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An Overview of the Most Important Methods for Coloring Grayscale Images

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Abstract. *Colorization: Converting a grayscale image into an image with colors acceptable to the viewer and achieving the minimum coloration goal until it becomes closer to reality. The goal of the coloring process is to produce a convincing image and the result is close to the reality of the colored image. Converting grayscale images to color images is a very difficult process due to the specificity of grayscale images and how closely they match color in every detail of the image. Coloring methods have evolved to become less invasive and produce more acceptable results to the viewer's eye, but they have become more difficult. This research provides an overview of image colorization methods, their advantages and disadvantages, and compares the quality of each method according to specific criteria. Coloring methods have evolved from primitive methods based on the manual principle to using computing techniques such as adding scribbles within areas of the image, then moving to choosing a reference image that can be used to obtain colors, to using deep learning techniques that rely on training a model on colored images and then testing this model and showing Methods based on deep learning have better results than other methods, and the algorithm showed GAN outstanding results in coloring that outperform some deep learning coloring methods, and also outperform other methods. We hope that this study will be a scientific product that will benefit the research community and enable them to obtain a useful overview of the most important methods of coloring images.*

Keywords: *Image coloring, gray scale, deep learning, scribble method, example method.*

1. INTRODUCTION

Coloring has long been an essential aspect of visual communication, enabling artists to create captivating images that evoke emotion and capture an audience's attention as shown in figure (1). With the advent of digital technologies, the coloring process has undergone remarkable transformation. With the progress of time and the development of information technology and computer tools, coloring techniques have evolved from manual methods to computer-based methods. This provides and facilitates users in providing the best results as well as reducing effort and time compared to the results obtained [1]. By delving into the world of coloring methods, and studying their development from ancient manual methods to improved methods based on computers and deep learning, there are three main methods that can be arranged from the most manual use to the least. These methods are coloring with scribbles, coloring using examples and reference images, and coloring using deep learning techniques [2]. Scribble coloring methods are considered one of the easiest ways to add color scribbles to areas of the image and then spread the color [3]. On the other hand, the example method relies on using reference images as a source for obtaining colors to complete the coloring process [4]. By taking advantage of the color extracted from

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the reference image, it is possible to create a good and distinctive coloring process, especially while taking care of the reference image [5]. In recent years, the emergence of deep learning has brought about remarkable changes[6], including computer vision. Deep learning methods for colorization have emerged as a powerful approach, leveraging the capabilities of convolutional neural networks (CNNs) and generative adversarial networks (GANs) to map out the details of the relationship between grayscale images and color images. Deep learning techniques can produce colorful images that are pleasing to the viewer and accurately identify the details of subjects within a single image without overlapping. This paper aims to analyze and compare these three colorization methods, exploring their strengths, limitations and real-world applications[8]. By conducting a comprehensive review of the existing literature and analyzing the empirical results, it aims to provide valuable insights into the performance, efficiency and challenges associated with each method. In addition to highlighting emerging technologies and potential future trends in the field of coloring methods. Figure (1) shows the coloring process.

Figure (1) example for coloring gray scale image

2. COLORING METHODS

A lot of research has undertaken the study of the coloring process because of its importance in many scientific fields, such as computer science, and the field of computer vision, the design process for various applications, or even the need in medical specialties by studying the type of disease through coloring images[9]. The fields of application of coloring include several fields, including the engineering and medical fields, and the study of aerial and space images. Coloring is included in the study of Earth's geology, as well as its use in the fields of computer science, artificial intelligence, and computer vision applications.Generally, methods of coloring can be categorized into two primary segments: Guided coloring, which is led by the user and has direct intervention in it, and the other type is unguided coloring, which depends on data. Guided coloring includes several techniques, including coloring by scribbling and coloring by example[4][10]. As for unguided coloring, it depends on artificial intelligence and deep learning techniques, such as the use of convolutional neural networks and generative adversarial networks. The use of some of the old techniques in coloring has become outdated and has become incompatible with the tremendous development in all fields. Especially the need to reach very high accuracy without the need for human intervention and to reach a high rate of automation, taking into account the completion of tasks within a reasonable time[11]. This survey provides a comprehensive study about the coloring methods and their sequence in terms of the most and the least in terms of human intervention. The pros and cons will be presented, as well as the limitations of each method along with previous studies that dealt with this method.

