Machine Learning based Oil Painting Authentication and Features Extraction

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Summary
After the amount of the available artwork in digital form is being increased, the need of finding simple and costless way to authenticate paintings is being more important. The process of artworks authentication is done using different analysis ways; manually by experts or automatically by computer processing. In this paper, oil paintings authentication system using digital image processing techniques and algorithms was proposed. Features were extracted from color and texture. Machine learning methods were used to classify the tested painting on original or forgery, based on rules from the mentioned extracted features. Five different tests and two datasets were used to evaluate the proposed system. The first dataset was used on previous work, and the second was built on this research. Color and texture features were extracted from both datasets. Two classifiers were used to study the effect of classification method on the accuracy of the authentication results. Results show an improvement on the classification accuracy using the proposed system compared with previous works.

Key words:
Painting authentication, Feature extraction, Machine Learning

1. Introduction

The amount of the available artwork in digital form is being increased [1]. Authentication in the area of art works means the process of determining whether the painting is original or forgery [2]. Different analysis ways are applied on the paintings to gain the identified features for each artist which uniquely characterize his paintings style.

Art historians employ multiple methods manually by experts or automatically by computer processing for identifying, authenticating, classifying, and dating artworks. These methods are [3]: Human expert's authentication; Technical analyses of the pigments; Micro chemical analysis of paint samples; X-ray and infrared imaging; Canvas thread counting; Categorizing painting styles and techniques. By using these methods to analyze art work, small attributes may be not observed, more time is needed, more money, and hard effort [4].

Recently, with the development of digital image processing techniques and algorithms, researchers use computer analysis approaches to analyze color, texture, and brushstroke on paintings to automate the authentication job [5]. Computer analysis helps to deal with much larger number of paintings and extract patterns more than is possible through manual work [6].

The increment in digitized form of paintings leads to have large amount of copies works, online shops and galleries offer every day paintings for sales with a lower prices than originals. The development in computer analysis techniques which help authenticator work are faced by more professional copies, forgers also benefit from the new techniques also. There is less availability on dataset that contains pairs of originals and related copies; a small dataset is founded on [7]. Originals and copies works have to be digitized on fix conditions which are: The scan resolution, the light, a consistent temperature distribution, fixed distance from where the photos are took.

The proposed authentication method contains three primary stages, these stages are: painting's image division, feature extraction, and classification. Dividing each image into patches helps to study the local features on paintings and solve the problem of small datasets [3]. Features are extracted from color level and gray level. Two classifiers are deployed to evaluate the proposed method using two datasets.

The contributions of this research are: Study the effect of multi features extraction on the authentication accuracy. A new dataset was built for authentication purpose as a part of this paper. Our dataset contains four pair of originals and their corresponding copies paintings which are done by two painter. Two classifiers results were deployed to compare the effect of classification method on the accuracy of the authentication results.

2. Related works

2.1 Artworks analysis

A summarized report of the tools and methodology used by Princeton research team was provided [2]. Art historians formulated challenges for the research teams from several universities. Three paintings were used, the results showed that Random Forest (RF) classifier was the most accurate in attributing each paintings into one of two periods, the accuracy was 70.5%. The authentication best results were achieved by using patches only from the painting under

Manuscript received January 5, 2017
Manuscript revised January 20, 2017

testing and its copy. It was concluded that there is still needed work to improve the analysis of paintings, and only the equal image's quality can be compared.

A research by [5] in the digital analysis of painting field were reviewed, this survey paper presented the researchers works on painting analysis using color, texture, brushstrokes, and statistical. Color features analysis is studied as a basic component of any image. It was reported that art painting image color semantics (APICSS) [8], is a good system because it is close to the artist's color wheel. APICSS focuses on hue, saturation, luminance (HSL), and hue, saturation, value (HSV) color spaces. Gabor filters is considered as an appropriate way to determine whether two textures are the same or different.

