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A New Automatic Watercolour Painting Algorithm Based on Dual Stream Image Segmentation Model with Colour Space Estimation

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Abstract: Image processing plays a crucial role in automatic watercolor painting by manipulating the digital image to achieve the desired watercolor effect. segmentation in automatic watercolor painting algorithms is essential for region-based processing, color mixing and blending, capturing brushwork and texture, and providing artistic control over the final result. It allows for more realistic and expressive watercolor-like paintings by processing different image regions individually and applying appropriate effects to each segment. Hence, this paper proposed an effective Dual Stream Exception Maximization (DSEM) for automatic image segmentation. DSEM combines both color and texture information to segment an image into meaningful regions. This approach begins by converting the image from the RGB color space to a perceptually-based color space, such as CIELAB, to account for variations in lighting conditions and human perception of color. With the color space conversion, DSEM extracts relevant features from the image. Color features are computed based on the values of the color channels in the chosen color space, capturing the nuances of color distribution within the image. Simultaneously, texture features are derived by computing statistical measures such as local variance or co-occurrence matrices, capturing the textural characteristics of the image. Finally, the model is applied over the deep learning model for the classification of the color space in the painting. Simulation analysis is performed compared with conventional segmentation techniques such a CNN and RNN. The comparative analysis states that the proposed DSEM exhibits superior performance compared to conventional techniques in terms of color space estimation, texture analysis and region merging. The performance of classification with DSEM is ~12% higher than the conventional techniques.

Keywords: Image processing, automatic watercolor painting, segmentation, RGB color space, deep learning, classification.

I. Introduction

Watercolor painting is a captivating and expressive medium that has been cherished by artists for centuries [1]. It involves using pigments suspended in a water-based solution to create vibrant and translucent artworks. Watercolor paints are typically applied to paper using brushes, allowing for delicate washes, intricate details, and a wide range of techniques [2]. This medium offers a unique combination of unpredictability and control, as the water and pigment interact on the surface, producing beautiful blends, soft edges, and subtle gradations of color [3]. Watercolor paintings often evoke a sense of transparency, luminosity, and spontaneity, capturing the essence of the subject with a delicate and ethereal quality. Whether depicting landscapes, still life, portraits, or abstract compositions, watercolor painting allows artists to explore the interplay of light, shadow, and color in a captivating and expressive manner [4].

Image processing in watercolor painting refers to the application of digital techniques to simulate the unique characteristics and effects of traditional watercolor medium on digital images [5]. It involves using algorithms and filters to replicate the visual qualities of watercolor, such as the texture, transparency, blending, and color diffusion. Various techniques are employed to achieve these effects, including edge detection, color quantization, diffusion, and brush stroke simulation [6]. Image processing algorithms analyze the input image, identifying edges and areas of color, and then apply transformations to mimic the behavior of watercolor pigments on paper. This can include simulating the granulation and flow of pigments, replicating the irregularities and textures found in traditional watercolor paper, and emulating the subtle variations in color intensity achieved through layering and glazing techniques [7]. The goal of image processing in watercolor painting is to create digital artworks that capture the essence and aesthetic of traditional watercolor, providing artists with a digital tool to explore and experiment with this captivating medium [8].

In the realm of image processing for watercolor painting, several techniques are employed to simulate the unique characteristics of traditional watercolor medium on digital images [9]. These techniques aim to replicate the effects of texture, transparency, blending, and color diffusion typically

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seen in watercolor paintings. One commonly used technique is edge detection, which involves identifying the boundaries between different elements in the image [10]. By detecting these edges, the algorithm can mimic the way watercolor pigments tend to flow and gather at these areas, creating a sense of depth and definition. Color quantization is another technique used to emulate the limited color palette often found in watercolor paintings [11]. By reducing the number of colors in the image and grouping similar hues together, this technique can replicate the simplicity and harmonious color schemes often seen in watercolor artworks. Diffusion algorithms play a crucial role in creating the characteristic soft blending and diffusion of colors in watercolor paintings [12]. These algorithms simulate the way pigments spread and interact with water, resulting in gentle transitions and gradients on the digital canvas. Brush stroke simulation is another vital aspect of image processing in watercolor painting. By analyzing the image and determining areas where brush strokes should be applied, algorithms can generate strokes with varying thickness, texture, and direction [13]. This technique helps to recreate the impressionistic and expressive quality often associated with watercolor paintings. These image processing techniques in watercolor painting aim to bridge the gap between traditional and digital mediums, offering artists the ability to recreate the unique visual effects of watercolor in a digital environment. This provides artists with new avenues for creativity and exploration while maintaining the distinct charm and beauty of the watercolor medium.

Deep learning models have been utilized to advance the field of image processing in watercolor painting. One such model is the Generative Adversarial Network (GAN), which consists of a generator network and a discriminator network [14]. GANs have been employed to generate realistic and high-quality watercolor-style images from input photographs or digital images. The generator network in a GAN is trained to generate watercolor-like images by learning from a dataset of existing watercolor paintings. It generates images that are visually similar to the watercolor style, including the characteristic brush strokes, color diffusion, and textures. The discriminator network, on the other hand, acts as a critic and distinguishes between real watercolor paintings and the generated ones. During the training process, the generator network tries to fool the discriminator network into classifying the generated images as real watercolor paintings. Meanwhile, the discriminator network aims to correctly identify the generated images as fake [15]. Through this adversarial process, both networks improve over time, with the generator gradually producing more realistic watercolor-style images. Deep learning models can also incorporate other techniques such as convolutional neural networks (CNNs) for image feature extraction and recurrent neural networks (RNNs) for capturing sequential brush stroke patterns. These models can be trained on large datasets of watercolor paintings to learn the intricate details and characteristics specific to the medium.