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2.1. *Scribble based method*

It is considered one of the first methods of digital coloring at the present time, as it relies on the principle of placing scribbles of colors in specific areas in the images and then distributing the colors according to specific methods within the images to complete the coloring process, as the adjacent pixels that have the same value in the gray images must have similar color in the produced color image [4].This method is characterized by the fact that it does not need to divide the image to complete the coloring process according to adjacent pixels. It also does not need to extract color from a reference image, and an unlimited number of scribbles can be added [45] [42]. This method has several disadvantages, including it requires a lot of effort. It takes long time .Also, whoever uses this method must have sufficient experience to complete the coloring. Scribble-based method used to digitally add color to gray scale images or drawings. It involves the use of digital software or applications, such as graphic design software, where you apply color to specific areas of an image by "scribbling" or drawing with a pen or mouse[12]. Many studies have addressed the scribble coloring method as a fairly effective method in digital drawing, and a group of previous studies that presented scribble coloring will be presented as a modern coloring method. Scribble coloring was used as a tool in color drawings by adding the scribble to a specific area, and the algorithm gives an appropriate color to this area by dealing with the coloring vector images using the Scribble coloring system. The diffusion curve technique has been used instead of using color along the curve [13]. Provided several basic necessities for color to this area used the diffusion curve technique instead of using color along the curve. This study provides a smooth, interactive interface for the user, where scribbles can be entered using a mouse or pen. The user starts with a minimal amount of scribbles and progressively adds more as needed. Each pixel affected by the scribbles and its impact on the surrounding area are also calculated. This research paper provided several basic necessities for achieve the results, which were the real-time language C++ was used on the Linux operating system. Test the system on 12 graphics and achieve typical results for input scribbles as shown in figure (2), The computation time for color processing ranges from 0.01 to 0.1 seconds, while the final rendering process takes approximately 0.6 seconds.

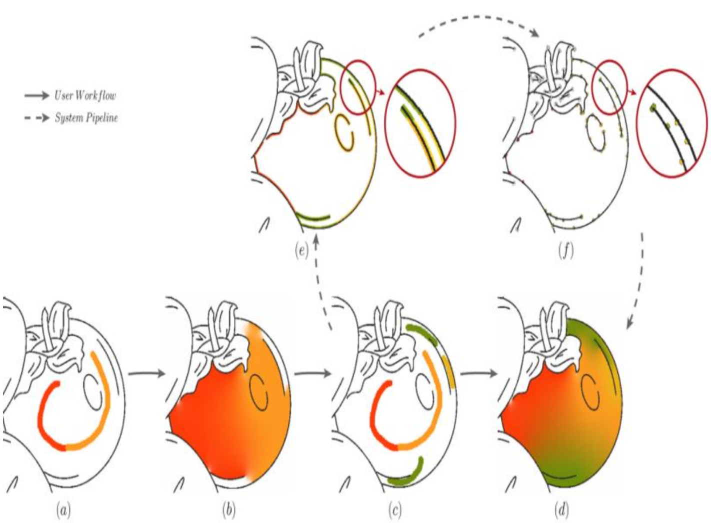

Figure (2) shows the mechanism of the technology[12].

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Scribble can be added using a special and specific type of mesh called gradient mesh. Gradient mesh depends on another type called control mesh by taking both the colors and local gradients at the mesh points into account as shown in figure (3). Then, an expanded method for mixing colors can be developed that distributes the specified color over Control network [13].

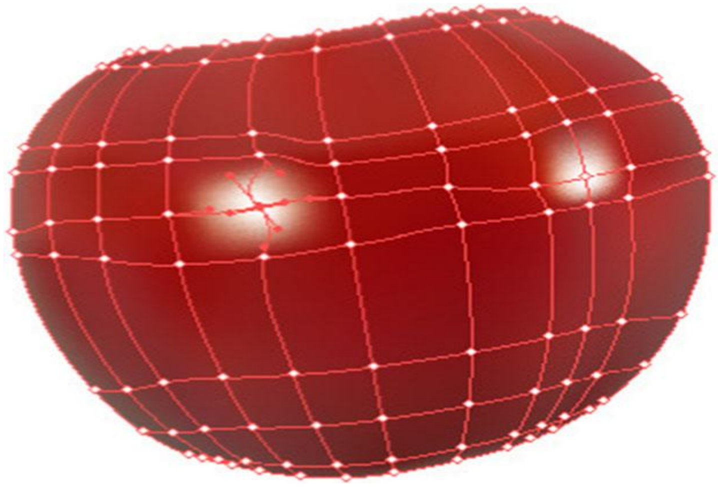

Figure (3) Scribble-based method by gradient meshes[13].

