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Extensive Classification of Visual Art Paintings for Enhancing Education System using Hybrid SVM-ANN with Sparse Metric Learning based on Kernel Regression

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Abstract

In recent decades, the collection of visual art paintings is large, digitized, and available for public uses that are rapidly growing. The development of multi-media systems is needed due to the huge amount of digitized artwork collections for retrieving and archiving this large-scale data. This multimedia system benefits from high-level tasks and has an essential step for measuring the similarity of visual between the artistic items. For modeling the similarities between the artworks or paintings, it is essential to extract useful features of visual paintings and propose the best approach for learning these similarity metrics. The infield of visual arts education, knowing the similarities and features, makes education more attractive by enhancing cognitive development in students. In this paper, the detailed visual features are listed, and the similarity measurement between the paintings is optimized by the Sparse Metric Learning-based Kernel Regression (KR-SML). A classification model is developed using hybrid SVM-ANN for semantic-level understanding to predict painting's genre, artist, and style. Furthermore, the Human-Computer Interaction (HCI) based formulation model is built to analyze the proposed technique. The simulation results show that the proposed model is better in terms of performance than other existing techniques.

Keywords

Support Vector Machine, Human-Computer Interaction, Artificial Neural Network, Sparse Metric Learning, Feature Extraction, Machine Learning, Visual Arts Education, Digitization of Paintings.

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I. Introduction

In this modern era, the fine-art collections have been digitized in a vast amount and can be used by several researchers to study and analyze their importance. These collected data are distinguished as modern, contemporary, and classical artworks. Several multimedia systems are developed for retrieving and archiving these data. In the early modern days, the most common collections are meta-data describing the theme, the artist, the type and data of art curators and historians, etc. [1] [2]. The present artwork is displayed in the online galleries, useful for developing recommendation systems that retrieve similar paintings, which users wish to buy. Moreover, the investigation of visual similarity metrics should be highlighted, which is much needed for optimizing the painting-domain [3].

Digital systems are categorized and recognized the scenes and objects in videos and images by computer vision. The advances of this technology are widely distributed due to the surveillance cameras installed in every place. The enlightened inferences are made when a person views a painting rather than just identifying the chair, the figure of Christ, or tree. Any individual can assume the genre, year of creation, and painting style without knowing visual-art training [4]. The extent of exposure and comprehension of art history by the spectator predicts the precision of their conclusions. Judging and understanding such complex visual ideas is a wonderful opportunity to grasp humanity. The main goal of this research is to expand a semantic-level judgment machine for predicting the painting's genre, style, and artist. This knowledge provides the similarity measurement is optimized in the available domain of art- history simplification. In this research, several researchers benefit from the concept behind the evolution in art analysis based on the computer system. The measurements intimate the art historian's skill to identify painting according to the artist who created it, its theme and genre. Visual characteristics are extracted from the image in the first step. These visual characteristics vary from low to high. In the next step, we learn how to modify these functions for various classification activities by studying the necessary dimensions. The metric has been learned to develop paintings from a big, raw, visual space into a meaningful, much smaller space. The third approach projects visual attributes using various metrics and fuses the resulting optimized spaces to achieve a

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final function vector for classification. In this low-dimensional space, a classifier can quickly be applied to large sets. This is an effective technique since each approach uses various parameters to accomplish the measure of the similarity [5].

Moreover, many digitized visual-art datasets are used to evaluate systematic methods [6] comprehensively. The paintings are described in various concepts by the artists in whom stylistic elements like texture, line, space, tone, and color are used. Secondly, principles like unity, pattern, contrast, movement, variety, proportion, and balance are also used. Several visual features are investigated and engineered by the researchers in computerized art analysis. Artistic concepts are encoded like color and brush strokes and low-level features like color histograms and texture statistics. When paintings are digitized, the variations of texture and color are highly vulnerable, also the age of paintings can affect the color [7]. It is inconvenient to design visual features of the concepts mentioned above of art. A deep neural network is recently used to advance computer vision, having a major advantage of feature learning from the given data rather than fully engineering the concept. However, learning visual features is a major concern and impractical, consisting of visual art concepts. Extensive annotation is required for every image's concepts within the huge testing and training dataset [8]. Human-Computer Interaction (HCI) is a computer model that uses the dialogue between the system and man language. It determines the information exchange between the computer processes and people. The identification and segmentation of images play a vital role by HCI, and it is the human visual perception [24]. Enhancement in education takes place by visual art learning and development in cognition. Visual art increases students' thinking capabilities, mental analysis, solving issues, creative thinking, reasoning ability, conceptualization, classifying, and so on. These lead to association with enhanced cognitive development as it has a prominent feature, which consists of temperament and personality.

