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The Effect of Derived Features on Art Genre Classification with Machine Learning

Didem ABİDİN*[1]

Abstract

Classification of the artwork according to their genres is being done for years. Although this process was used to be done by art experts before, now artificial intelligence techniques may help people manage this classification task. The algorithms used for classification are already improved, and now they can make classifications and predictions for any kind of genre classification. In this study, two different machine learning algorithms are used on an artwork dataset for genre classification. The primary purpose of this study is to show that the derived features about the artwork have a remarkable effect on correct genre classification. These features are derived from the metadata of the dataset. This metadata contains information about the nationalities and the period that the artist lived. Image filters are also applied to the images but the results show that applying only image filters on the dataset used in the study did not perform well. Instead, adding derived features extracted from the metadata increased the classification performances dramatically.

Keywords: genre classification, machine learning, Random Forest, J48.

List of Symbols and Abbreviations

Machine Learning	ML
Artificial Neural Networks	ANN
Deep Neural Networks	DNN
Support Vector Machines	SVM
Convolutional Neural Network	CNN
Random Forest	RF
Deep Learning	DL

1. INTRODUCTION

Genre classification is a very popular study on which researchers work on different data sets with growing amounts of data. These data may consist of numerical values as well as images. Artificial intelligence techniques have been widely used for genre classification for many years on these types of data. When dealing with image data, researchers also use various filtering methods to obtain better classification results. Machine Learning (ML) is a branch of artificial intelligence, which is used for data science applications on a formatted data. Among the ML techniques, Artificial Neural Networks (ANN) play an important role on the classification of image data. ANN can be defined as a simulation of the working principles of neurons in human body, that takes one input, processes it and gives an output while learning the data. ANN techniques are developed by applying hidden layers of neurons between the input and output layers to obtain more accurate results in learning process. Because of its high learning capability, it can be used in various application areas like classification [1], prediction [2][3], recognition in general (including pattern, handwriting

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recognition) [4] and so on. ANN with more than three hidden layers between input and output layers is called Deep Neural Networks (DNN). Although the use of deep learning techniques for the processing and classification of visual data is becoming widespread, other ML techniques can still be used on visual data, and many ML algorithms can yield efficient results. In particular, the application of image filters on visual data makes the data ready for a classification problem application. In addition to filters, textual or numerical data that can be obtained from images also contribute to successful classification. The data that can be extracted from the images can be called as "derived features" and this study aimed to show that more efficient genre classification is possible on a data set where image filtering is used together with calculated fields. The values of the calculated fields can easily be included to the image filters' data and they together generate a stronger input to train any ML algorithm in use.

The layout of the paper is as follows: Section 2 explains the related work listed in literature about art genre classification, where Section 3 explains the proposed methodology with the details of the dataset used. Section 4 gives the results for the experiments of the study and Section 5 is the conclusion.

2. RELATED WORK

Machine Learning has been a very popular classification technique for the past two decades. Using ML algorithms in art genre classification is equally popular as other application areas of ML. below, some studies related with art genre classification with ML algorithms are listed. [5] studied on art genre classification for five genres of paintings (abstract expressionism, cubism, impressionism, popart and realism) and used Naïve Bayes [6], k-Nearest Neighbor [7], ANN [8], Support Vector Machines (SVM) [9] and AdaBoost [10] algorithms. The best performing algorithm appeared to be the AdaBoost with 68.3% accuracy.

In some studies, self-organizing maps are used for art genre classification. For example, [11] proposed a methodology that classifis painting styles by extracting some features from the paintings. They achieved their goal by using self-organizing maps. Another study extracted the light, line and color features and classified the art paintings by using k-Nearest Neigbor [12]. In this study, self-organizig maps also took place in the analysis of the classification process. [13] used dual-tree complex wavelet transforms and Hidden Markov Trees for the stylistic analysis of the paintings, where [14] used Genetic Algorithm (GA), to classify paintings into two and three classes. They used nearest neighbor algorithm for the training step and obtained better solutions than a classical nearest neighbor algorithm. In another study, a method to recognize painters having styles Impressionism, Expressionism, and Surrealism as a genre is proposed [15]. A study that derives features from a deep Convolutional Neural Network (CNN) obtained a performance of 77.57% in the classification of seven genre categories [16]. [17] worked on classification of fine-art paintings by using SVM and CNN [18]. They worked on the performances of different visual features in fine-art paintings. [19] worked on the classification of paintings with CNN and they were successful on the discovery of over 250,000 new object annotations across 93,000 paintings.