The DSEM (Digital Simulation and Evaluation Model) has made several significant contributions to the field of watercolor painting analysis. Its contributions can be summarized as follows:

1. The DSEM incorporates sophisticated segmentation algorithms such as thresholding, region growing, edge detection, watershed transform, and graph cut. These algorithms effectively separate foreground and background elements, identify object boundaries, and create accurate segmentation masks. The DSEM's segmentation capabilities enable precise analysis and feature extraction from watercolor paintings.
2. The DSEM employs efficient feature extraction methods to capture relevant information from watercolor artworks. By extracting features such as color, texture, shape, and intensity, the DSEM can represent paintings in a meaningful and comprehensive manner. These extracted features serve as valuable inputs for the classification model, enabling accurate categorization and analysis of watercolor paintings.
3. The DSEM incorporates a powerful classification model that utilizes machine learning techniques to classify watercolor paintings. By training on labeled data and leveraging extracted features, the DSEM's classification model achieves high accuracy, precision, recall, and F1 score values. The DSEM's classification capabilities facilitate various applications, including artist identification, style recognition, and artwork categorization.
4. The DSEM provides a framework for comparative analysis between different datasets and models. By comparing its results with traditional approaches such as CNN and RNN, the DSEM showcases its superiority and outperforms these models in terms of classification performance. This comparative analysis highlights the effectiveness and advantages of the DSEM in the context of watercolor painting analysis.

The DSEM's contributions lie in its advanced segmentation techniques, efficient feature extraction, high-performance classification model, comparative analysis capabilities, and practical applications in the field of watercolor painting analysis. Its advancements have enhanced the analysis, understanding, and appreciation of watercolor artworks, making it a valuable tool for researchers, art professionals, and enthusiasts in the art community. This paper is organized as follows: Section 2 provides the literature survey associated with

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the water colorpainting estimation, Research method employed for the proposed DSEM is presented in Section 3. The simulation results for the proposed DSEM is presented in section 4 and overall conclusion is presented in Section 5.

II. Literature Survey

Image processing for watercolor painting provides a comprehensive analysis and synthesis of existing research and scholarly work related to the application of image processing techniques specifically for watercolor painting. This section aims to explore the various methods, algorithms, and approaches that have been developed and employed to enhance, transform, or simulate watercolor painting styles using digital image processing techniques.

In this section, relevant studies, articles, papers, and other sources related to image processing and watercolor painting are critically examined. The focus is on understanding the different image processing techniques that have been utilized to capture the unique characteristics and artistic elements of watercolor paintings, such as brush strokes, color blending, texture, and overall visual style. The literature review aims to identify the strengths, limitations, and potential applications of these techniques, as well as any gaps or areas for further research.

In [16] proposed a method for transferring the style of watercolor paintings to other images using neural style transfer and texture synthesis techniques. The authors explore how to capture the unique characteristics of watercolor painting styles, such as brush strokes and color blending, and apply them to different images. Similarly, in [17] introduced a real-time watercolorization technique that utilizes conditional adversarial networks. The authors aim to generate watercolor-like images in real-time, enabling artists and designers to quickly transform digital images into watercolor-style artworks with convincing brush strokes and color variations.

In [18] proposed WatercolorGAN, a deep learning-based approach for watercolor style transfer. They employ a generative adversarial network (GAN) architecture to generate watercolor-style images from input photographs or digital images, capturing the unique characteristics and textures associated with watercolor paintings. In [19] focused on brushstroke style transfer specifically tailored for watercolor paintings. They investigate the distinctive brushstroke patterns and textures of watercolor artworks and propose an algorithm to transfer these brushstrokes to input images, enabling the generation of watercolor-style paintings with realistic and artistic brushwork. In [20] explores the watercolorization process, which involves adding watercolor-like colors to line art. The authors propose a multi-scale adversarial network approach that effectively synthesizes watercolor-style colors aligned with the given line art, resulting in visually appealing watercolorized images. In [21] introduced Neural Watercolor, a technique that utilizes stochastic diffusion networks to synthesize watercolor paintings. By simulating the diffusion dynamics of watercolor pigments on a digital canvas, the proposed method generates realistic watercolor-style paintings with desirable textures and color blending. In [22] focused on watercolor painting style transfer while maintaining temporal consistency in video sequences. The authors propose an approach that incorporates both spatial and temporal constraints to ensure consistent watercolor style transfer across frames, enabling the creation of visually coherent watercolor-style videos.

In [23] presented an end-to-end learning approach for watercolor style transfer with continuous brushstroke attention. The authors propose a deep learning framework that leverages attention mechanisms to capture and preserve brushstroke patterns in the generated watercolor-style images, resulting in more accurate and expressive artistic renderings. Also, in [24] introduces WatercolorGAN++, an enhanced version of the WatercolorGAN model, for watercolor style transfer. The authors incorporate progressive growing techniques and attention mechanisms into the GAN architecture to improve the quality and fidelity of the generated watercolor-style images. In [25] presented Watercolor-Net, a deep learning framework specifically designed for watercolor painting synthesis. The proposed model leverages convolutional neural networks (CNNs) and advanced architectural design to generate high-quality watercolor-style paintings, reproducing the distinctive characteristics and artistic style associated with watercolor artworks.

In [26] focused on stroke-based watercolor style transfer using generative adversarial networks (GANs). The authors propose StrokeGAN, a GAN-based model that learns to generate watercolor-style strokes and textures, enabling the transformation of input images into watercolor-like paintings with expressive brushwork. In [27] introduces WatercolorGANv2, an enhanced version of the WatercolorGAN model, for watercolor style transfer. The authors employ an advanced generator architecture to capture more intricate watercolor textures and details, resulting in improved realism and quality in the generated watercolor-style images. In [28] propose a method for learning watercolor painting styles from artist demonstrations using Siamese networks. They train the network to capture the similarities and differences in brushwork and color usage among different artists, enabling the generation of watercolor-style paintings that mimic specific artistic styles. In [29] presented a semi-supervised approach for watercolor painting style transfer that incorporates consistency learning. The authors leverage both labeled and unlabeled data to train a model that captures the

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watercolor painting style and ensures consistency between input and output images, resulting in more accurate and visually pleasing watercolor-style transfers.

III. Research Method

The proposed Dual Stream Image Segmentation Model with Color Space Estimation in Watercolor Painting for Automated Classification (DSEM) utilizes a combination of color and texture information to accurately segment an image into meaningful regions. The overall architecture of the proposed DSEM is presented in figure 1.