An alternative strategy is followed in this paper for the challenge mentioned earlier to learning or engineering appropriate visual features of paintings. Various visual elements are investigated mainly that range from low-level to semantic-level. The proposed sparse metric learning based on kernel regression is used for obtaining similarity metrics of various paintings that make effective use for the prediction tasks, namely genre, artist, and style classification. In this paper, many visual features are investigated and a learning methodology is proposed for the above-explained prediction tasks. Here, sparse metric learning-based kernel regression is proposed for optimizing the prediction tasks, and the simulation results are compared with other existing metric learning techniques. Also, a hybrid SVM-ANN model is proposed for improving the classification performance based on the three prediction tasks. The metrics' primary goal is to evaluate the experiment for three separate tasks, including genre, artist, and style prediction. In the following pages, the metric efficiency of the SVM-ANN hybrid classification is analyzed in several features. The proposed Sparse Metric Learning-based Kernel Regression (KR-SML), firstly, as depicted in the figure, extracts visual characteristics from images of paintings. On each of these prediction tasks and a similarity metric tailored is applied, i.e., style-optimized metric, genre-optimized metric, and artist-optimized metric. Any metric induces a projector to a feature space that is optimized for the task. If the metric is mastered, we project the raw visual characteristics into a new optimized function space and SVM-ANN learns the required prediction task. Visual characteristics and metric methods are used to acquire an optimized measure of resemblance between paintings. This provides a computer capable of making semantic decisions relevant to aesthetics, such as an identification of a painting's theme, genre, and artist, and delivering optimized similarity measures based on the knowledge of art history analysis accessible. Our analyses demonstrate the importance of using this indicator of similarity.

The main contribution of the study is:

- Designing KR-SML to obtain detailed visual features of painting and improve accuracy.
- Analyzing the HCI based formulation model to evaluate the proposed technique.
- Once the numerical results have been obtained, the proposed KR-SML uses SVM-ANN for semantic-level understanding to predict painting characteristics and classify paintings, enhancing the genre and artist prediction compared to other methods.

The remaining paper is structured as follows: section I corresponds to the present introduction to the work and sector II describes the related works. In section III, the KR-SML method has been suggested for improving the accuracy of painting and style predictions. In section IV, the numerical results have been obtained. Finally, section V concludes the research paper.

II. Related Works

In this modern technology, computer systems are used for a different set of tasks in paintings. Image processing methods help art historians measure tools such as mathematical brushstroke quantification, pigmentation analysis, etc. Several researchers study the encoding of information about the paintings to find suitable features that could help classify visual art. Major research concerns the painting classification by utilizing low-level features, including shadow, edges, color, and texture. Lombardi [9] analyzed the artist classification's feature types from a small set using unsupervised and supervised machine learning techniques. The proposed methodology identifies the painting's style for finding the artist who designed it.

A comparative study of the style classification task is presented by Arora et al. [10]. Low-level features like Color Scale-invariant feature transform (SIFT) and SIFT are evaluated versus semantic-features like Classemes that include the image object present in it. The authors concluded that the semantic level features perform much better than the low-level for this task. Our study attempts to create a technology that will be able to make semantic judgments on an aesthetic level like predicting the style, genre, and artist of a painting, along with to have optimized similarity actions based on the information available in the field of art historical perception. The role of style classification determines low-level characteristics and the color semantic level characteristics that encode the image object presence. Semantic-level features for this role were found to surpass substantially low-level features. The evaluation of this performance is done in a small dataset that contains 70 paintings with seven styles. Carneiro et al. [11] indicate that color features and a low-level texture have not been reached because they define the visual type of pictures as unpredictable texture and color patterns.

Furthermore, metric learning techniques are used by Saleh et al. [12] for detecting influence paths between the painters, which are based on their paintings. The authors used the HOG feature of low-level and optimized using three metric-learning approaches. Bar et al. [13] identified the style based on characteristics by proposing a convolutional neural network for image categorization. Takeda et al. [14] analyzed the denoising in images by proposing Kernel Regression (KR) algorithm and used local pixel-space statistics for learning the Mahalanobis matrix. Moreover, this proposed method is restricted to particular applications and cannot be presented for all cases.