2.2 Artwork Authentication

In order to have ground truth dataset with paintings are known as originals or copies, a new dataset was built on the research of [3]. Art student was asked to paint seven paintings and seven related copies. Different set of materials were used for each pair all originals and copies were scanned at 800 dpi, dataset is available online [7]. Paintings were divided into 1024 x 1024 patches. Dataset was very varied, the results was affected by the ground of paintings and the tested criteria, there was no testing on the whole dataset, and the classification accuracy for each pair was listed independently.

Features were extracted using multi fractal analysis, which was proofed to be suitable for Pollock's works because his paintings show a fractal order [9]. Other features were extracted from fractality pink noise pattern topological genus and curvature properties. The results showed that conjunction features gave the best classification accuracy. The classification test using DT alone gave an error estimates of 40%, but when DT was used as a weak learner in Adaboost the error estimation was reduced to be 25%. The research is restricted to one painter, this system may not applicable on different painter styles.

2.3 Artwork Identification

Two approaches were evaluated on oil paintings by [4], the approaches are: synthesis based and analysis based. The research focused on two case studies; a painting known as "The Ghent Altarpiece" painted by brothers Van Eyck in the fifteenth century, and two paintings from Caspers data set. Both approaches analysis-based and synthesis-based were performed well. The two paintings of Caspers are originals work, the distinguishing process here was between the painter styles. The results comparison of two approaches showed the advantage of the proposed analysis-based over synthesis-based in detecting the differences in style between original and copy.

2.4 Artwork Classification

A new method for automated recognition of painter and school of art was proposed by [10] based on the painter signature styles. The dataset includes paintings of nine artists from three different schools of art: Impressionism, expressionism, surrealism. Large set of textures and statistics features were extracted from several transforms of images. The large set of features work as the perception of artist who focuses on many techniques at a time. The classification accuracy of painter class was 77%, and to relate the painting with its school of art the accuracy was 91%. Large set of features added more complexity to classification process. Each kind of school need to take in account a number of special features to distinguish it from other.

A study of multifractal analysis role in classification the painting's texture was provided by [11]. Caspers dataset was used. Two type of testing were performed; pairwise test where patches from the same location in originals and copies were compared, and non-pairwise test where the compared patches are not from the same locations. Multifractal parameters were trained for testing. The results showed that for the first three pairs, where soft and hard brushes were used, discrimination was achieved by both type of test; pairwise and non-pairwise. Pairs five and seven the originals and copies were distinguished only using pairwise test. The strong canvas structure for paintings four and six was reported as a justification about no discrimination is achieved on both pairs. Color feature was not used in this research, texture features alone not enough.

From literature, it is clear that digital analysis of artwork is an important task which is faced by many challenges. Therefore, combination of features from texture and color were extracted to realize the experts from the effort of finding the small attributes on the paintings, and improve the classification results. Two different classifiers are deployed to study the effect of different classifiers on the system evaluation. A new dataset is provided by our research, which is suitable for authentication experiments; the capturing process on this dataset is done within a fixed condition. Automatic analysis of paintings will help the expert's authentication decision.

3. Authentication System Overview

3.1 Authentication Proposed System

Oil paintings authentication system is proposed in this paper. The flow diagram of the proposed system is shown in Figure 1. The system starts with image loading step. The scanned image which is shown in block (a) will goes in three processing steps: The first step is shown in (b), which is division of images into patches to partition the scanned images into patches of size 512x512. The second step in block (c), is features extraction which collects the features from each patch and store them into knowledge database. The third step is classification block (d) which evaluates the system ability to distinguish between originals and copies paintings using the knowledge database.