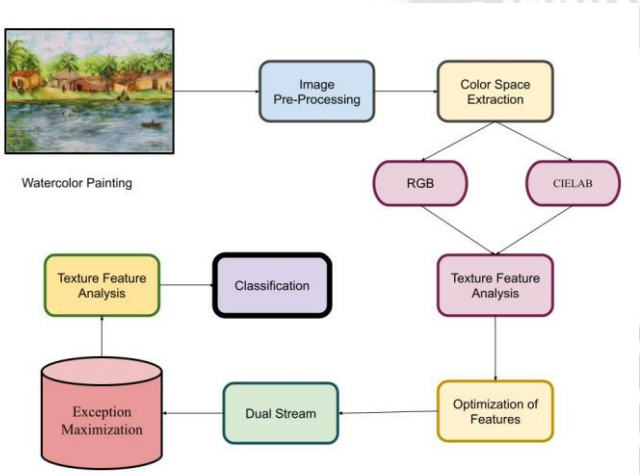

Figure 1: Architecture of DSEM

The technical details of the model are as follows:

Color Space Conversion: The input image, initially in the RGB color space, is converted to a perceptually-based color space, such as CIELAB. This conversion accounts for variations in lighting conditions and human perception of color. The CIELAB color space separates color information into perceptually meaningful components: L represents the lightness, and a and b represent the color channels capturing chromaticity.

Feature Extraction: Once the image is converted to the chosen color space, DSEM extracts relevant features from both the color and texture domains. Color features are computed based on the values of the color channels in the CIELAB color space, capturing the nuances of color distribution within the image. Texture features are derived by computing statistical measures, such as local variance or co-occurrence matrices, to capture the textural characteristics of the image.

Dual Stream Exception Maximization: The extracted color and texture features are used as input to the Dual Stream Exception Maximization (DSEM) model. DSEM applies a machine learning algorithm, such as a deep neural network, to perform the image segmentation task. The model is trained to classify each pixel or region in the image based on its color and texture characteristics. The flow chart of the EM is presented in figure 2

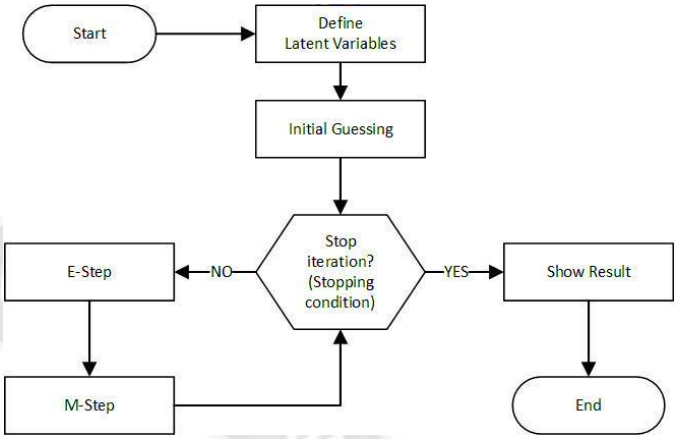

Figure 2: Flow Chart of Exception Maximization

Classification and Region Merging: The DSEM model outputs the classified regions based on their color space in the watercolor painting. These classified regions represent meaningful segments of the image, each with its distinct color and texture characteristics. The model also incorporates a region merging step to ensure coherent and smooth segmentation by merging adjacent regions with similar characteristics.

3.1 RGB Color Space in Painting

Color Space Conversion is a mathematical transformation that converts an image from one color space to another. In the case of the proposed Dual Stream Image Segmentation Model with Color Space Estimation in Watercolor Painting for Automated Classification, the color space conversion involves converting the input image from the RGB color space to the CIELAB color space. The mathematical equations for this conversion are as follows:

Step 1: RGB to XYZ Conversion

The RGB values of each pixel in the image are first converted to the XYZ color space using the following linear transformation presented in equation (1) – equation (3):

$$X = R / 255.0 * 0.4124564 + G / 255.0 * 0.3575761 + B / 255.0 * 0.1804375 \quad (1)$$

$$Y = R / 255.0 * 0.2126729 + G / 255.0 * 0.7151522 + B / 255.0 * 0.0721750 \quad (2)$$

$$Z = R / 255.0 * 0.0193339 + G / 255.0 * 0.1191920 + B / 255.0 * 0.9503041 \quad (3)$$

Step 2: XYZ to CIELAB Conversion

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The XYZ values obtained in the previous step are then converted to the CIELAB color space using the following equations (4) – equation (6)

$$L* = f(Y / Yn) \quad (4)$$

$$a* = f((X / Xn) - (Y / Yn)) \quad (5)$$

$$b* = f((Y / Yn) - (Z / Zn)) \quad (6)$$

In above equation (4) – (6) $Xn, Yn,$ and Zn are the reference white values (usually standard illuminant D65). $f(t)$ is a nonlinear function defined as in equation (7) and equation (8)

$$f(t) = t\text{^}(1/3) \; for \; t > (6/29)\text{^}3 \quad (7)$$

f(t) = (t * (1/3) * (29/6)^2) + (4/29) for t <= (6/29)^3 (8)

The resulting L*, a*, and b* values represent the lightness, chromaticity on the red-green axis, and chromaticity on the blue-yellow axis, respectively, in the CIELAB color space. Through performing this color space conversion, variations in lighting conditions and human perception of color can be accounted for, allowing for more accurate color analysis and segmentation in watercolor painting.