In a relatively new study compared to the above-mentioned studies, [20] handled the classification of painting styles problem with transfer learning. In [21], they used CNN the classification of the paintings and also used the timeframe feature as done in our study.

Some recent studies used DNN to classify the styles in paintings like [22], where they obtained successful results in a large scale collection of paintings. [23]worked on Wikipaintings dataset with 25 different styles. They used DNN to perform a classification with an accuracy of 62%. [24] trained and classified fine-art paintinds with Deep Convolutional Neural Network. They used three different pretrained CNNs and three of them showed a remarkable improvement over the others.

In the studies listed, very few of them have dealt with deriving calculated fields for the art paintings datasets. This study focuses on the importance of derived features in genre classification.

3. PROPOSED METHODOLOGY

3.1. The Dataset

The dataset used contains artworks of 50 artists with 8355 pieces in total. It has been obtained from Kaggle [25] with a .csv file with the artist's information. This file contains the following columns: Id, name, years (birth-death), genre, nationality, bio (biography), Wikipedia (Wikipedia link), and paintings (number of paintings in the dataset). There are 21 genres in the dataset which are listed as: Abstract expressionism, Baroque, Byzantine art, Cubism, Early Renaissance, Expressionism, High Renaissance, Impressionism, Mannerism, Neoplasticism, Northern Renaissance, Pop art, Post-impressionism, Primitivism, Proto-Renaissance, Realism, Romanticism, Social Realism, Suprematism, Surrealism and Symbolism. The .csv file for artist information is given in Figure 1.

id	name	years	nationality	genre	paintings
19	Albrecht Durer	1471 - 1528	German	Northern Renaissance	328
20	Alfred Sisley	1839 - 1899	French,British	Impressionism	259
0	Amedeo Modigliani	1884 - 1920	Italian	Expressionism	193
7	Andrei Rublev	1360 - 1430	Russian	Byzantine Art	99
45	Andy Warhol	1928 - 1987	American	Pop Art	181
35	Camille Pissarro	1830 - 1903	French	Impressionism,Post-Impressionism	91
25	Caravaggio	1571 - 1610	Italian	Baroque	55
3	Claude Monet	1840 - 1926	French	Impressionism	73
2	Diego Rivera	1886 - 1957	Mexican	Social Realism,Muralism	70
27	Diego Velazquez	1599 - 1660	Spanish	Baroque	128

Figure 1 Artists.csv file

The artworks are given in 50 folders for 50 artists and the resized files are also available for the same paintings in another folder. In this study, the resized files are used.

3.2. Data Preprocessing

Classification algorithms are executed on the dataset in the WEKA environment [26]. WEKA can use .arff file format and the preprocessing steps on the data to be used for classification are given below:

Generating the inıtial .arff file: For image filtering, two main attributes are needed for the instances in the .arff file. These attributes are the file name and class information. In addition to the aforementioned columns, year, nationality and genre columns are added for every instance in the dataset to be used after the filtering process. To add these columns, the artist.csv file is used. In this file, year, nationality and genre columns are first converted to encoded values with Python using LabelEncoder library [27]. This is done to give numeric values to categorical features. The source code and the numeric values for year, nationality, and genre fields are given in Figure 2 below.

