza, 2015), yet its performance in the context of handwritten music notation remains unexplored.

The remaining of the paper is organized as follows: the classification approach is described in depth in Section 2. The set of experiments carried out over a comprehensive dataset of isolated music symbols is presented in Section 3. Finally, Section 4 concludes the work and proposes future work to be explored.

2 CLASSIFICATION WITH META-FEATURES BASED ON WEAK CLASSIFIERS

Classification systems have been widely studied in pattern recognition tasks. Typically, these schemes work on a sequential fashion: first of all, a set of features is extracted from the sample at issue; then, these features are fed into a classification scheme, which has been trained previously with a set of examples, to obtain a hypothesis about its class (Duda and Hart, 1973). Under this premise, a great variety of techniques have been proposed in order to improve classification accuracy, being Artificial Neural Networks (Jain et al., 1996) and Support Vector Machines (Burges, 1998) some representative examples of remarkably successful methods.

The evolution in this field has led to the development of new schemes. Among the large amount of techniques proposed, *ensemble methods* constitute a particular methodology with considerable relevance in this work. The idea behind these schemes is that it is more robust to combine a set of simple hypotheses obtained with a set of basic classifiers than to use just one complex hypothesis computed by a more complex scheme (Kittler et al., 1998).

This paper bases on the idea of ensemble classifiers and expands it by considering a more sophisticated approach for the particular case of the classification of isolated music symbols: first, a set of weak classifiers is considered, each of which provides the probability of belonging to each of the possible classes for a given sample to classify; then, all these probabilities are combined to form a meta-feature set that is used as input to a final classifier. An overview of the process is illustrated in Fig. 2.

In formal terms, let Ω be the set of possible class labels and D the set of weak classifiers considered. A matrix M of dimensions $|D| \times |\Omega|$ is computed, which contains the confidence (represented as probabilities) that each of the $|D|$ weak classifiers gives to the sample at issue of belonging to each of the $|\Omega|$ classes. That is, M_{ij} represents the probability of sample belonging to the class Ω_i based on the weak classifier D_j. The matrix can thus be viewed as a new feature representation (meta-features) that can be used to feed the final classifier rather than using the original features. This idea is based on the *Decision Templates* proposed by (Kuncheva, 2001). The difference in our case is that the probabilities are computed from just one classifier, instead of using many of them.

The construction of this matrix therefore requires different groups of features to be extracted from the original image. Each weak classifier is trained for a particular set of features, thus producing confidence values that work on the different points of view of the input data. Note that all weak classifiers retrieve a vector of size $|\Omega|$ (probability of the sample of belonging to each of the possible classes) independently of the dimensionality of the input for each of them, thus allowing to group the results in a single matrix. However, as the different weak classifiers are totally independent, each one may use different methods or measures to estimate the probability.

The use of such Confidence Matrix (CM) repre-

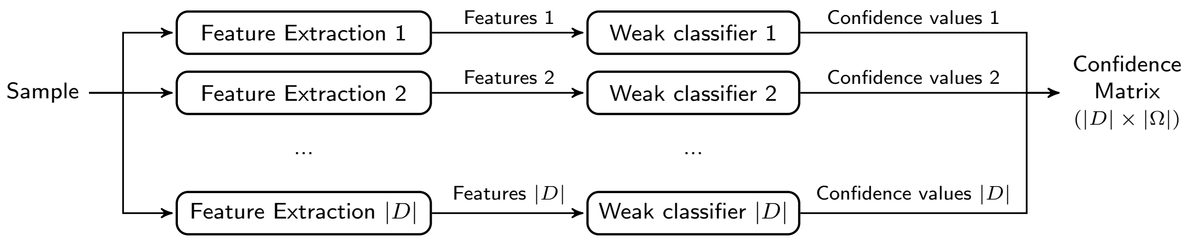


Figure 2: Graphical scheme of the construction of a Confidence Matrix representation.

sentation entails a set of intrinsic advantages. A first one is that, unlike classical approaches in which the final classifier has the responsibility of discovering the different points of view of the signal, the final classifier in this matrix representation is already provided with this segmentation by weak classifiers. Furthermore, in contrast to ensemble classifiers, this new scheme avoids the need for defining distinct dissimilarity measures or types of weak classifiers as features may be grouped according to their nature, which is often relatively simple for a user with domain expertise.