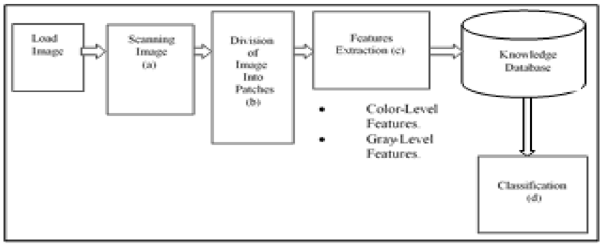


Figure 1: Flow Diagram of the Proposed Authentication System

3.2 Division of Images into Patches

In study of [4] Casper dataset was used, the size of the images was down sampled to 512X512 pixels, the training patches size was 8X8 pixels. By the research of [12] each image was subdivided into non-overlapping regions of 256×256 pixel for each. In [13] the paintings have been divided into patches of size 512 × 512 pixels. Figure 1 block (b), the scanned images are divided into patches of size 512x512 pixels. Division will help in extracting the feature locally from each patches, reducing the processing time of dealing with the large images, and solving the problem of small datasets.

3.3 Feature Extraction

Figure 1 block (c), digital image processing are performed on each patch of the scanned images to collect the features. Features are extracted from two level of images; color level and gray level. Color level features are: Color histogram HSV, color moment, and discrete cosine transform (DCT). Gray level features, textures features, are: Gabor-DCT, Gray-Level Co-Occurrence Matrix (GLCM), and segmentation-based fractal texture analysis (SFTA). All of these features are formed on one feature vector of length 1x153 that represents one patch. The extracted features are stored in knowledge database.

- Color Histogram Features

HSV (hue, saturation, value) was considered as more useful color spaces for artwork analysis than other color spaces [14] and [15]. The input RGB image is converted into HSV to represent its histogram and gain the color features. To formulate the feature vector each channel is assigned to number of bins, because Hue (H) is considered as an important component in the human visual system more than saturation (S) and value (V) components, eight bins are assigned to hue and two bins are assigned for each of saturation and value. The input patch is quantized in HSV color space into 8x2x2 bins, the output is 1x32 features vector.

- Color Moment Features

Mean, standard deviation, skewness, and kurtosis are the four extracted features by the proposed system, these features represent the average color in the image, the distribution, and how this distribution differs from the normal. For each input patch the above mentioned four moments will be extracted from each R, G, and B channel, the output is 1X12 feature vector. Color moment is used to measure the similarity between two images on image classification and image retrieval applications [16] [17] [18].

- Discrete Cosine Transform DCT

A discrete cosine transform DCT is an algorithm that converts data into sets of frequencies [19]. The resulted frequencies are arranged on away such that the first frequencies are the most meaningful which need to be stored, the least meaningful frequencies come later and can be neglected [20]. DCT is widely used [21] [22]. For each input patch, DCT is computed. The first element in the output transformation is the considered feature, which is dc element, since it contains the most important information as referred previously.

- Gabor-DCT Feature

Gabor: Gabor feature was used in classification paintings into their school of art [23]. Gabor filter with five scales and eight orientations is used to filter each patch [24]. The proposed system converts the input patch to grayscale, Gabor filter [25] with five scales and eight orientations is used to filter each patch. Gabor filter produces forty arrays of Gabor features for each patch, if these arrays are formulated directly to features vector, the length will be equal to the patch size multiplied by the number of arrays filter, which is 512*512*40. The resulted length feature vector needs to be reduced. DCT is computed, one DC value for each array is considered, which the DC element is, the forty output arrays for each patches will produce 1X40 length features vector using DC element. The final output features vector represents the variations in different frequencies and orientations on the painting.

- Gray-Level Co-Occurrence Matrix GLCM

The researcher of [26] suggested a set of fourteen features to represent the texture features. GLCM has proved to be an efficient method of texture features extraction [27]. For each input patch, GLCM is constructed and twenty two features are extracted. The features are: Energy, entropy, contrast, dissimilarity, correlation, inverse difference, autocorrelation, cluster shade, cluster prominence, maximum probability, sum of squares, sum average, sum variance, sum entropy, difference variance, difference entropy, information measures of correlation (1), information measures of correlation (2), maximal correlation coefficient, inverse difference moment normalized (IDN), and inverse difference normalized (INN).