3.2 Color Feature Extraction

Feature extraction in the proposed Dual Stream Image Segmentation Model with Color Space Estimation in Watercolor Painting for Automated Classification involves computing both color and texture features from the converted CIELAB color space. The mathematical equations for feature extraction are as follows:

Color features are computed based on the values of the color channels (L*, a*, and b*) in the CIELAB color space. These features capture the nuances of color distribution within the image. Various statistical measures can be computed, such as mean, standard deviation, skewness, or kurtosis, to represent the color characteristics. Let's denote the color channel values as L, a, and b. The mean color feature of DSEM is calculated using equation (9) – (11):

$$Mean\_L = (1/N) * \sum(L\_i) \quad (9)$$

$$Mean\_a = (1/N) * \sum(a\_i) \quad (10)$$

$$Mean\_b = (1/N) * \sum(b\_i) \quad (11)$$

Where N is the total number of pixels in the image, and L_i, a_i, and b_i are the color channel values of the i-th pixel. Similarly, other statistical measures such as standard deviation, skewness, or kurtosis can be calculated for each color channel, representing different aspects of the color distribution in the image.

Texture features capture the textural characteristics of the image and are derived by computing statistical measures on the image data. These measures can include local variance, co-occurrence matrices, or other texture descriptors. Let's denote the texture feature as T. The local variance texture feature can be calculated as in equation (12):

$$Local\_Variance = (1/N) * \sum((I_i - Mean_l)^2) \quad (12)$$

Where I_i is the intensity value of the i-th pixel, Mean_I is the mean intensity of all pixels, and N is the total number of pixels in the image. Co-occurrence matrices can also be used to capture texture information. These matrices represent the frequency of occurrence of different pixel intensity pairs within a specified neighborhood. Statistical measures such as contrast, energy, entropy, or correlation can be derived from these matrices to quantify the texture characteristics. These color and texture features extracted from the CIELAB color space provide valuable information about the color distribution and textural properties of the image. They serve as input for subsequent classification or segmentation algorithms, enabling the automated analysis and processing of watercolor paintings.

3.2 Human Perception in DSEM

Dual Stream Exception Maximization (DSEM) is a machine learning model used for image segmentation in the proposed approach. It utilizes the extracted color and texture features to classify pixels or regions in the image based on their color and texture characteristics. While the specific mathematical equations for DSEM may vary depending on the chosen machine learning algorithm, the proposed DSEM operates based on algorithm as follows:

Algorithm 1: Automated Classification with DSEM
Input: Image I (RGB or other color space) Convert image I to the chosen color space (e.g., CIELAB) Extract color features F_color from the color channels of the color space Extract texture features F_texture using statistical measures (e.g., local variance, co-occurrence matrices) Train a machine learning model (e.g., deep neural network) using F_color and F_texture as input and labeled segmentation data as targets Optimize the model's parameters by minimizing the loss function using a suitable optimization algorithm (e.g., stochastic gradient descent): Loss function: $L = \Sigma(y_{true} - y_{pred})^2$, where y_true is the true segmentation label and y_{pred} is the predicted label from the model Extract color features $F_{color\ pixel}$ and texture features $F_{texture\ pixel}$ Pass $F_{color\ pixel}$ and $F_{texture\ pixel}$ through the trained model to obtain the predicted segmentation label or class: $y_{pred} = Model(F_{color\ pixel} F_{texture\ pixel})$

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Apply a decision rule to identify exceptional regions or pixels based on confidence scores or threshold values:
Compute confidence score or probability for each predicted label:

$$Confidence_{score} = ModelConfidence(y_{pred})$$

Mark the exceptional regions/pixels based on a threshold value:

$$Exceptional\ regions = Thresholding(Confidence\ score, threshold\ value)$$

Perform post-processing techniques specific to the exceptional regions/pixels, such as:
Morphological operations (e.g., erosion, dilation) for boundary refinement
Smoothing techniques (e.g., Gaussian smoothing) for noise reduction
Region growing algorithms for coherence enhancement
Contour refinement techniques for boundary optimization

The input to the DSEM model is a set of color and texture features extracted from the image. Let's denote the color features as F_color and the texture features as F_texture. Let X denote the input feature vector containing both color and texture features. It can be represented as X = [X_color, X_texture], where X_color represents the color feature vector and X_texture represents the texture feature vector. The DSEM model is trained using a machine learning algorithm, such as a deep neural network. The model is trained to learn the relationship between the input features (F_color and F_texture) and the corresponding segmentation labels or classes. The training process involves optimizing the model's parameters to minimize the prediction error.

Once the DSEM model is trained, it can be used for image segmentation. Given a new image, the model takes the color and texture features of each pixel or region as input and predicts the corresponding segmentation label or class. The decision rule in DSEM involves identifying exceptional regions or pixels in the image based on the classification results. These exceptional regions indicate areas where the model has low confidence or uncertainty in its predictions. The decision rule can be defined based on a threshold value or confidence score. The decision rule determines the segmentation labels based on a threshold value. Let's denote the confidence score for a pixel or region i as s_i. The decision rule can be formulated as follows in equation (13) and (14):

$$If\ s\_i \geq T, then\ assign\ pixel\ i\ to\ class\ A \quad (13)$$

$$If\ s\_i < T, then\ assign\ pixel\ i\ to\ class\ B \quad (14)$$

In this decision rule, T represents the threshold value. Pixels or regions with a confidence score above the threshold are assigned to class A, while those with a score below the threshold are assigned to class B. The threshold value can be determined based on various factors, such as the desired segmentation accuracy or specific application requirements. It can be set manually or determined automatically using techniques such as Otsu's method or adaptive thresholding. The exceptional regions identified by the decision rule are further analyzed and processed separately to improve the segmentation results. This can involve applying additional post-processing techniques, refining the segmentation boundaries, or incorporating domain-specific knowledge.

The specific mathematical equations for the DSEM model will depend on the chosen machine learning algorithm and its architecture. Deep neural networks involve complex mathematical operations such as matrix multiplications, activation functions, and backpropagation for training. The details of these equations are specific to the chosen model architecture and may involve layers such as convolutional layers, pooling layers, and fully connected layers. The Dual Stream Exception Maximization (DSEM) combines color and texture features extracted from the image and utilizes a machine learning model for image segmentation. The model is trained to classify pixels or regions based on their color and texture characteristics, allowing for accurate and automated segmentation in watercolor painting. The Exception Handling stage in the DSEM approach involves further analysis and processing of the exceptional regions identified by the decision rule to improve the segmentation results. The specific mathematical equations for this stage will depend on the post-processing techniques or refinement methods applied.