From an algorithmic point of view, some additional advantages are its straightforward implementation and that the pipeline of the algorithm can be easily parallelized so that each weak classifier runs at the same time. Additionally, there may be some scenarios in which the CM is not only helpful but also necessary. For example, when several input features from the same sample come from different, incompatible structures (eg. trees, strings or feature vectors). In these cases, scores from weak classifiers trained separately with each kind of structure can be easily combined within the matrix representation.

Note, however, that this new scheme does not produce a final decision. It merely maps the input features into another space (meta-features). This signifies that it is necessary to use an algorithm that employs the matrix to make a decision using it as a set of features.

We shall now introduce the different elements comprising the proposed scheme: the initial features directly retrieved from the image, the features obtained considering the set of weak classifiers, and the schemes considered for the final classification stage.

2.1 Groups of Features from Isolated Music Symbols

Given an input image depicting an isolated music symbol that has undergone a binarization process, a preprocessing stage is performed first. A morphological closing filter (Serra, 1982) is applied in order to correct any gaps and spurious points that may have appeared in the binarization process. In the next step, the character is located in the image and the region of interest (ROI) is selected.

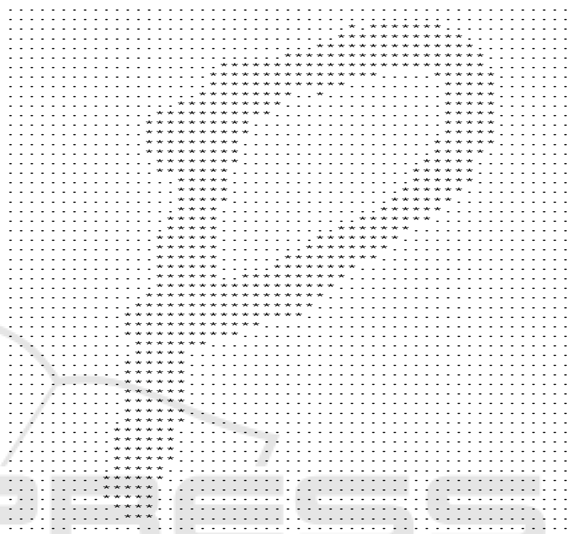


Figure 3: Example of binary input representing an isolated handwritten *Half Note* (𝅗𝅥).

Once the image has been preprocessed, the feature extraction takes place. The image is divided into a sub-structure of smaller regions in order to extract local features. The number of sub-regions must be fixed empirically.

For the sake of clarity in the explanation, let us consider the input image shown in Fig. 3 as example, which depicts an isolated *Half Note*. Three groups of features are considered for this work:

- Foreground area: a vector with the foreground area in terms of pixels for each sub-region of the image is produced (see Fig. 4). Note that, if one pixel belongs to more than one region it is counted proportionally within each one.
- Background area: this feature extraction, which is based on that of (Vellasques et al., 2006), computes four projections (up, down, left, and right) for each pixel in the image; a counter is set to zero for each pixel in the image and, when any of these projections touches the foreground object, the counter associated to that pixel increases in

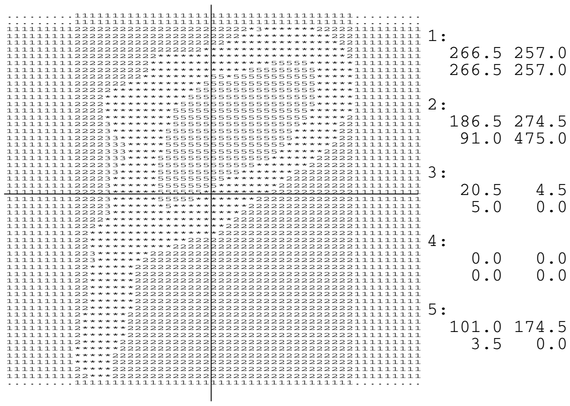


Figure 4: Background features extracted from input considering 4 sub-regions.

Figure 5: Foreground features extracted from input considering 4 sub-regions.

one unit. This process allows to distinguish four different categories of background pixels, according to their projection values $(1,2,3,4)$. Zero-valued counters are discarded. An additional category with value 5 is added to provide disambiguation information: this value substitutes the value of 4 if the pixel lies in an isolated background area. Eventually, the feature vector derived for each sub-region contains five descriptors which depict the proportion of pixel area covered by each of the projection categories considered. An example can be seen in Fig. 5.

- Contour area: the contour of the object is encoded by the links between each pair of 8-neighbor pixels using 4-chain codes in the manner proposed by (Oda et al., 2006). These codes are used to extract four vectors (one for each direction), and the proportion of pixel area covered by the number of each code is counted for the different sub-regions considered. Figure 6 shows an example of this feature extraction process.