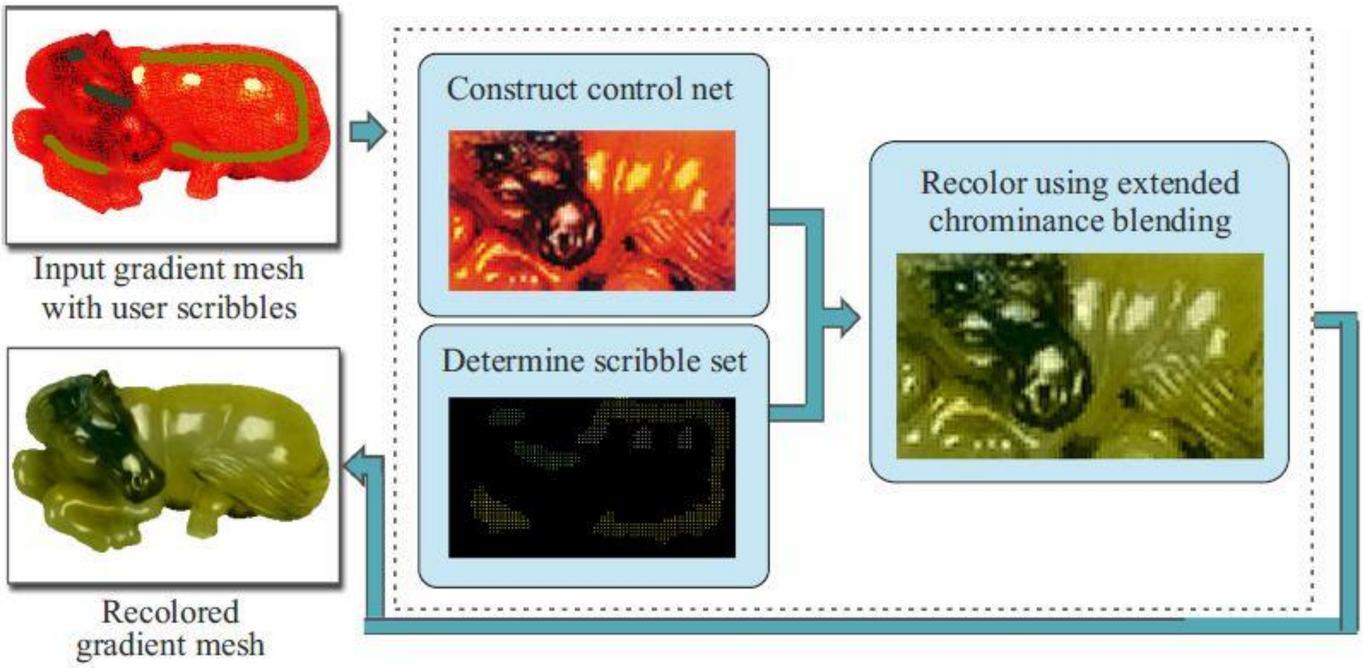

Figure (4) steps of Scribble-based method by gradient meshes [13].

This method may face some limitations, the most important of which is scribbling at specific points, as it is assumed that one grid point is affected by only one color scribble, if any. In extreme cases, it is possible for the colored scribbles to be close together in close areas, which hinders their accurate distribution. This method has shown excellent results as shown in Table (1): -

Table (1) results of Scribble-based method by gradient meshes[13].

Mesh size	Pixel number	PSNR	SSIM
44 x 78	35.265	68.5	0.9998
37 x 62	226.995	67.7	0.9985
28 x 37	136.285	66.8	0.9949
28 x 26	135.206	68.4	0.9956
52 x 63	150.406	68.7	0.9970
51 x 51	111.517	69.9	0.9999