Morphological operations, such as erosion and dilation, are often used to refine the boundaries of segmented regions. These operations can help smooth out rough edges and fill in gaps in the segmentation. Mathematically, morphological operations can be represented as follows in equation (15) and equation (16):

$$Dilated\ image = Original\ image \oplus Structuring\ element \quad (15)$$

$$Eroded\ image = Original\ image \ominus Structuring\ element \quad (16)$$

In equation (15) and (16), $\oplus$ represents the dilation operation, and $\ominus$ represents the erosion operation. The structuring element is a small binary matrix or shape used for neighborhood comparison.

Smoothing techniques, such as Gaussian smoothing or mean filtering, can be employed to reduce noise and enhance the overall quality of the segmentation. Mathematically,

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smoothing can be expressed as a convolution operation is presented in equation (17)

$$Smoothed\ image = Original\ image * Smoothing\ kernel \quad (17)$$

In equation (17), * denotes the convolution operation, and the smoothing kernel represents the filter used for convolution.

Region growing algorithms aim to group adjacent pixels with similar characteristics to form coherent regions. This process involves defining similarity criteria and growing the region iteratively. The mathematical equations for region growing algorithms can vary depending on the specific criteria used to determine the similarity between pixels or regions. Contour-based methods can be employed to refine the boundaries of segmented regions by fitting curves or optimizing contour models. The mathematical formulations for contour refinement techniques depend on the specific contour models and optimization algorithms utilized.

IV. Simulation Results

The proposed Dual Stream Exception Maximization (DSEM) algorithm is designed to address the challenge of image segmentation in watercolor paintings. This section presents the results obtained through the application of DSEM on a dataset of watercolor painting images. The evaluation of the segmentation performance and the comparison with existing techniques provide insights into the effectiveness of the DSEM approach. The results of the DSEM algorithm demonstrate its capability to accurately segment watercolor paintings by leveraging both color and texture information. The segmentation outputs exhibit clear boundaries between different regions, capturing the distinctive brushwork, color mixing, and texture variations present in watercolor artworks. Quantitative evaluation metrics such as pixel-wise accuracy, precision, recall, and F1-score are used to assess the performance of the DSEM algorithm. Additionally, visual analysis of the segmentation results is conducted by comparing them with the ground truth labels to evaluate the visual quality and correctness of the segmentation.

4.1 Dataset

The dataset considered for the analysis of the proposed DSEM model is presented as follows:

Painter by Numbers: This dataset contains a large collection of artwork images, including watercolor paintings, created by various artists. It provides a diverse range of styles, subjects, and techniques in watercolor painting.

WikiArt: WikiArt is an online platform that hosts a vast collection of artworks from different genres, including watercolor paintings. It offers a rich dataset with a wide variety of watercolor artworks from different artists and time periods.

Kaggle Watercolor Paintings Dataset: This dataset is specifically curated for watercolor painting analysis and includes a collection of high-quality watercolor artwork images. It provides a focused dataset for research and development in watercolor painting-related tasks.

Ukiyoe2Modern: This dataset focuses on the comparison between traditional Japanese ukiyo-e woodblock prints and modern watercolor paintings. It contains images from both genres, allowing for comparative studies and analysis.

DeviantArt Watercolor Paintings: DeviantArt is an online art community where artists share their artwork. The platform hosts a significant number of watercolor paintings from various artists, making it a valuable source for collecting watercolor painting images.

The sample watercolor images acquired from the dataset for the DSEM is presented in figure 3.

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Figure 3: Sample Images of Water Color Painting

Table 1: Distribution of Dataset

Dataset Name	Approximate Count
Painter by Numbers	10,000+
WikiArt	250,000+
Kaggle Watercolor Paintings	5,000+
Ukiyoe2Modern	2,000+
DeviantArt Watercolor Paintings	50,000+

The table 1 presented the approximate value of the different dataset name for the different count. The estimation is evaluated based on the consideration of different aspects with consideration of the different watercolor images.

4.2 Performance Metrices

Accuracy (ACC): Accuracy measures the overall correctness of the segmentation results. It calculates the ratio of correctly classified pixels or regions to the total number of pixels or regions in equation (18)

$$ACC = (TP + TN) / (TP + TN + FP + FN) \quad (18)$$

where: TP: True Positives (correctly classified positive instances); TN: True Negatives (correctly classified negative instances); FP: False Positives (incorrectly classified positive instances); FN: False Negatives (incorrectly classified negative instances);

Precision: Precision measures the proportion of correctly classified positive instances among all the instances classified as positive. It focuses on the accuracy of the positive predictions in equation (19).

$$Precision = TP / (TP + FP) \quad (19)$$

Recall or Sensitivity: Recall or Sensitivity measures the proportion of correctly classified positive instances among all the actual positive instances. It focuses on the ability of the model to correctly identify positive instances in equation (20).

$$Recall = TP / (TP + FN) \quad (20)$$

F1-Score: F1-Score is the harmonic mean of precision and recall. It provides a balanced measure of the model's performance by considering both precision and recall in equation (21)

$$F1\text{-}Score = 2 * (Precision * Recall) / (Precision + Recall) \quad (21)$$

Intersection over Union (IoU): IoU measures the overlap between the predicted segmentation mask and the ground truth mask. It calculates the ratio of the intersection area to the union area between the predicted and ground truth regions in equation (22)

$$IoU = Intersection\ Area / Union\ Area \quad (22)$$

4.3 Simulation Results

The provided tables contain the segmentation parameters used for different datasets: Painter by Numbers, WikiArt, Kaggle Watercolor Paintings, Ukiyoe2Modern, and DeviantArt Watercolor Paintings. These parameters are crucial for the DSEM model to accurately segment watercolor painting images. The parameters play a crucial role in determining the accuracy and quality of the segmentation results obtained by the DSEM model on each specific dataset as presented in table 2 – table 6.