For each feature both minimum and maximum values are considered. GLCM features vector is represented by 1X44 features vector.

• Segmentation-based Fractal Texture Analysis

SFTA extraction algorithm was proposed on [28]. In [29] SFTA was used in content based image retrieval and medical images to classification. By the proposed system, the input image of each patch is transformed into grayscale, SFTA texture features were extracted from the grayscale image, , with four threshold values nt=4, the number of binary resulted image is eight, from each image the mean, size and fractal dimension are extracted, the output is 1X24 feature vector.

3.4 Classification

Classification stage is shown in Figure 1 block (d). For each entry on the datasets, a class label must be pre-defined. The classification model is built using different methods, as functions, trees algorithms, or classification rules. The second step is to deploy the model in classifying unknown entry. The known classes of the tested patches is compared with the model's classification result. The accuracy of the model is the percentage of correctly classified tested entries using the classification model.

To evaluate the proposed authentication system, supervised learning task is considered. For each patch on the dataset a predefined class is used. Two classes are used; {o} for original, and {c} for copy. The model is represented using two different classification methods to study the accuracy of the proposed systems depends on the type of classifiers. Weka, a popular suite of machine learning software, written in Java [30] was used to classification issue. Stochastic gradient descent (SGD) [31] is a gradient descent optimization method for minimizing function written as a sum of differentiable functions. PART is a rule based classification technique which gives accurate rule set without global optimization [32]. These classifiers are: stochastic gradient descent SGD with hinge loss SVM function, learner and ten iteration, and partial decision tree PART

4. Experiments

4.1 Dataset

Searching on websites to find dataset for testing and machine learning resulted in a different size paintings with different qualities, dealing with various conditions will affect the classification result. A new dataset was built with fixed conditions while capturing the images, the size and the paintings ground are consistent for all paintings. Datasets are reviewed in this paper with more details.

• Casper Data Set 2008

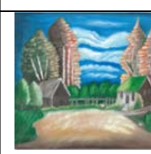
Charlotte Caspers, an art student specializing in art reconstruction, was asked to paint seven of small paintings considered as originals and, other seven paintings are painted by the same artist and considered as copies. The average time spent to complete each original painting was 20 minutes, copies took about two hours. After two weeks, the paintings digitized using an Epson 1640XL flatbed scanner at 800 dpi. Original and copy within each pair were painted with the same materials, but a different set of materials were used for each pair. Five paintings out of seven were painted using oil color, these five paintings are considered in this paper.

• The New Dataset

A new dataset was built with same conditions on capturing images for originals and copies. The new dataset consists of four paintings as originals works, and four paintings related copies. The eight paintings have the same size 35X50 centimeter each. One to ten months were taken to paint each original work; the copies took 6 hours for each (on average). The copies paintings were allowed to dry for approximately one month, then the originals and copies are placed directly face-down on a Xerox 6705 Wide Format scanner and scanned at 600 dpi, a high-resolution digital images are achieved. All original and copy pairs were painted on the same ground without restriction on the brushes.

Table 1 is figure's table which shows the eight paintings on our dataset with painting's names. All pairs are oil paintings on canvas ground. The first column for the pair number, second and third are for originals and copies respectively; a brief description on the last column for each pair. The first and third pairs were painted on transverse form, containing landscape content; dark color was used at the boundaries of pair one while pair three has light color with restricted number of colors. The second and fourth pairs were painted on longitudinal form with dark background color and grouped colors on the middle area, a platter fruits content on pair two and vase of flowers on pair four.

Table 1: Four Oil Painting in our Dataset.

Pair Number	Original Paintings	Copy Paintings	Description
Pair 1			Landscape content. Dark color at the boundaries.
Pair 2			Platter fruits content. Dark color on the back ground.