Karayev et al. [15] analyzed the deep features which have been used for several performances in different fields, also the performance for hand-crafted features such as GIST (Gradient information scales and orientations), color histogram, and visual saliency are efficiently processed. N. Senthil Murugan and G. Usha Devi [16]-[18] analyzed the machine learning concepts and proposed hybrid models for analyzing a large amount of data, and several features have been processed. G Manoharan et al. [19] analyzed the human interaction with computers for analyzing the big data. The intelligent and adaptive model of HCI is discussed by Z Duric et al. [25] and analyzed human motion using compute vision. The author also discussed the models performing low arm movement detection, gaze analysis, and face processing. Cedras and Shah [26] presented the categories within the motion classification extraction based on motion correspondence or optical flow. The problem of human-motion capture is defined as the recognition of action, individual recognition, body estimation, and configuration. Peterson [27] suggested a set of behavioral parameters associated with enhanced cognitive development based upon a review of the brain-mind's science. Gredler and Shields [28] state that visual art and instruction play a crucial role in children's mental improvement. Academic ideas are important in conceptual development and ultimately leading to the development of concepts.

To overcome the existing issues, a KR-SML has been proposed for the similarity measurement of visual features. The proposed MHCBTF used the SVM-ANN method to categorize the measurements and classify the paintings according to style, genre, and artist.

III. Proposed Methodology

In this section, the most suitable combination for the visual features is obtained and proposed KR-SML metrics are used to improve accuracy in similarity measurement. Furthermore, the measurements which categorized the paintings in terms of genre, artist, and style are used for classification based on hybrid SVM-ANN. Firstly, the visual features are extracted from the particular image that ranges from low-level to high-level. Secondly, the proposed metric based on KR-SML is used to adjust the extracted features that are processed for various classification tasks. Based on this metric learning, the paintings can be projected from a high-dimensional to low-dimensional space, which is more meaningful. Finally, the proposed hybrid SVM-ANN is used for classifying the painting based on the low-dimensional features.

A. Dataset Collection

The online dataset named "Wikiart Paintings" [20] is publicly available and contains a large collection of digitized-artworks used for the proposed methodology. The dataset contains 81,499 images of fine-art paintings, and 1199 artists range from the 15th century to the modern artist. Moreover, 27 different styles are included in this painting, like Byzantine, Abstract, Baroque, etc., and 46 various genres such as Landscape, Interior, etc.

Previous researchers used numerous sources to gather minimal data volume regarding genre, and style with restricted heterogeneity. Moreover, the classification is done automatically for the paintings in terms of genre, style, and artist using the visual features extracted by applying computer-vision algorithms. The tasks contained in the existing works have their limitations and challenges. In particular, the date's subset is used for style classification with 27 styles in which each one consists of 1500 paintings and has a total number of 78,439 images. The genre-classification uses the subset of 10 genre-classes containing 1500 paintings, having a total of 63,721 images. For the artist's classification, 23 artists subset is used, which contains 500 paintings with 18,589 images. Table I shows the set of the genre, artist, and style labels.

TABLE I. List of Genres, Artists, and Styles

Task-Name	List of Members
Genre	Abstract-Painting; Genre Painting; Cityscape; Portrait; Landscape; Still Life; Religious Painting; Sketch and Study
Artist	Boris Kustodiev; Childe Hassam; Edgar Degas; Nicholas Roerich; john Singer Sargent; Marc Chagall; Salvador Dali; MartirosSaryan
Style	Action Painting; High Renaissance; Symbolism; Realism; Rococo; Minimalism; Cubism; Moder Art; Abstract Expressionism; Pop Art; Post Impressionism; Ukiyo-e; Synthetic Cubism; Pointillism; Romanticism

B. Visual Attributes

The state-of-the-art representative is investigated in this work, which includes two main categories:

- Low-Level Attributes-The GIST features are extracted for capturing the visual information of low-level that is holistic attributes that are developed for scene categorization; Furthermore, the real-valued 512 GIST features are represented, which indirectly captured the image's ruling spatial-structure.
- Semantic-Level Attribute-Here, three images represented based on an object are extracted, such as Picodes, CNN-based variables, and Classeme, for the semantic representation. From these three variables, the image's object-category confidence is represented by each element's feature vector.