In [5]:
```
from sklearn.preprocessing import LabelEncoder
var_mod = ['years','genre','nationality']
le = LabelEncoder()
for i in var_mod:
    df[i] = le.fit_transform(df[i])
df.dtypes

df
```

Out[5]:

	id	name	years	genre	nationality	bio
0	0	Amedeo Modigliani	5	5	8	Amedeo Cl (Italian pror
1	1	Vasiliy Kandinskiy	5	5	11	Wassily Wa Kandinsky
2	2	Diego Rivera	5	17	9	Diego Marí Juan Nepo
3	3	Claude Monet	5	7	6	Oscar-Clau [klod monɛ]
4	4	Rene Magritte	5	19	2	René Franç Magritte (Fr

Figure 2 Artists.csv file after LabelEncoder

The meanings of encoded values for genres and nationalities are given in Table 1 and Table 2 respectively.

Table 1 Genre encoding

No	Genre
0	Abstract Expressionism
1	Baroque
2	Byzantine Art
3	Cubism
4	Early Renaissance
5	Expressionism
6	High Renaissance
7	Impressionism
8	Mannerism
9	Neoplasticism
10	Northern Renaissance
11	Pop Art
12	Post-impressionism
13	Primitivism

14	Proto-Renaissance
15	Realism
16	Romanticism
17	Social Realism
18	Suprematism
19	Surrealism
20	Symbolism

Table 2 Nationality encoding

No	Nationality
1	Austrian
2	Belgian
3	British
4	Dutch
5	Flemish
6	French
7	German
8	Italian
9	Mexican
10	Norwegian
11	Russian
12	Spanish

Detecting artists' era: The years attribute is encoded according to the timeframes which the artists had lived and it has values from 0 to 30. The period from 1275 to 2000, including the life periods of all artists, is divided into 25 years' timeframes and every timeframe is encoded. Then the timeframes corresponding to the birth and death dates of the artists are represented with two numeric values for more accuracy. The timeframe encoding is done according to the scale shown in Figure 3. For example, the birth and death dates of Pablo Picasso (1881-1973) fall into timeframes 25-28.

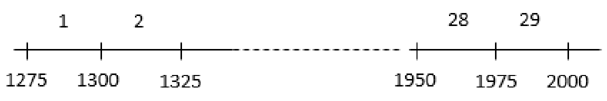

Figure 3 The timeframe scale

Adding derived features: To add these three encoded columns to .arff file, a small Java program is implemented. For every artist, the derived year, nationality, and genre data is read from .csv file to initial .arff file. The final .arff file is given in Figure 4 with *borns*, *dies*, and *nationality* attributes. Genre is already represented with the class column.

```
@relation art
@attribute filename string
@attribute borns numeric
@attribute dies numeric
@attribute nationality numeric
@attribute class {c1,c3,c5,c6,c7,c10,c12,c13,c16,c19,c20}

@data
Albrecht_Durer_1.jpg,9,10,7,c10
Albrecht_Durer_10.jpg,9,10,7,c10
Albrecht_Durer_100.jpg,9,10,7,c10
Albrecht_Durer_101.jpg,9,10,7,c10
Albrecht_Durer_102.jpg,9,10,7,c10
Albrecht_Durer_103.jpg,9,10,7,c10
Albrecht_Durer_104.jpg,9,10,7,c10
Albrecht_Durer_105.jpg,9,10,7,c10
Albrecht_Durer_106.jpg,9,10,7,c10
Albrecht_Durer_107.jpg,9,10,7,c10
Albrecht_Durer_108.jpg,9,10,7,c10
Albrecht_Durer_109.jpg,9,10,7,c10
```