Pair 3			Landscape content. Light color. Restricted number of colors.
Pair 4			Vase of flowers content. Dark color on the back ground. Colors are grouped on the middle area.

4.2 Evaluation Tests on Casper Dataset

The original and copies on Casper dataset paintings were divided into patches and the features were extracted. 153 features were combined to form 1X153 feature vector which represents one patch.

- Princeton University (Pr) Tests

Test one: The training set contains all patches from all pairs of originals and copies except the tested pair. The test set includes all patches of the original and copy of the tested pair, there are no patches on the training set painted with the same materials as in the testing set [3].

Test two: The training set includes all patches from original and copies with some corresponding originals and copies patches of the tested pair. Testing set includes the remainder corresponding original and copies patches of the tested pair. This new criteria added some patches as examples for the machine learning with the same material of the tested pair.

Test three: This test Studies the accuracy of predicting when training patches are taken only from the tested pair. Patches of the image were divided into four disjoint sets, two of them were taken to training purpose and the other two for testing. The disjointed division prevents having training and testing patches from the same location which could help the classifier. This test authenticate the painting using the training set and testing set of the paintings with the same material [3].

4.3 Evaluation Tests on our Dataset

Three tests of Princeton University were applied on our dataset.

4.4 Test Four: Cross Validation Test Pair-level

The previous tests include division that performed manually. To achieve more comprehensive test which cover all the validation division, a cross validation test was done on each pair independently for the three datasets; Caspers dataset and our dataset.

4.5 Test Five: Cross Validation Test Dataset-Level

Test five is a cross validation test on dataset level. The aim of this test is to overcome the limitation of studying the paintings of each pair alone as in Test four, and to have a more comprehensive test which is able to classify any patches from the dataset. Test five was performed by taking group of patches randomly from each dataset as a training set and choose testing set from the same dataset randomly without overlapping, then classify them into original or copy without consideration of the corresponding painting, material, or patches location, multiple rounds of cross validation were performed using different partitions, and the validation results were averaged over the rounds. This test was performed on Caspers dataset alone, our dataset alone, and the two datasets together.
The proposed method was evaluated in Matlab 2014a on PC with these attributes: windows 8, Intel (R) Core(TM) i7 – 3630QM CPU@ 2.40GHz, RAM 6.00 GB, 64 bit OS.

5. Results and Discussions

5.1 Experiments on Caspers Dataset

- The proposed System Results on Pr Tests

Tables of results in this section are arranged as follow: column one for the pair number, rest of table is divided into five sections; the first section for Pr work results named SVM Pr related to the SVM classifier that used on Pr work, and the next two sections are used for the proposed approaches results using two different classifiers. These classifiers are: SGD and PART. The abbreviations that appears in all tables are: Tot. : Total, Co.: Copy, Or. : Original, Avg.: Average. The tables provide the percentages for the total test set, as well as for the original and copy separately [3].

Test one: The percentages of patches which were classified correctly in test one for the proposed approach compared with (Pr) research, are shown in Table 2. The two classifiers gave closest results. For pair one and two, the accuracies were 58% and 65% using SGD classifier which are higher than Pr results. Pr results for the previously mentioned pairs were 48% and 58%. Proposed system doesn't achieve correctly classified instance for pairs five and seven more than Pr approach result. The accuracy of pairs one, four and seven was 54%, 56% and 60% using PART.

Table 2: The Percentage of Patches Classified Correctly on Test One.