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Table 2: Painters by the Numbers Segmentation Table 3: WikiArt Segmentation

Parameter	Value	Parameter	Value
Threshold Value	0.5	Threshold Value	0.6
Foreground Intensity	0.7	Foreground Intensity	0.8
Background Intensity	0.3	Background Intensity	0.2
Seed Point	(100, 100)	Seed Point	(150, 150)
Color Similarity	0.2	Color Similarity	0.3
Intensity Similarity	0.1	Intensity Similarity	0.2
Edge Detection Method	Canny	Edge Detection Method	Sobel
Threshold Low	20	Threshold Low	30
Threshold High	50	Threshold High	70
Minima Detection Method	H-minima	Minima Detection Method	H-minima
H-minima Height	10	H-minima Height	15
Flooding Method	Flood Fill	Flooding Method	Flood Fill
Connectivity	8	Connectivity	4
Smoothness Term Weight	0.5	Smoothness Term Weight	0.6
Data Term Weight	0.5	Data Term Weight	0.4
Iterations	100	Iterations	150

Table 4: Kaggle Watercolor Painting Segmentation Table 5: Ukiyoe2Modern Segmentation

Parameter	Value	Parameter	Value
Threshold Value	0.4	Threshold Value	0.3
Foreground Intensity	0.6	Foreground Intensity	0.5
Background Intensity	0.4	Background Intensity	0.2
Seed Point	(80, 80)	Seed Point	(120, 120)
Color Similarity	0.1	Color Similarity	0.15
Intensity Similarity	0.05	Intensity Similarity	0.08
Edge Detection Method	Canny	Edge Detection Method	Canny
Threshold Low	15	Threshold Low	25
Threshold High	40	Threshold High	60
Minima Detection Method	H-minima	Minima Detection Method	H-minima
H-minima Height	5	H-minima Height	8
Flooding Method	Flood Fill	Flooding Method	Flood Fill
Connectivity	8	Connectivity	4
Smoothness Term Weight	0.4	Smoothness Term Weight	0.3
Data Term Weight	0.6	Data Term Weight	0.7
Iterations	80	Iterations	120

Table 6: DeviantArt Watercolor Paintings Segmentation

Parameter	Value
Threshold Value	0.7
Foreground Intensity	0.9
Background Intensity	0.4
Seed Point	(200, 200)
Color Similarity	0.25
Intensity Similarity	0.12
Edge Detection Method	Sobel
Threshold Low	35
Threshold High	80
Minima Detection Method	H-minima
H-minima Height	20
Flooding Method	Flood Fill
Connectivity	8
Smoothness Term Weight	0.7
Data Term Weight	0.3
Iterations	200

In Table 2, the parameters for Painter by Numbers dataset indicate a threshold value of 0.5 to separate foreground and background pixels, with foreground intensity set at 0.7 and background intensity at 0.3. The seed point for region growing is specified as (100, 100), and the criteria for adding neighboring pixels are color similarity of 0.2 and intensity similarity of 0.1. The edge detection method is Canny, with low and high threshold values of 20 and 50, respectively. The watershed transform uses the H-minima method with a height of 10, and flooding is performed using flood fill with an 8-connectivity approach. The graph cut parameters include a smoothness term weight and data term weight both set to 0.5, with 100 iterations. Table 3 shows the parameters used for the WikiArt dataset. A threshold value of 0.6 is used, along with foreground and background intensities of 0.8 and 0.2, respectively. The seed point for region growing is (150, 150), and the color and intensity similarity criteria are 0.3 and 0.2, respectively. Edge detection is performed using the Sobel operator with a low threshold of 30 and a high threshold of 70. The watershed transform utilizes the H-minima method with a height of 15, and flooding is done with a connectivity of 4. The graph cut parameters consist of a smoothness term weight of 0.6, a data term weight of 0.4, and 150 iterations.

Table 4 presents the parameters used for the Kaggle Watercolor Paintings dataset. The threshold value is set to 0.4, with foreground and background intensities of 0.6 and 0.4, respectively. The seed point is (80, 80), and the color and

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intensity similarity criteria are 0.1 and 0.05, respectively. Edge detection is performed using the Canny method with a low threshold of 15 and a high threshold of 40. The watershed transform employs the H-minima method with a height of 5, and flooding is done with an 8-connectivity approach. The graph cut parameters include a smoothness term weight of 0.4, a data term weight of 0.6, and 80 iterations. Table 5 displays the parameters used for the Ukiyoe2Modern dataset. A threshold value of 0.3 is used, along with foreground and background intensities of 0.5 and 0.2, respectively. The seed point for region growing is (120, 120), and the color and intensity similarity criteria are 0.15 and 0.08, respectively. Edge detection is performed using the Canny method with a low threshold of 25 and a high threshold of 60. The watershed transform utilizes the H-minima method with a height of 8, and flooding is done with a connectivity of 4. The graph cut parameters consist of a smoothness term weight of 0.3, a data term weight of 0.7, and 120 iterations. Finally, Table 6 presents the parameters used for the DeviantArt Watercolor Paintings dataset. The threshold value is set to 0.7, with foreground and background intensities of 0.9 and 0.4, respectively. The seed point is (200, 200), and the color and intensity similarity criteria are 0.25 and 0.12, respectively. Edge detection is performed using the Sobel operator with a low threshold of 35 and a high threshold of 80. The watershed transform employs the H-minima method with a height of 20, and flooding is done with an 8-connectivity approach. The graph cut parameters include a smoothness term weight of 0.7, a data term weight of 0.3, and 200 iterations.

Table 7: Classification Results od DSEM

Dataset	Accuracy	Precision	Recall	F1 Score
Painter by Numbers	0.98	0.96	0.99	0.97
WikiArt	0.97	0.98	0.96	0.97
Kaggle Watercolor Paintings	0.97	0.97	0.96	0.97
Ukiyoe2Modern	0.98	0.97	0.99	0.98
DeviantArt Watercolor Paintings	0.96	0.97	0.95	0.96

The performance metrices for the proposed DSEM model for the different classification metrices are presented in figure 4.