Figure 4 .arff file with birth, death, nationality and genre data

Applying image filters: Filtering is applied to transform pixel intensity values of images to obtain some numeric data [28]. By doing so, features are extracted from image data and this data is written to the dataset. The arff files generated are used as input in WEKA and several algorithms are used to find the best performing one in classifying the paintings by genre. In [29], the best image filter combination to classify art images was found as the combination of EdgeHistogramFilter [30] and SimpleColorHistogramFilter [31]. EdgeHistogramFilter focuses on the edges of an image and takes shape information of the image into consideration for image indexing [32]. SimpleColorHistogramFilter extracts color histogram features. It has three histograms for red, green and blue, each one having 32 bins. Each bin has the count of pixels that fall to that bin. These two image filters are applied on .arff files and image filter data is merged with existing and derived columns. The .arff file after applying image filters is given in Figure 5. The same filter combination is applied to both versions of the data used in this study.

```
@relation
'art-weka.filters.unsupervised.instance.imagefilter.EdgeHistogramFilter-DD
5' numeric@attribute 'RGB Color Histogram16' numeric@attribute 'RGB Color
stogram39' numeric@attribute 'RGB Color Histogram40' numeric@attribute 'RG
Color Histogram63' numeric@attribute 'MPEG-7 Edge Histogram0' numeric@attr
7 Edge Histogram22' numeric@attribute 'MPEG-7 Edge Histogram23' numeric@at
bute 'MPEG-7 Edge Histogram45' numeric@attribute 'MPEG-7 Edge Histogram46'
eric@attribute 'MPEG-7 Edge Histogram68' numeric@attribute 'MPEG-7 Edge Hi
@attribute borns numeric
@attribute dies numeric
@attribute nationality numeric
@attribute class {c1,c3,c5,c6,c7,c10,c12,c13,c16,c19,c20}
@data
Albrecht_Durer_1.jpg,3,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,64,0,0,0,0,
Albrecht_Durer_10.jpg,7,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,18,0,0,0,0
Albrecht_Durer_100.jpg,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,34,0,0,0,
Albrecht_Durer_101.jpg,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,21,0,0,0,
Albrecht_Durer_102.jpg,3,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,28,0,0,0,
Albrecht_Durer_103.jpg,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,9,0,0,0,0
Albrecht_Durer_104.jpg,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,13,0,0,0,
Albrecht_Durer_105.jpg,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,10,0,0,0,
```

Figure 5 .arff file with image filters applied

The artists and the number of paintings they have in the dataset are given in Table 3. Among these, the ones that have paintings from the rarest genres (shaded ones in Table 1) are excluded and 39 artists' paintings are used. The excluded artists are also shown in shades in the table.

Table 3 Artists and the number of paintings

Name	paintings
Albrecht Durer	328
Alfred Sisley	259
Amedeo Modigliani	193
Andrei Rublev	99
Andy Warhol	181
Camille Pissarro	91
Caravaggio	55
Claude Monet	73
Diego Rivera	70
Diego Velazquez	128
Edgar Degas	702
Edouard Manet	90
Edvard Munch	67
El Greco	87
Eugene Delacroix	31
Francisco Goya	291
Frida Kahlo	120
Georges Seurat	43
Giotto di Bondone	119
Gustav Klimt	117
Gustave Courbet	59
Henri de Toulouse-Lautrec	81
Henri Matisse	186
Henri Rousseau	70
Hieronymus Bosch	137
Jackson Pollock	24
Jan van Eyck	81
Joan Miro	102
Kazimir Malevich	126
Leonardo da Vinci	143
Marc Chagall	239
Michelangelo	49
Mikhail Vrubel	171
Pablo Picasso	439
Paul Cezanne	47
Paul Gauguin	311
Paul Klee	188
Peter Paul Rubens	141
Pierre-Auguste Renoir	336
Piet Mondrian	84
Pieter Bruegel	134
Raphael	109
Rembrandt	262
Rene Magritte	194
Salvador Dali	139
Sandro Botticelli	164
Titian	255
Vasiliy Kandinsky	88
Vincent van Gogh	877
William Turner	66

3.3. Input Data

The input dataset contains the following columns:

- Attributes of SimpleColorHistogram (64 columns)
- Attributes of EdgeHistogram (80 columns)
- borns: It is the corresponding 25-year interval (timeframe) in which the artist's date of birth coincides (values from 1 to 30).
- dies: It is the corresponding 25-year interval (timeframe) in which the artist's date of death coincides (values from 1 to 30).
- nationality: Encoding values given in Table 2.

Class column is the output for the proposed system. Genre encoding values are given in Table 1. Additionally, image filters' features are added to the dataset automatically when any of the filters are applied in WEKA.