Pair	SVM Pr			SGD			PART		
	Tot.	Or.	Co.	Tot.	Or.	Co.	Tot.	Org.	Co.
1	48 %	75 %	22 %	58 %	78 %	38 %	54 %	63 %	45 %

2	58%	58%	58%	65%	69%	60%	57%	47%	66%
4	50%	11%	89%	49%	42%	56%	56%	47%	65%
5	63%	83%	43%	58%	78%	37%	41%	57%	24%
7	67%	50%	83%	51%	35%	66%	60%	40%	79%

Pairs one, two, and four were classified with accuracy higher than Pr results. Pair two, which was painted on CP canvas using soft and hard brushes, was the best painting classified. Pair four was painted on strong texture material bare linen canvas, the strong texture of the ground may reflect its effects on the extracted features. This may justify the lowest classification accuracy for this pair, the observation was also discussed on [11]. The low classification accuracy for pair five and four may be related to the small size of these painting compared with others in the dataset. Another interpretation is the use of only soft brushes. As a result, the classification rule on paintings with different materials and brushes cannot be generalized. More work is needed to study the effect of soft brush and thick impasto.

Test two: The percentages of patches were classified correctly in test two, for the proposed approach compared with (Pr) research are shown in Table 3. Learning from the addition test patches raised the result of pair seven, the classification accuracy raised from 60% in test one to 70% in test two, using PART classifier. Pair four was classified with the best accuracy using PART classifiers, which was 53%. Pair four had the lowest classification accuracy among the five pairs. The low accuracy of pair four came from low classification accuracy in the original parts. The copies patches were detected with accuracy of 84% using SGD classifier, while original patches were classified with 19% using the same classifier, this observation was found also on pairs five and seven; they share the properties of being painted with only soft brushes.

Table 3: The Percentage of Patches Classified Correctly on Test Two.

Pair	SVM Pr			SGD			PART		
	Tot.	Or.	Co.	Tot.	Or.	Co.	Tot.	Org.	Co.
1	58%	72%	44%	75%	81%	68%	68%	72%	64%
2	75%	83%	67%	72%	65%	79%	65%	62%	68%
4	50%	56%	44%	52%	19%	84%	53%	33%	73%
5	58%	66%	50%	54%	41%	67%	46%	48%	44%
7	72%	72%	72%	64%	36%	92%	70%	51%	88%

This test achieved higher results on classifying pairs one and four more than previous work. The addition patches from each tested pair to the training set helped to achieve higher accuracy results. SGD and PART classifier performed well in pairs one, two, and seven. In general, for the pairs sharing only soft brushes, the proposed approaches succeed on copies part classification more than originals classification. On the other hand, Pr work succeeded on classifying original parts with accuracy more than the copies on the pairs that painted with only soft brushes.

Test three: The percentage of patches classified correctly in test three for Pr research and for the proposed approach are shown in Table 4. Pair one was classified with the highest accuracy of 91% using SGD classifier. Pair one results was higher than 78% that was achieved on previous work. Pair four classified using PART classifier with accuracy of 67%, which is still lower than 75% that previous work reached. For Pair five, a successful classification was performed using SGD, 71% classification accuracy of total patches was higher than 50% on the previous work. Pair seven was classified with accuracy of 74% higher than previous result which was 55%.

Table 4: The Percentage of Patches Classified Correctly on Test Three

Pair	SVM Pr			SGD			PART		
	Tot.	Or.	Co.	Tot.	Or.	Co.	Tot.	Org.	Co.
1	78%	78%	78%	91%	90%	92%	78%	82%	74%
2	78%	89%	67%	65%	56%	74%	60%	82%	38%
4	75%	100%	50%	45%	50%	39%	67%	56%	78%
5	50%	100%	0%	71%	79%	62%	56%	43%	69%
7	55%	88%	22%	69%	74%	64%	74%	74%	74%

For pairs one, five, and seven the results were higher than previous results. Pairs one, two, and seven share the Commercially Prepared (CP) ground. They were classified better than other pairs. PART classifier performed the best for pair four. SGD performed the best for pair five. Pairs four, five, and seven were classified with inconsistent classification accuracy through originals and copies parts in previous work, these gab in the accuracy was reduced by the proposed approach, the classification accuracy among originals and copies are more closet.