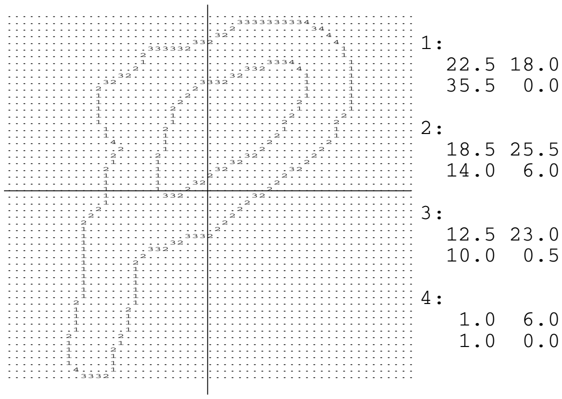


Figure 6: Contour features extracted from input considering 4 sub-regions.

2.2 Meta-features based on Weak Classifiers

As discussed previously, a set of weak classifiers with which to map each group of features onto confidence values is needed. In this regard, each weak classifier has been obtained considering a formula based on the Nearest Neighbor (NN) rule (Cover and Hart, 1967) given its conceptual simplicity.

Each weak classifier is trained using a leaving-one-out scheme: each single sample is isolated from the training set T and the rest are used in combination with the NN to produce the confidence values. The formula detailed below is inspired by (Pérez-Cortés et al., 2000). If x is a training sample, then the confidence value for each possible class $w \in \Omega$ to represent instance x is based on the following equation:

$$p(w|x) = \frac{1}{\min_{x' \in T_w, x \neq x'} d(x,x') + \varepsilon} \qquad (1)$$

where T_w is the training set for w label and ε is a non-zero value provided to avoid infinity values. In our experiments, the dissimilarity measure $d(\cdot,\cdot)$ is the Euclidean distance. After calculating the probability for each class, the values are normalized such that $\sum_{w\in\Omega} p(w|x) = 1$.

Once each training sample has been mapped onto the probability matrix M, the samples can be used in the test phase.

2.3 Final Classifiers

Once the meta-features have been calculated they are fed into a conventional classifier to compute a class hypothesis. Given that each of the $|D|$ weak classifiers is retrieving a vector of $|\Omega|$ features, two classification paradigms may be considered for this last stage: on the one hand, we may construct the M matrix by grouping all the features from the weak classifiers and then use a single classification algorithm; on the other hand, a meta-classifier which takes as separate inputs the $|D|$ feature vectors from the weak classifiers may be also considered.

The underlying idea of meta-classification is to solve a labeling problem by combining the decisions of individual classifiers in order to combine them into a unique final decision (late fusion). Thus, the main reason for considering the aforementioned strategies for the final classification stage is to discard the possibility of observing an improvement in the results with the proposed idea produced by the use of too simple classifiers. In addition, note that our intention in this work is to check whether the proposed representation can improve the performance achieved with classical feature vectors for the precise task of classifying isolated music symbols and not necessarily trying to outperform the existing late fusion techniques.

In terms of actual algorithms, we considered three different classifiers for each of the two mentioned categories: as of conventional classifiers we considered Nearest Neighbor, Support Vector Machine, and Multi-Layer Perceptron; in terms of meta-classifiers, we chose Maximum Average Class Probability, Stacking-C, and Rotation Forest. For all of them, we have considered the Waikato Environment for Knowledge Analysis (WEKA) library (Hall et al., 2009), each one with their default parameterization. We shall now briefly introduce these schemes.

2.3.1 Nearest Neighbor

The previously introduced Nearest Neighbor (NN) rule can also be directly used for classification. Let $X = (x_1, \ldots, x_n)$ be a set of labeled samples and let $x' \in X$ be the sample that minimizes a dissimilarity measure $d(x, x')$ to a test point x. The NN rule (Aha et al., 1991) assigns to x the label associated with x'.

2.3.2 Support Vector Machines

Support Vector Machine (SVM) is a supervised learning algorithm developed by Vapnik (Vapnik, 1998). It seeks for a hyperplane which maximizes the separation (margin) between the hyperplane and the nearest samples of each class (support vectors). SVM assumes a binary classification problem and thus needs an extension to tackle multi-class problems. In this work we shall use the *one-vs-one* scheme, which creates an SVM classifier for each pair of classes. Additionally, as SVM relies on the use of a Kernel function to deal with non-linearly separable problems, we shall consider a first-order polynomial kernel for that purpose.