3.4. Proposed System

To classify artworks into genres, supervised learning techniques are used. In supervised techniques, the class information for every instance is given to the algorithm and the algorithm "learns" and generates a model with this data on the training set. Later, the generated model is used for testing. Among all ML algorithms, this study uses Random Forest (RF) and J48 algorithms.

RF builds many classification trees as a forest of random decision trees [33] and these trees are then merged to obtain a more accurate prediction. Each tree uses a specific subset of the input features. Each tree outputs a classification (vote) and the algorithm chooses the one having most votes among all the trees in the forest [34]. As the number of trees in the forest increases, the generalization error for the forests converges to a limit value. This error value depends on the strength of the individual trees in the forest and the correlation between them [35]. RF algorithms can be used for both classification and regression problems. It adds additional randomness to the model while the trees grow. It searches for the best feature among a subset of features selected randomly. This means a wide diversity that generally results in a better model [36].

ID3 was the first version of the C4.5 algorithm of Quinlan [37] and J48 [38] is the Java implementation of C4.5 [39]. C4.5 is a classifier that accepts nominal classifiers and can use both discrete and continuous attributes. Also training data with missing attribute values is accepted. J48 adds some more features to C4.5 like processing for missing values, decision tree pruning, continuous attribute value ranges, and derivation of rules. C4.5 classifiers are also considered as decision trees and they can construct classifiers in a more comprehensible rule set form [40].

After the preprocessing step for the dataset is completed, it is used for executing classification algorithms.

4. EXPERIMENTAL RESULTS

The results were obtained for two versions of the dataset. In the first version (V1), all 50 artists from 21 genres were included. In the second version (V2) rare genres and their instances were excluded since they have very few examples. V2 dataset has 39 artists from 11 genres. These 11 genres are Baroque, Cubism, Early Renaissance, Expressionism, High Renaissance, Impressionism, Northern Renaissance, Post-impressionism, Primitivism, Romanticism, Surrealism and Symbolism. The genres which are already in the original dataset but not included in the second version are shaded in grey in Table 1. Table 4 shows the properties of both versions of the dataset for comparison.

Table 4 Artists and the number of paintings

	V1	**V2**
# genres	21	11
# instances	8355	7252
# artists	50	39
# attributes	148	148
Image filters	EdgeHistogram SimpleColorHistogram	EdgeHistogram SimpleColorHistogram
Algorithms	RF J48	RF J48

For both versions of datasets, the same image filters and the same classification algorithms were used. Among the classification algorithms, RF and J48 had the best performances.

RF and J48 results for dataset V1 are given in Table 5 and Table 6 and RF and J48 results for dataset V2 are given in Table 7 and Table 8 respectively.

Table 5 RF Results for V1

Time taken to build model : 6.76 seconds
Correctly Classified Instances: 82.9823 %
Kappa statistic : 0.8101
Mean absolute error : 0.0557
Root mean squared error : 0.1455
Relative absolute error : 64.3106 %
Root relative squared error : 69.9367 %
Total Number of Instances : 8355

Precision	Recall	F-Measure	Class
0.629	0.676	0.975	c0
0.928	0.923	0.998	c1
0.857	0.863	0.997	c2
0.855	0.849	0.997	c3
0.477	0.548	0.993	c4
0.835	0.827	0.992	c5
0.857	0.853	0.997	c6
0.827	0.793	0.982	c7
0.709	0.727	0.999	c8
0.473	0.554	0.985	c9
0.921	0.914	0.985	c10
0.84	0.845	0.996	c11
0.896	0.882	0.988	c12
0.761	0.754	0.975	c13
0.91	0.911	0.997	c14
0.183	0.315	0.982	c15
0.959	0.957	1	c16
0.289	0.396	0.984	c17
0.564	0.609	0.988	c18
0.795	0.785	0.983	c19
0.708	0.704	0.972	c20
0.83	0.816	0.811	W. Avg.