5.2 Experiments on New Dataset

- The Proposed System Result on the new Dataset Using Pr Tests

Test one: Table 5 shows that PART performed the best for all paintings, pair three was classified with the highest accuracy among the four paintings using SGD and PART. Pair one was classified with SGD, and PART with the same accuracy of 66%. Pair four was classified by PART with the best accuracy of 67%.

Table 5: The Percentage of Patches Classified Correctly on Test One Using the new Dataset.

Pair	SGD			PART		
	Tot.	Or.	Co.	Tot.	Org.	Co.
1	66%	67%	64%	66%	61%	70%
2	50%	65%	35%	52%	69%	35%
3	68%	52%	83%	68%	75%	60%
4	51%	58%	44%	67%	74%	60%
Avg.	59%	61%	57%	63%	70%	56%

It can be noticed that using the same ground on all paintings on our dataset helped the classifiers. PART classifier succeeded on classifying original parts in general. The overall average for PART, which are the best on this test, is about 63%.

Test two: Adding patches from tested pair to the learning set improved the classification accuracy for all paintings, the results are shown in Table 6. The results were 73%, 88%, 83%, and 88% on the four pairs, respectively using PART classifier, which was the best classifier for this test. The accuracy of the copy patches for pair two raised from 35% on test one to 86% on test two using PART classifier. The overall best accuracy was 83% using PART.

Table 6: The Percentage of Patches Classified Correctly on Test Two Using the new Dataset.

Pair	SGD			PART		
	Tot.	Or.	Co.	Tot.	Org.	Co.
1	71%	79%	63%	73%	75%	71%
2	84%	98%	70%	88%	90%	86%
3	83%	86%	79%	83%	82%	84%
4	85%	97%	73%	88%	90%	85%
Avg.	81%	90%	71%	83%	84%	82%

The gab on the classification results between the originals and copies was reduced on this test, the results were more convenient among originals and copies. Pairs two and four share the properties of being painted on dark background and have multi-color on the middle area, these similar properties may lead both of them to classified with the best accuracies through different classifiers.

Test three: Table 7 shows test three results. Using learning patches from only tested pair on test three helped SGD classifier, which was the best classifier on this test, with an average accuracy of 89%. The accuracies for the paintings as using SGD were 77%, 99%, 82%, and 98%. Pairs number two and four which were classified with the lowest accuracy, using SGD in test one became the best classified pairs in test three. The classification accuracy of pair two and four in test one were 50% and 51%, respectively using SGD classifier, while in this test the accuracy were 99% and 98%, respectively using the same classifier.

Table 7: The Percentage of Patches Classified Correctly on Test Three Using the new Dataset.

Pair	SGD			PART		
	Tot.	Or.	Co.	Tot.	Org.	Co.
1	77%	79%	75%	68%	68%	67%
2	99%	98%	99%	95%	96%	93%
3	82%	75%	89%	74%	76%	71%
4	98%	97%	99%	87%	77%	97%
Avg.	89%	87%	91%	81%	79%	82%

Both pairs two and four were painted on dark background with details and colors grouped on the middle area of the painting, this may be the reason that these two pairs need to learn more from their content rather than from other paintings. Pairs one and three share properties of distributed color among the canvas, while pair two and four share the dark background. The dark background on pairs two and four reduced the different content samples and helped the classifiers. Sharing properties between pairs gave a closet classification accuracy for them. The best classifier on this test was SGD.

5.3 Test Four: Cross Validation Test Pair-Level

- Test Four Results on Caspers Dataset

Table 8 shows the results of test four on Caspers dataset, SGD performed the best, the average of accuracies was 78%. Pairs one, two, and seven are classified with the highest accuracy of 95%, 86%, and 84% respectively, soft and hard brushes, and the Commercially Prepared (CP) canvas may helped the classifiers on these three pairs. On the other hand, the strong texture of the bare linen canvas which was used on painting four may lead to have the lowest classification accuracy of 53% using SGD. Pair five classified the best using SGD classifiers with accuracy of 72%.