C. Classification Using the Proposed Methodology

The suggested Sparse Metrical Learning based on kernel regression to remove visual features is processed with artist and stylist to identify paintings according to their Genres, defined by a Hybrid SVM-ANN model. The main usage of learning metrics is to find the real-valued function based on pair-wise $F_M(z, z')$ and it is symmetric, non-negative, obeys the inequality triangle, and zero is returned if and only if z and z' are the same-point. The optimization problem for training the function as a general form is given in Eqn. (1):

$$\min_M ls(M, X) + \gamma R(M) \tag{1}$$

Two phases are included in this optimization in which the quantity of loss ls (M, X) for data samples X using metric M and the regularization term R(M), which is adjusted, are used. The accuracy is given by the first term from the metric trained, and capability is estimated from the second term for new data for avoiding the overfitting of the model.

KR-SML: Firstly, the visual features are extracted, as shown in Fig. 1, from the images present in the paintings. The prediction tasks for each image are learned by optimizing the proposed metric model. Each metric induces the projector to a corresponding space for the appropriate mission.

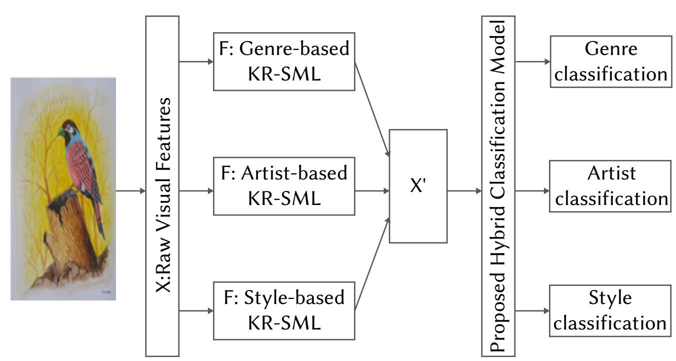

Fig. 1. Proposed Classification Model.

Moreover, the metric matrix of Mahalanobis is trained using the training dataset in which the objective of KR-SML is significant for the proposed work for ensuring the metric matrix is sparse, and error is small. Therefore, the loss function is made for learning the metric matrix of Mahalanobis of Kernel Regression, and the norm regularization with mixed (2, 1) over M is learned to be minimum. The proposed model of KR-SML is represented in Eqn. (2).

$$Ls(M) = \sum_{j=1}^{T_{training}} \left(x_j - \hat{x}_j\right)^2 + \sigma \|M\|_{(2,1)} \quad (2)$$

Where,

$Ls(M)$ is defined as the loss function at a minimum. The norm regularization is non-differentiable and non-convex in the objective function. The proposed algorithm of KR-SML is given below,

---

Step 1: Start

Step 2: Input Adapted step-size β, Matrix M, Adapted step-size σ for $Ls(M)$, μ-stop criterion, p ← 0

Step 3: **Do** p ← p + 1

Compute GF^{p-} objective function at p^{th} iteration

Where, $GF^p = 2\sum_{j=1}^{T_{training}} \left(\hat{x}_j - x_j\right) \frac{\sum_{i=1}^{k} (\hat{x}_j - x_i) Z_{ji} \vec{y}_{ji} \vec{y}_{ji}^{N}}{\sum_{i=1}^{k} Z_{ji}} + \theta I$

$M_{(p)} \leftarrow M_{(p-1)} - \beta GF^p$ is used for updating metric matrix

$M_{(p)} \leftarrow E^N \Delta_+ E$

The objective function value is computed

Until $\left|Ls(M_p) - Ls(M_{p-1})\right| \leq \boldsymbol{\tau}$

Step 4: Output of the M is produced

Step 5: End

Using the proposed metric learning (KR-SML), the features' dimensionality can be reduced when the M-metric is in low-rank. More specifically, knowledge is necessary for the ground truth of the input paintings used in a supervised-mode for non-linear and linear cases to research the most wanted metric. The quantity of regularization or the form of M is used for differentiating the various approaches. Moreover, the hybrid SVM-ANN classifier is used to classify metrics based on Style, Artist, and Genre.