Finally, the training of the SVM considered in this work is conducted by the Sequential Minimal Optimization (SMO) algorithm (Platt, 1999).

2.3.3 Muti-Layer Percepton

Artificial Neural Networks is a family of structures developed in an attempt to mimic the operation of the nervous system to solve machine learning problems. The topology of a neural network can be quite varied. For this work, the common neural network called Multi-Layer Perceptron (MLP) is used.

2.3.4 Stacking-C

Given that our classification scheme is based on the main idea of Stacking algorithms (i.e., training a system to classify with the results of other independent classifiers), we have included this algorithm to prove the improvement that can be obtained by means of the use of meta-features. We have selected one of the most successful algorithms from this family: Stacking-C (Seewald, 2002), an extension to Stacking to accurately address multi-class problems.

2.3.5 Rotation Forest

Rotation Forest (RoF) (Rodriguez et al., 2006) is an ensemble method that focuses on building accurate and diverse classifiers. It trains a set of decision trees (forest), each of which uses an independent feature extraction. RoF makes use of a base classifier to generate its decision trees. In our work, two alternatives will be considered: C4.5 (Quinlan, 1993) (J48 implementation (Hall et al., 2009)) and Random Forest (RaF) (Breiman, 2001). The first alternative is proposed by the original article, whilst the latter is considered due to its remarkably good performance shown in our preliminary experiments.

2.3.6 Maximum Average Class Profile

In contrast to the previous meta-classifiers considered, a decision can be taken by combining the individual decisions of each weak classifier. In this regard we have considered the Maximum Average Class Probability (MACP) (Kuncheva, 2004), which labels the input query with the class that maximizes the average of the probabilities given by each of the weak classifiers.

3 EXPERIMENTS

3.1 Corpus

The HOMUS dataset (Calvo-Zaragoza and Oncina, 2014) of musical symbols will be used in this experimentation[1]. This set contains 15200 handwritten musical symbols from 100 different musicians spread over 32 of the most common music symbols. It is important to stress that the corpus was collected encouraging the users to write the symbols as natural as possible, thereby leading to a high variability in the music notation found within the dataset, as depicted in Table 1.

3.2 Evaluation

The evaluation of our method consists in comparing the proposed strategy against conventional classification methods. It is also interesting to know whether results achieved by our proposal are caused by the group of features selected or by the CM representation based on weak classifiers. Therefore, experiments report the results with and without using the meta-feature representation considered. In the former case, both the raw input image (pixel values after rescaling the binarised image to 20×20, to compare with previous works (Rebelo et al., 2010)) and the set of features selected is considered.

Table 2 shows the average results in terms of error rates obtained in the experimentation considering a 4-fold cross-validation scheme. A first remark to point out is that classification results when considering the raw image exhibit high error rates since almost all classifiers depict error figures around 25 % and 35 %. The highest error value can be seen in the MLP classifier as it only properly performs in 25 % of the situations whereas the best performing algorithm is the Random Forest ensemble (RoF RaF).

When considering the group of features for encoding the image instead of its raw version, a remarkable improvement in the results is observed. Almost all classifiers exhibit a decrease ranging around 10 % and 15 % in their error rates, being SVM the one achieving the best classification performance. The only exception to this general improvement is found in the MLP classifier in which these features do not report an improvement compared to the raw image case, thus still exhibiting the lowest performance among the different methods considered.

[1]The dataset is freely available at http://grfia.dlsi.ua.es/homus/

Focusing now on the use of the CM representation, it can be checked that this representation entails some additional improvements in the results with respect to the group of features initially considered for the image. Particularly, the CM representation reduces the observed error rate in around 5 % to 7 % with respect to the previous representation, being again SVM the classifier outperforming the rest with roughly a 10 % of error rate, which represents a particularly good result given that there are more than 30 different classes. The NN classifier constitutes the only case for which the use of this representation does not suppose an improvement in the results. Lastly, and in spite of exhibiting the highest error rate for all classifier using the CM set of features, MLP results undergo a remarkable improvement with respect to the two previous data representations of close to a 50 % in terms of error rate.

This general improvement in the results when considering the CM representation for all algorithms (except for NN, in which results hardly change) suggests that the accuracy boost is due to this alternative feature representation and not to the use of meta-classification schemes rather than simpler methodologies. That is, independently of the classification scheme considered, an improvement is generally observed when the feature representation is based on CM.