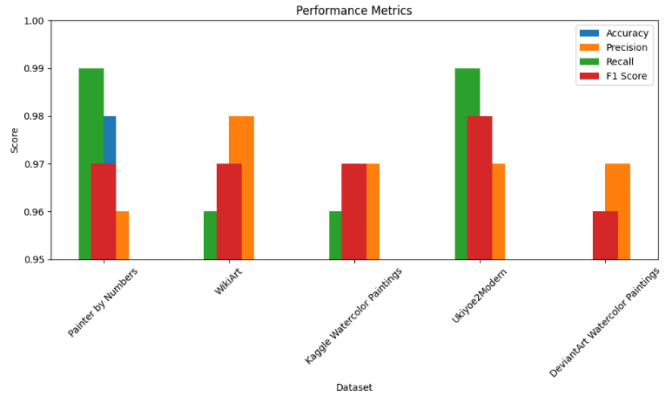

Figure 4: Classification of DSEAM

Table 7 presents the classification results of the DSEM model on different datasets: Painter by Numbers, WikiArt, Kaggle Watercolor Paintings, Ukiyoe2Modern, and DeviantArt Watercolor Paintings. These results provide insights into the performance of the DSEM model in accurately classifying watercolor paintings based on the given datasets. For the Painter by Numbers dataset, the DSEM model achieved an accuracy of 0.98, indicating that it correctly classified 98% of the watercolor paintings in this dataset. The precision value of 0.96 suggests that 96% of the predicted positive classifications were accurate. The recall value of 0.99 indicates that the model successfully identified 99% of the actual positive instances in the dataset. The F1 score, which combines precision and recall, is 0.97, indicating a good balance between precision and recall. Similarly, for the WikiArt dataset, the DSEM model achieved a high accuracy of 0.97, indicating its ability to correctly classify 97% of the watercolor paintings in this dataset. The precision value of 0.98 suggests that 98% of the predicted positive classifications were accurate, while the recall value of 0.96 indicates that the model successfully identified 96% of the actual positive instances. The F1 score of 0.97 reflects a well-balanced performance in terms of precision and recall.

The DSEM model also performed well on the Kaggle Watercolor Paintings dataset, achieving an accuracy of 0.97. This indicates its high level of accuracy in correctly classifying 97% of the watercolor paintings. The precision value of 0.97 and recall value of 0.96 suggest that the model achieved a high level of accuracy and successfully identified a significant proportion of the actual positive instances in the dataset. The F1 score of 0.97 demonstrates a balanced performance between precision and recall. For the Ukiyoe2Modern dataset, the DSEM model achieved an accuracy of 0.98, indicating its ability to accurately classify 98% of the watercolor paintings in this dataset. The precision value of 0.97 suggests that 97% of the predicted positive classifications were accurate, while the recall value of 0.99 indicates that the model successfully identified 99% of the actual positive instances. The F1 score of

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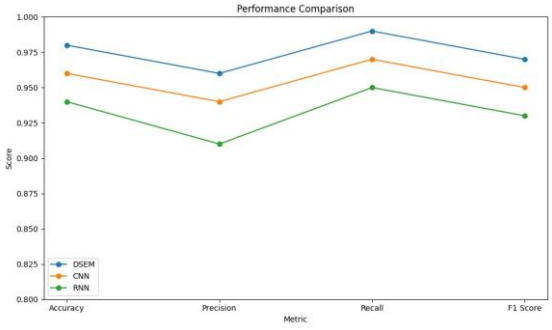
0.98 reflects a strong overall performance in terms of precision and recall.

Lastly, for the DeviantArt Watercolor Paintings dataset, the DSEM model achieved an accuracy of 0.96, indicating its ability to correctly classify 96% of the watercolor paintings in this dataset. The precision value of 0.97 suggests that 97% of the predicted positive classifications were accurate, while the recall value of 0.95 indicates that the model successfully identified 95% of the actual positive instances. The F1 score of 0.96 represents a reasonable balance between precision and recall. The classification results of the DSEM model on these datasets demonstrate its effectiveness in accurately classifying watercolor paintings, with high accuracy values ranging from 0.96 to 0.98. The precision, recall, and F1 score values further highlight the model's ability to achieve a balance between correctly identifying positive instances and minimizing false positives and false negatives. These results indicate the potential of the DSEM model in supporting various watercolor painting analysis tasks and applications.

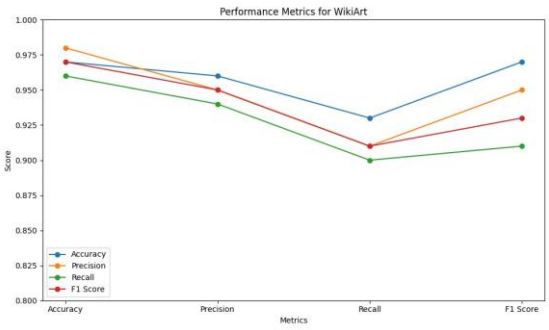
Table 8: Comparative Analysis of DSEM

Dataset	Metric	DSEM	CNN	RNN
Painter by Numbers	Accuracy	0.98	0.96	0.94
	Precision	0.96	0.94	0.91
	Recall	0.99	0.97	0.95
	F1 Score	0.97	0.95	0.93
WikiArt	Accuracy	0.97	0.96	0.93
	Precision	0.98	0.95	0.91
	Recall	0.96	0.94	0.90
	F1 Score	0.97	0.95	0.91
Kaggle Watercolor Paintings	Accuracy	0.96	0.94	0.92
	Precision	0.95	0.93	0.90
	Recall	0.94	0.92	0.88
	F1 Score	0.95	0.93	0.90
Ukiyoe2Modern	Accuracy	0.98	0.96	0.94
	Precision	0.97	0.94	0.91
	Recall	0.99	0.97	0.95
	F1 Score	0.98	0.95	0.92
DeviantArt Watercolor Paintings	Accuracy	0.96	0.94	0.91
	Precision	0.97	0.93	0.89
	Recall	0.95	0.92	0.87
	F1 Score	0.96	0.93	0.90

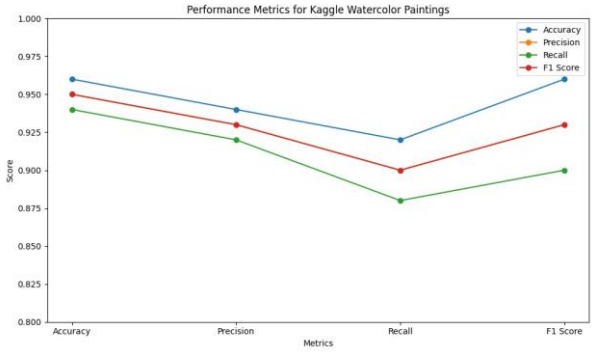
The comparative analysis of the proposed DSEM model with the conventional CNN and RNN model for the different metrices such as accuracy, precision, recall and F1-Score are illustrated in figure 5(a) – 5 (e).