D. Cognitive Enhancement

Education in children has an enormous effect on their development. These include emotional, physical, and development in cognition of students. Enhancing the student's cognition refers to improving the thinking capacity of students. It consists of knowledge enhancement, solving problems, skills improvement, and characters. Enhanced cognitive development leads to brain development. Peterson [27] states that the development of languages is the key focus on the development of cognition in students. Cognitive development in neuroscience mainly influences the process of bridging in the educational development of students. Efforts between neuroscience, psychological cognition, and enhanced education have absorbed how people obtain and utilize knowledge. Measuring the test of mental ability of how learning occurs in students is inclined by a grouping of genetic programming, maturation status, and environmental problems. Fig. 2 shows the educational enhancement using visual art, where fine art is used for classification using the proposed methodology. After classification, feature extraction takes process by splitting the texture and shape features separately from the visual art. Feature comparison amongst the shape and texture feature takes part in which the similarity between them is matched. Students visualize the art made after comparing features followed by analysis for making their personality and educational enhancement. The analysis process mainly constitutes the student cognitive development, educational improvement by making learning better by visual learning, and increases students' eye-hand coordination.

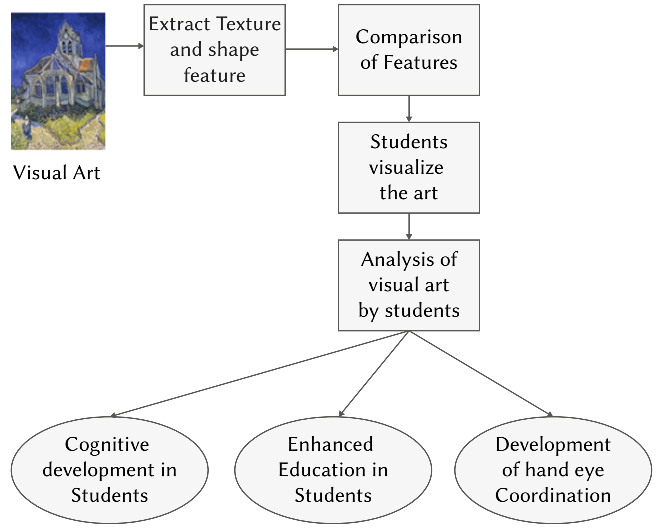

Fig. 2. Enhanced Education in Students using Visual Art.

E. HCI Based Formulation Model

In this section, an interactive system based on a software generation model is used for analyzing the human-interaction for the proposed approach. Two main subsystems are used in this HCI model: Query-Formulation Subsystem and Software-Generation Subsystem. The painting image is formulated by using the query formulation-interface. The generation subsystem of software is queried by formulation-subsystem with objective representation based on the proposed approach.

A software generator builds an appropriate software-based program, and images classified based on the proposed approach are yielded by executing this software based on the test set. The formulation could be reconsidered based on the predicted resulting image, and the new query is submitted with modification in the description of the input. The process gets stopped if the users get the resultant image. For conducting the experiments, the proposed KR-SML is used to extract features in the paintings, which are classified using the hybrid SVM-ANN model and stored as a library, and processed as software, and implemented using HCI architecture. Fig. 3 shows the generation system of the proposed HCI for analyzing the painting image.

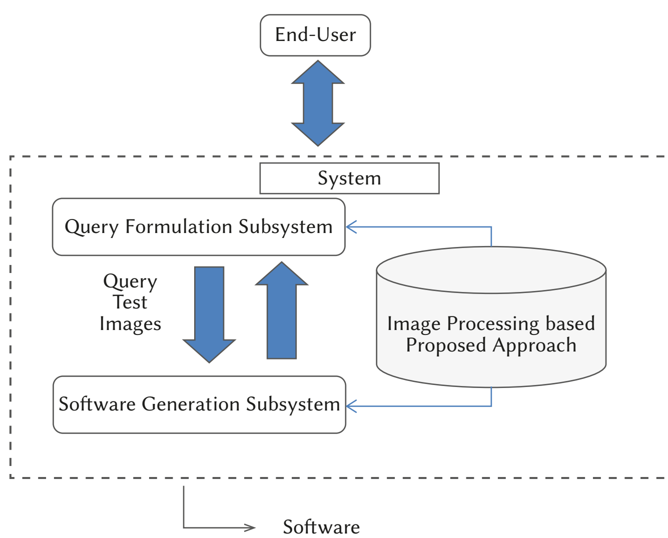

Fig. 3. HCI based Architecture using the Proposed Approach.