Table 6 J48 Results for V1

Number of Leaves	**:155**
Size of the tree	**: 309**
Time taken to build model	**: 0.92 seconds**
Correctly Classified Instances	**: 94.6386 %**
Kappa statistic	**: 0.941**
Mean absolute error	**: 0.0056**
Root mean squared error	**: 0.0696**
Relative absolute error	**: 6.4555 %**
Root relative squared error	**: 33.4437 %**
Total Number of Instances	**: 8356**

Precision	Recall	F-Measure	Class
1	1	1	c0
1	1	1	c1
1	1	1	c2
1	1	1	c3
1	1	1	c4
1	1	1	c5
1	1	1	c6
0.877	0.847	0.938	c7
1	1	1	c8
1	1	1	c9
1	1	1	c10
1	1	1	c11
0.963	0.957	0.983	c12
0.892	0.886	0.96	c13
1	1	1	c14
0.868	0.865	0.977	c15
1	1	1	c16
1	1	1	c17
1	1	1	c18
1	1	1	c19
0.766	0.748	0.905	c20
0.946	0.946	0.938	W. Avg.

Table 7 RF Results for V2

Time taken to build model	**: 11.59 seconds**
Correctly Classified Instances	**: 88.7204 %**
Kappa statistic	**: 0.8709**
Mean absolute error	**: 0.0941**
Root mean squared error	**: 0.1831**
Relative absolute error	**: 58.6993 %**
Root relative squared error	**: 64.681 %**
Total Number of Instances	**: 7252**

Precision	Recall	F-Measure	Class
0.943	0.939	0.998	c1
0.915	0.91	0.998	c3
0.888	0.88	0.995	c5
0.978	0.977	0.999	c6
0.867	0.832	0.983	c7
0.92	0.912	0.988	c10
0.91	0.895	0.99	c12
0.824	0.824	0.977	c13
0.956	0.954	1	c16
0.844	0.836	0.99	c19
0.716	0.713	0.972	c20
0.887	0.885	0.872	W. Avg.

Table 8 J48 Results for V2

Number of Leaves	**: 144**
Size of the tree	**: 287**
Time taken to build model	**: 1.09 seconds**
Correctly Classified Instances	**: 94.2774 %**
Kappa statistic	**: 0.9351**
Mean absolute error	**: 0.0114**
Root mean squared error	**: 0.0983**
Relative absolute error	**: 7.1129 %**
Root relative squared error	**: 34.7342 %**
Total Number of Instances	**: 7252**

Precision	Recall	F-Measure	Class
1	1	1	c1
1	1	1	c3
1	1	1	c5
1	1	1	c6
0.886	0.853	0.947	c7
1	1	1	c10
0.964	0.958	0.985	c12
0.884	0.877	0.957	c13
1	1	1	c16
1	1	1	c19
0.767	0.746	0.911	c20
0.943	0.943	0.932	W. Avg.

The confusion matrices for the best performing algorithm on V1 and V2 are given in Table 9 and Table 10 below respectively. The confusing genres are marked in grey on both tables.

Table 9 Confusion Matrix for V1 with J48 Algorithm

c0	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14	c15	c16	c17	c18	c19	c20	
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**c0**
0	495	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**c1**
0	0	99	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**c2**
0	0	0	439	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**c3**
0	0	0	0	164	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**c4**
0	0	0	0	0	469	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**c5**
0	0	0	0	0	0	556	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**c6**
0	0	0	0	0	0	0	1458	0	0	0	0	22	23	0	18	0	0	0	0	126	**c7**
0	0	0	0	0	0	0	0	87	0	0	0	0	0	0	0	0	0	0	0	0	**c8**
0	0	0	0	0	0	0	0	0	84	0	0	0	0	0	0	0	0	0	0	0	**c9**
0	0	0	0	0	0	0	0	0	0	748	0	0	0	0	0	0	0	0	0	0	**c10**
0	0	0	0	0	0	0	0	0	0	0	181	0	0	0	0	0	0	0	0	0	**c11**
0	0	0	0	0	0	0	32	0	0	0	0	1005	7	0	0	0	0	0	0	4	**c12**
0	0	0	0	0	0	0	40	0	0	0	0	6	376	0	0	0	0	0	0	7	**c13**
0	0	0	0	0	0	0	0	0	0	0	0	0	0	119	0	0	0	0	0	0	**c14**
0	0	0	0	0	0	0	21	0	0	0	0	0	0	0	128	0	0	0	0	0	**c15**
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	388	0	0	0	0	**c16**
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	70	0	0	0	**c17**
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	126	0	0	**c18**
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	435	0	**c19**
0	0	0	0	0	0	0	127	0	0	0	0	7	8	0	0	0	0	0	0	457	**c20**