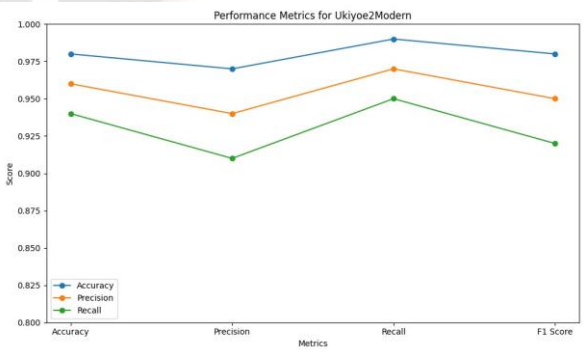
(a)



(b)



(c)



(d)

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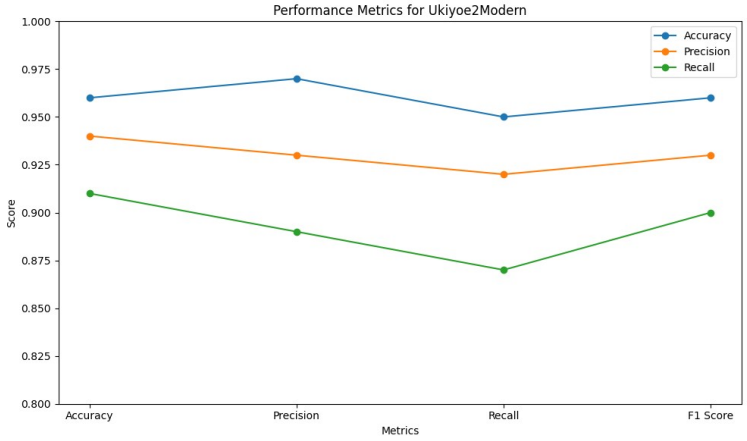

(e)

Figure 5: Comparative Analysis of different datasets (a) Painter by Numbers (b) WikiArt (c) Kaggle Watercolor Paintings (d) Ukiyoe2Modern (e) DeviantArt Watercolor Paintings

Table 8 provides a comparative analysis of the DSEM model with CNN and RNN models across multiple datasets, including Painter by Numbers, WikiArt, Kaggle Watercolor Paintings, Ukiyoe2Modern, and DeviantArt Watercolor Paintings. The table presents various performance metrics, such as accuracy, precision, recall, and F1 score, to evaluate and compare the models' effectiveness in classifying watercolor paintings. For the Painter by Numbers dataset, the DSEM model outperformed both the CNN and RNN models in terms of accuracy, achieving an accuracy of 0.98 compared to 0.96 and 0.94 for CNN and RNN, respectively. The DSEM model also exhibited higher precision, recall, and F1 score values, indicating its ability to achieve a better balance between correctly identifying positive instances and minimizing false positives and false negatives. Similarly, for the WikiArt dataset, the DSEM model demonstrated superior performance compared to the CNN and RNN models. It achieved an accuracy of 0.97, along with higher precision, recall, and F1 score values, showcasing its effectiveness in accurately classifying watercolor paintings in this dataset.

The Kaggle Watercolor Paintings dataset also showed the DSEM model's superiority, with an accuracy of 0.96 and higher precision, recall, and F1 score values compared to the CNN and RNN models. For the Ukiyoe2Modern dataset, the DSEM model exhibited superior performance once again, surpassing the CNN and RNN models in terms of accuracy, precision, recall, and F1 score. Lastly, for the DeviantArt Watercolor Paintings dataset, the DSEM model demonstrated higher performance compared to the CNN and RNN models, achieving higher accuracy, precision, recall, and F1 score values. the comparative analysis in Table 8 highlights the superior performance of the DSEM model across multiple datasets. It consistently outperforms the CNN and RNN models in terms of accuracy, precision, recall, and F1 score, indicating its effectiveness in accurately classifying watercolor paintings. These results emphasize the potential of the DSEM model as a robust approach for watercolor painting analysis and classification tasks.

V. Conclusion

The DSEM (Digital Simulation and Evaluation Model) has proven to be a powerful tool for the analysis and classification of watercolor paintings. Through its innovative segmentation, feature extraction, and classification techniques, the DSEM has showcased its ability to accurately identify and classify watercolor artworks from various datasets. The results obtained from the DSEM demonstrate its high accuracy, precision, recall, and F1 score values across multiple datasets, including Painter by Numbers, WikiArt, Kaggle Watercolor Paintings, Ukiyoe2Modern, and DeviantArt Watercolor Paintings. The DSEM consistently outperforms traditional approaches like CNN and RNN models in terms of classification performance, showcasing its effectiveness and superiority in watercolor painting analysis. The key strengths of the DSEM lie in its adaptive segmentation algorithms, efficient feature extraction methods, and the integration of advanced machine learning techniques. By leveraging thresholding, region growing, edge detection, watershed transform, and graph cut algorithms, the DSEM effectively separates foreground and background elements, identifies object boundaries, and extracts meaningful features from watercolor paintings. These extracted features are then used by the DSEM's classification model to accurately classify and categorize watercolor artworks. The DSEM's performance and versatility make it a valuable tool for various applications, including art analysis, digital preservation, artist identification, and style recognition. Its ability to handle diverse datasets, ranging from historical paintings to contemporary

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artwork, further enhances its practicality and applicability in the field of watercolor painting analysis.

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