IV. Simulation Results

A. Simulation Setting

The GIST features are extracted as visual attributes in low-level such as Picodes, Classeme, and CNN-based variables as high-level semantic-features. The implementation of Torralba and Oliva [21] is followed in this research to gather a feature vector of 512 dimensions. The Bergamo et al. [22] implementation is used for Picodes and Classeme, which results in 2045 dimensions for Picodes and 2658 dimensions for Classeme. Furthermore, a 1000 dimensional variable vector is extracted by using Lenc and Vedaldi [23]. The dimensionality of the feature vector is higher than produced images based on object representation and GIST features. The main intention of metric learning is to analyze the experiment labeled for three various tasks of Genre, Artist, and Style Prediction. The metrics performance is investigated in the following sections on various features for classifying using the hybrid SVM-ANN. All metrics are learned from segment 3 for all the 15 styles in the paintings present in a given dataset.

B. Classification Based on Style

Table II shows the results of style classification using the hybrid SVM-ANN after processing various metrics on a set of variables. Columns below contain different characteristics and metrics used before grouping the types in rows for calculating attributes. The ITML and Boost metric approaches give high accuracy for the classification of style for various features. Moreover, the proposed KR-SML approach produces a high accuracy for all types of features when classified using the hybrid SVM-ANN model for almost all the extracted visual features. Fig. 4 shows the overall accuracy of the proposed model.

TABLE II. Style Classification

Metrics/Variables	Classemes	CNN-based	GIST	Picodes	Dimension
Boost-Approach	33.45	16.12	16.07	28.58	512
ITML-Approach	30.67	15.19	13.04	28.42	512
LMNN-Approach	27	16.84	12.53	24.12	100
NCA-Approach	28.8	16.33	13.27	24.68	27
Proposed Approach	**41.34**	**21.34**	**19.87**	**31.34**	**512**

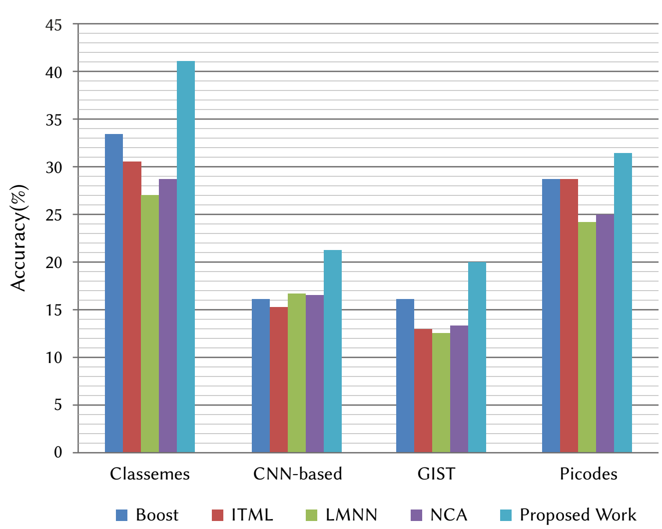

Fig. 4. Accuracy based on Style Classification.

C. Classification Based on Genre

In this classification, a total of 8 genres are used from the dataset for getting several samples reasonably for every task. Table III shows the proposed metric model's classification performance based on eight genres using the hybrid classifier. Various features and metrics which are used for computing the distance are represented in table III. The genre classification performance using the proposed method gives high accuracy compared with other existing classifiers. Moreover, the total number of genre collections is lesser than the style collected in the dataset. Fig. 5 shows the overall accuracy of genre classification based on the proposed approach.

TABLE III. Genre Classification

Metrics/Variables	Classemes	CNN-based	GIST	Picodes	Dimension
Boost-Approach	57.87	57.33	31.02	46.15	512
ITML-Approach	57.88	57.32	33.11	46.83	512
LMNN-Approach	54.98	54.32	39.07	49.97	100
NCA-Approach	51.34	52.76	30.45	49.56	10
Proposed Approach	**62.87**	**63.56**	**43.56**	**51.29**	**512**

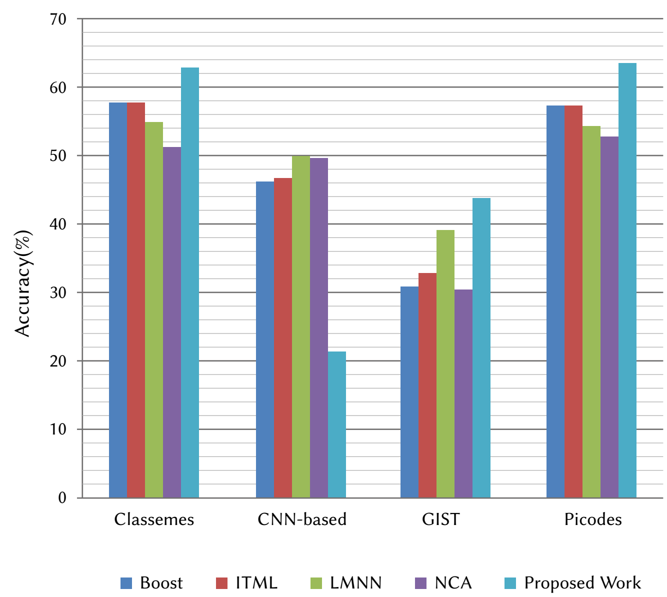

Fig. 5. Classification based on Genre.