Finally, results obtained with the MACP strategy also point out that a basic combination of the decisions of each weak classifier instead of using them as features for a final classification stage may be enough for achieving a competitive error rate (around 17 % for the data considered). More precisely, as it can be observed, MACP outperforms on average rather complex schemes such as MLP or Stacking-C.

In order to provide consistent conclusions of our work, these results must be validated objectively through statistical tests (Demsar, 2006). In this case we have considered the Wilcoxon rank-sum tests that allow a pairwise comparison between different classification configurations. Our main intention is to check whether our approach improves significantly the conventional classification scheme consisting of a set of extracted features plus direct classification. To this end, Table 3 shows the results of this test comparing classification with the proposed set of meta-features (CM) against the results obtained considering the raw input image and the group of features initially extracted from the image. The significance of p has been established to 0.05. Note that a comparison between each classifier with CM and the MACP ensemble is also checked. While we are aware that results from a 4-fold cross-validation scheme may not

Table 1: Examples of variability in handwritten musical symbols from HOMUS dataset among different musicians.

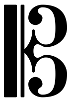
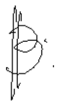
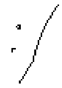
Label	Symbol	Musician 1	Musician 2	Musician 3	Musician 4
C-Clef					
Eighth Note					
Sixteenth Rest					

Table 2: Comparison of the error rate (%) shown by the different classifiers considered when the input representation is based on the raw image, the set of image features or the matrix representation based on weak classifiers. The subregion parameter for the feature extraction has been optimized for each particular classifier. Additionally, the results when considering the MACP scheme for combining the decisions of each weak classifier is included.

Classifier	Input representation		
	Raw image	Groups of features	Confidence Matrix
NN	32.5	19.7	21.0
SVM	32.4	18.6	11.8
MLP	75.2	75.4	24.2
StackingC	33.4	23.2	18.9
RoF J48	35.6	20.8	16.1
RoF RaF	25.1	18.9	15.4
MACP		17.4	

be enough for a robust statistical analysis, it allows depicting the general behavior of the algorithms.

As observed, the use of the CM features entails a significant accuracy improvement over the raw image for all classifiers considered. Additionally, when compared to the initial group of features extracted from the image, CM also significantly outperforms the results except for the case of the NN classifier, in which this analysis does not evidence any statistical difference between the use of these two set of features.

Finally, the statistical comparison between the MACP combination of single decisions and the use of a last classification stage for the CM features shows some interesting results. Rotation Forest ensembles (both RoF J48 and RoF RaF) as well as SVM are able to significantly outperform the MACP strategy. On the contrary, NN and MLP show a significantly worse performance than the aforementioned decision combination strategy. Lastly, Stacking-C does not show a statistically relevant difference in performance with respect to MACP.

4 CONCLUSIONS

The classification of handwritten music symbols is a remarkably useful process in the field of Optical Music Recognition which turns to be a quite challenging

Table 3: Results obtained for the statistical significance tests comparing the accuracy of the classifier depicted in the row using CM-based classification against the accuracy of the same final classifier when considering the raw image and the features from the figure (columns). An additional comparison with the MACP ensemble technique is made to assess the performance of CM against a basic combinations of decisions. Symbols ✓, ✗ and = state that results achieved by elements in the rows significantly improve, decrease or do not differ respectively to the results by the elements in the columns. Significance has been set to $p < 0.05$.

CM Ensemble	Raw features	Groups of features	MACP
NN	✓	=	✗
SVM	✓	✓	✓
MLP	✓	✓	✗
StackingC	✓	✓	=
RoF J48	✓	✓	✓
RoF RaF	✓	✓	✓

problem given the variability expected in the musical symbols.

In this paper we considered an ensemble-based strategy which consists in extracting heterogeneous features that are eventually mapped onto a Confidence Matrix (CM) as a set of posterior probability values obtained by a group of weak classifiers. This approach enables the features to be transformed into a new space (meta-features), thus allowing the dimensionality of the data (in our case) to be reduced and a more meaningful value to be provided in each dimension. This is expected to help to reduce the error rate of the final classifier.

Our results show that the use of this alternative space provides significant improvements in the results with respect to the use of image-based features for most classifiers studied. Among the figures obtained, Support Vector Machine with the Confidence Matrix representation yields the best results, which is eventually estimated in around 10 % of error rate for the considered handwritten music symbol data.

Future work considers the inclusion of this proposal in a functional Optical Musical Recognition system to study its impact in a real-world context. Additionally, with the intention of still lowering the error rate obtained, we aim at exploration Convolutional Neural Networks given their reported success in image processing tasks.

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