Table 10 Confusion Matrix for V1 with J48 Algorithm

c1	c3	c5	c6	c7	c10	c12	c13	c16	c19	c20	
495	0	0	0	0	0	0	0	0	0	0	**c1**
0	439	0	0	0	0	0	0	0	0	0	**c3**
0	0	469	0	0	0	0	0	0	0	0	**c5**
0	0	0	556	0	0	0	0	0	0	0	**c6**
0	0	0	0	1468	0	27	28	0	0	124	**c7**
0	0	0	0	0	747	0	0	0	0	0	**c10**
0	0	0	0	28	0	1008	6	0	0	6	**c12**
0	0	0	0	41	0	6	373	0	0	9	**c13**
0	0	0	0	0	0	0	0	388	0	0	**c16**
0	0	0	0	0	0	0	0	0	435	0	**c19**
0	0	0	0	129	0	3	8	0	0	459	**c20**

Image filters on their own did not perform well for the two datasets. However, with the addition of the derived features, the classification process became more significant. Table 11 and Table 12 show the classification performances with only the image filters, and the image filters together with the derived features for both datasets.

Table 11 Classification performances without/with derived features in V1

Condition	Algorithm	Performance (%)
Only Filters	RF	42.13
	J48	26.24
Filters + derived features	RF	82.63
	J48	94.63

Table 12 Classification performances without/with derived features in V2

Condition	Algorithm	Performance (%)
Only Filters	RF	47.13
	J48	21.67
Filters + derived features	RF	88.18
	J48	94.27

5. CONCLUSION AND DISCUSSION

In this study, the art genre classification with ML algorithms is done by using derived features of the artwork in the dataset with the best performing image filters. Here, not the images, but the information about the images is in question, that is why no CNN or DL techniques are used. Instead, classical ML algorithms were enough to make proper classification on image data including.the derived features.

The two version of the same dataset is used in two different sizes, one with 21 different genres of work and the smaller one with 11 genres of artwork image data. Some of these genres are close to each other in terms of the time period they were used. One genre may be following the other one as a slight developed/transformed version of the previous. For this reason, it is possible to confuse the genres of some othe pieces in the dataset. The most confusing genres are identified as symbolism, impressionism, and post-impressionism.

Although reducing the number of genres affects the performance in a positive way for both of the algorithms, this effect is more evident for RF. On both datasets, J48 performs better than RF, but the size of the dataset does not affect the performance of J48. With V1, as the greater dataset, the performance is measured as 95.81%; where it is 95.34% with V2. Less number of genres and fewer attributes do not affect the performance. Contrarily, more instances in the dataset played a positive role in the accuracy of the result.

What is meant to be emphasized here, together with the best performance values obtained for the proposed system, are the performance values obtained for the genres that are more difficult to classify. For example, symbolism genre has emerged as the one with the worst performance value among genres confused with each other for both data sets. 70.8%, which is the worst performance value for this genre, is not a bad performance value when compared with the art genre classification studies in the literature.

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This study does not require ethics committee permission or any special permission.

The Declaration of Research and Publication Ethics

The authors of the paper declare that they comply with the scientific, ethical and quotation rules of SAUJS in all processes of the paper and that they do not make any falsification on the data collected. In addition, they declare that Sakarya University Journal of Science and its editorial board have no responsibility for any ethical violations that may be encountered, and that this study has not been evaluated in any academic publication environment other than Sakarya University Journal of Science.

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