D. Classification Based on Artist

Table IV shows the accuracy of the proposed metric approach using the hybrid SVM-ANN approach in terms of features extracted from the images for eight artists and compared the results with other models. Based on the maximum confidence, the artist is determined from the images. The proposed model performance shows a high accuracy when classifying based on an artist compared to other metric learnings. The dimension used for the artist classification is 512, and the accuracy obtained for the features of Classemes, GIST, Picodes, and CNN are higher when comparing with Boost, ITML, and LMNN approaches. Fig. 6 shows the results of the proposed approach.

TABLE IV. Artist Classification

Metrics/Variables	Classemes	CNN-based	GIST	Picodes	Dimension
Boost-Approach	57.72	55.50	25.75	29.56	512
ITML-Approach	51.88	53.87	19.95	31.06	512
LMNN-Approach	53.97	53.98	20.42	30.93	100
NCA-Approach	49.61	19.65	21.77	21.33	23
Proposed Approach	**59.13**	**59.23**	**28.93**	**39.12**	**512**

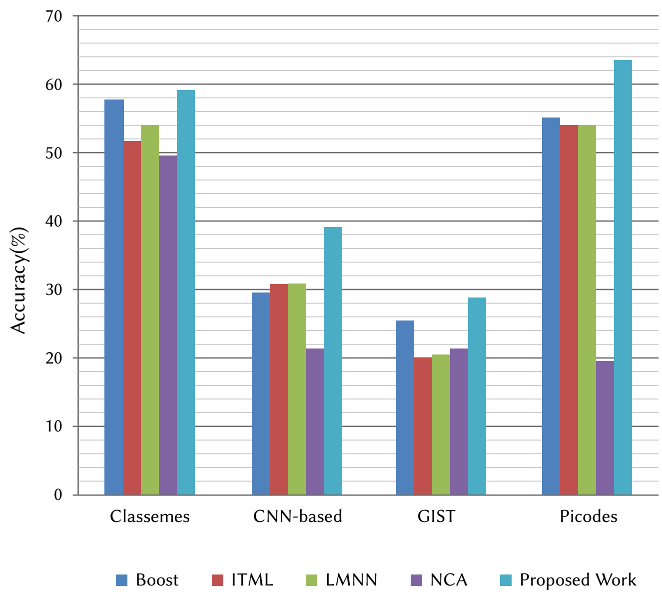

Fig. 6. Classification based on Artist.

E. Metric and Feature Integration

The integration of the metric and features of the proposed model is analyzed to find each approach's performance. The classification performance is analyzed for the task mentioned before by combining the various extracted visual features. Table V shows the results of the integration performance based on the hybrid classifier. The style classification performance is made by half of the images taken from the dataset. The accuracy achieved by the proposed model is about 51.23% when using the features of Picodes, GIST, Classeme, and CNN, while the other approaches like LMNN, NCA, ITML, and Boost produce less accuracy of 45.94%, 40.61%, 45.05%, and 41.74%.

TABLE V. Classification Based on Integration

Model	Artist	Genre	Style
Boost-Approach	61.24	58.51	41.74
ITML-Approach	60.46	60.28	45.05
LMNN-Approach	63.06	58.48	45.97
NCA-Approach	55.83	64.34	40.61
Proposed Approach	68.45	64.34	49.78

Moreover, the compact representation of features is learned in the proposed model by performing the state-of-the-art. The feature vector analyzed from the proposed metric learning is more efficient and useful for representing the images, and the best accuracy for the classification is obtained. The proposed work is considered for image retrieval application in future research. From these results, the proposed approach outperforms the state-of-the-art works and the capacity for image representation is reduced more than 90%. Fig. 7 shows the overall accuracy of the proposed classification performance for Style, Artist, and Genre and compared with other existing approaches.