Table 8: The Percentage of Patches Classified Correctly on Test Four Using Caspers Dataset.

Pair	SGD	PART
	Tot.	Tot.
1	95%	83%
2	86%	75%
4	53%	51%
5	72%	53%
7	84%	83%
Avg.	78%	69%

- Test Four Results on the new Dataset

Table 9 shows the accuracy of cross validation test on our dataset with 10 folds testing using two classifiers. SGD produced the best results. Pair two and four benefited from this test; they appeared to be classified more correctly when the training set contains patches just from theirs areas, the classification accuracies of pairs two and four were 97% and 99% respectively using SGD classifier.

Table 9: The Percentage of Patches Classified Correctly on Test Four Using the new dataset.

Pair	SGD	PART
	Tot.	Tot.
1	80%	81%
2	97%	96%
3	92%	85%
4	99%	95%

5.4 Test Five: Cross Validation Test Dataset-Level

Table 10 summarized the results of cross validation test on dataset level, using 10 folds. Test five was performed in the whole datasets at a once, using the complete dataset on one cross validation test. Test five was applied on Caspers dataset, new dataset, and (Caspers and new) datasets. PART performed the best with different datasets; the accuracy was 69%, 86% and 79% using the previously mentioned dataset, respectively. The highest accuracy of the new dataset may be related to the consistency on the material that used for all pairs in our dataset, which helped the classifier with a training patches of similar properties. Row three when merging two datasets both (Caspers and new) datasets, the classification accuracy was 79% using PART classifier, which was higher than 69% using Caspers dataset alone, row one, the addition samples from our dataset helped the classifier to perform better than using Casper dataset alone.

Table 10: The Percentage of Patches Classified Correctly on Test Five

Data-set name	SGD	PART
Caspers dataset	67%	69%
The new dataset	83%	86%
(Caspers and new) datasets	76%	79%

6. Conclusion and Future Works

Oil paintings authentication system was proposed on this paper, a combination of features were extracted from color and texture patterns. Two dataset were deployed, Casper dataset and new dataset, the second dataset was built on this paper and digitized. The accruing conditions are the same for both originals and copy, to achieve the equality between the images being compared. To evaluate the proposed system the extraction features were used on machine learning to distinguish between originals and copies paintings. On the evaluation five tests were deployed, the achieved results of the proposed system using the two dataset are summarized on the following list:

- Using Caspers dataset, the proposed system results are overcome the previous work results in tests two and three.
- PART give the best predicting among the four classifier for the strong texture ground, which is the most difficult ground on authentication within the used dataset.
- The predicting accuracy is the best when training patches are taken from only the investigated pair, using paintings that performed with soft and hard brushes, and using the same ground on all paintings on the dataset.
- Adding samples from the new datasets to Caspers dataset, gave accuracy on cross validation test higher than the accuracy on classifying paintings on Casper dataset alone.
- The proposed system succeed on classifying paintings using training set contains patches from different paintings, and without restriction on their location.

The results lead to the following recommendations:

- It is not possible to generalize a rule from different paintings ground and materials.
- To detect the copy paintings the proposed system by this paper is good. To detect original paintings Pr research is more suitable.
- SGD are the best classifiers among different testing criteria.
- For best detection the training patches are taken from only the investigated pair.

There still a need to search on more discriminative features with larger dataset to have more accurate results. From the results, ground texture add its features on the extraction step, this point need to be analyzed more. An adaptive system which change the parameter of the extracted features method based on the ground texture will be a future research.

Acknowledgments

We would like to thank our families for their encouragement. We using this opportunity to express our gratitude to everyone who supported us.

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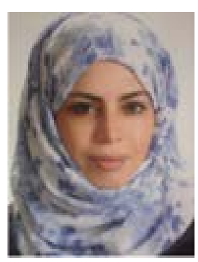

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