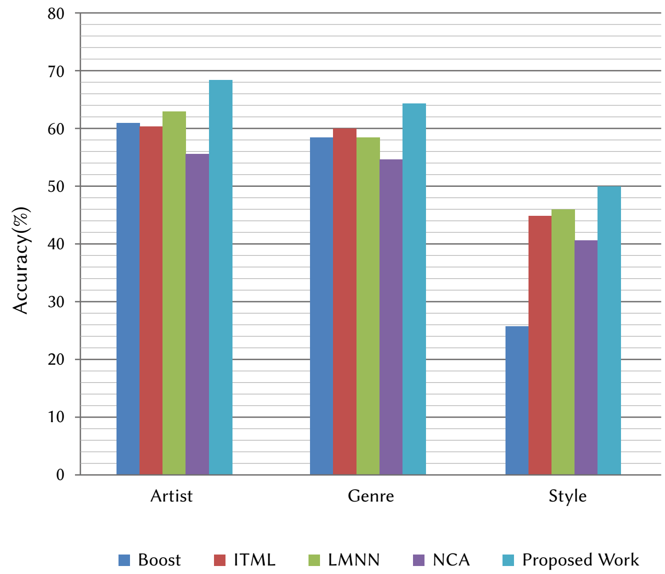

Fig. 7. Classification Performance based on Style, Artist, and Genre.

F. HCI Based Image Identification

Fig. 8 shows the image detection for the given test inputs in which the identification of painting images is analyzed and detected using the interactive software generation system. After the user queries an input image, the generation system analyses and detects the images based on the proposed approach, and the resulting image is displayed. Furthermore, the HCI system reconsiders the user's formulation if he/she submits a new query.

Fig. 8. Resulting Image using the HCI system.

V. Conclusions

In this research, the proposed KR-SML metric learning is investigated for the painting dataset, and various visual features are extracted and its similarity and performance are measured from fine-art-paintings. Several media systems for the recovery and archiving of these data are created. The early modern collections contain meta-data documenting the subject, the artist, the art curators, historians, etc. A wide selection of digitized artworks used in the proposed methodology is available on-line and called Wikiart Painting. The similarity measurement between the paintings is implemented based on the proposed metric learning and classified using the hybrid SVM-ANN model by using three major concepts. Metric learning techniques are implemented to measure the resemblance of various visual characteristics of the fine art paintings series. Meaningful measures are used to measure the resemblance between paintings. The metrics are learned in a supervised way to get paintings from one principle closer to far from each other. Three principals have been used in this work: Style, Genre, and Artist. We used these learned metrics to transform raw visual attributes into a separate space that can enhance the output of three key tasks, including classifications of styles, and genres. To test the efficiency of the above activities, our comparative studies were carried out on the largest publicly accessible data collection of fine-art paintings. These are Genre, Artist, and Style. The accuracy obtained from the proposed model's performance results is about 68.45% for the artist, 64.34% for Genre, 49.78% for style classification, and the other metric approaches. The visual features extracted based on the metric learning are Classemes, GIST, Picodes, and CNN, which classifies the tasks using a hybrid approach. Prediction of the type, artist, and style of painting is created for semantic comprehension. In addition, the formulation model based on metric learning is designed to evaluate the methodology proposed. The findings of the simulation demonstrate that the model suggested is more effective than other strategies. The feature vector size is reduced by more than 90% when using the KR-SML metric learning for classification tasks. The consequence is that we train the SVM classifier on top of dimensional vectors. This outperforms state of the art and offers a clearer depiction of the pictures, which decreases the room by 90%.

Furthermore, the HCI system based on model interaction and formulation is used for obtaining the user's query for gathering paintings image in which implementing the interactive-software generation system. Features extracted from visual art help students visualize the art by analyzing the feature, enhancing cognitive development, improving student curriculum, and maintaining hand-eye coordination. As part of an understanding technique, visualization encourages students to consider the actual scale of unfamiliar objects by contrasting them with familiar objects and using a technique to allow students to create cognitive representations more easily. Therefore, the educational system can be enhanced using visual art by teaching it in the curriculum. As future work, the image retrieval task and recommendation system are appropriate and can be verified by using the proposed approach. Several annotations based metric learning can be analyzed for better feature extraction and classification. Making this visual art-based learning can improve the mental as well as cognitive development in students. The inclusion of these visual art-based learning will make educational systems enhanced. Also, new software generation systems of HCI can be implemented for improving performance.

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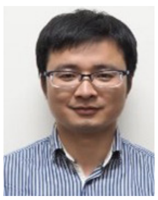

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