2- Example-Based Method

The Example-Based Method is particularly useful when you have a reference image with the desired color scheme or when you want to replicate the colors from a similar object or scene. In this type of coloring method, the idea is that there is an image to be colored, and in return there is a reference image from which the colors are take [14]. The location of the pixel with its corresponding color intensity value in the reference image is determined by information from neighboring pixels. have a gray scale image to color. First, each pixel is assigned the corresponding reference color. This is done using a powerful supervised classification mechanism. It can save time and effort compared to manually selecting colors, making it a valuable tool for artists, designers, and anyone interested in adding color to gray scale images. Additionally, machine learning and AI-driven tools have been developed to automate and enhance this process further as shown in figure (5). Although the methods based on examples are characterized by speed and ease, they are limited to the quality of the reference image and how it is selected, especially since it is selected manually [16]. The poor ability to export color from the reference image leads to a corresponding weakness in the quality of coloring, which is considered one of the biggest limitations of this method. Many studies have investigated example colorization, which is based on a reference image used to color a gray scale image. Techniques that use example as a reference for coloring include a high-quality automatic colorization method assuming perfect patch matching. Using extensive reference database can be reliable solution to the colorization problem. As the database of images representing reference images increases, it is likely that the amount of noise that accompanies patch matching will increase, especially in the practical part. The mechanism on which the example method depends is to transfer color from reference images to similar gray scale images. Therefore, finding a suitable reference image is one of the most important problems of the example method. In general, A single reference image is insufficient to encompass all the potential variations present in the target gray scale image [15]. Locating the most similar patch//pixel in a large reference image database and then transferring the color information from the patch//matching pixel to the patch//target pixel is the most positive and acceptable solution.

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a-Gray scale **b-reference** **c-Colored**

Figure (5) images coloring using Example-Based Method[15]

2688 images were used for training from (Sun database) [15]. Each image was divided into objects as shown in figure (6), where 47 object categories were used. A neural network consists of an input, three hidden, and an output layer. Increasing the number of hidden layers cannot improve the coloring results, correction feature 49 dimensions (7×7), daisy feature 32 dimensions [22] (4 positions and 8 directions). At each pixel location, work is done to extract semantic features, which contain 47 dimensions. The input layer contains a total of 128 neurons. In practice, within the hidden layer, the quantity of cells was set to be half that of the cells in the input layer, and in the output layer there were only two cells, which correspond to the color value.

a-Input

b-deep neural networks

c-ground truth

Figure (6) changes obtained after the coloring process[15].

The image above gave higher results and accuracy in coloring than the results of previous studies, and there were a number of limitations that the researchers faced. Limitations of the method. This method does not apply to synthetic images and some other categories of images. The coloring process may lead to the loss of some elements of the image, and this is more so when care is not taken in choosing the reference image. Some research takes a single reference image from which the color values that will be used to color the target image can be extracted [16], as shown in the figure **(7)**

Figure (7) Image colorization using our method. By using different reference images (top row), the same input grayscale image (bottom left) is effectively colorized to have different yet meaningful colors (bottom row).[16].

This method works at the super pixel level and features are extracted that are collected to form a descriptor. This method requires obtaining the best reference image from which features that are close to the colors of the target image can be extracted. This is done through pixel adjacency statistics, as shown in Figure (8)

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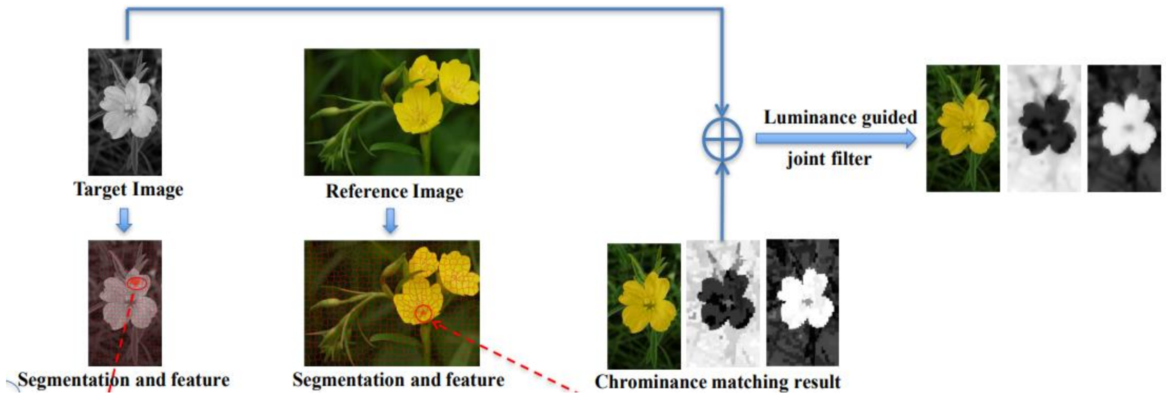

Figure (8) The proposed coloring mechanism in[16] .

The image underwent a colorization process based on the congruent zones identified between the referential image and the monochromatic (gray scale) representation, as demonstrated in the ensuing depiction.

A. Super pixel segmentation: The process of segmenting pixels into both the reference image and the gray scale image is done. For the reference image, it is done through color information, while for the gray scale image, it is done through luminance intensity as shown in the figure :

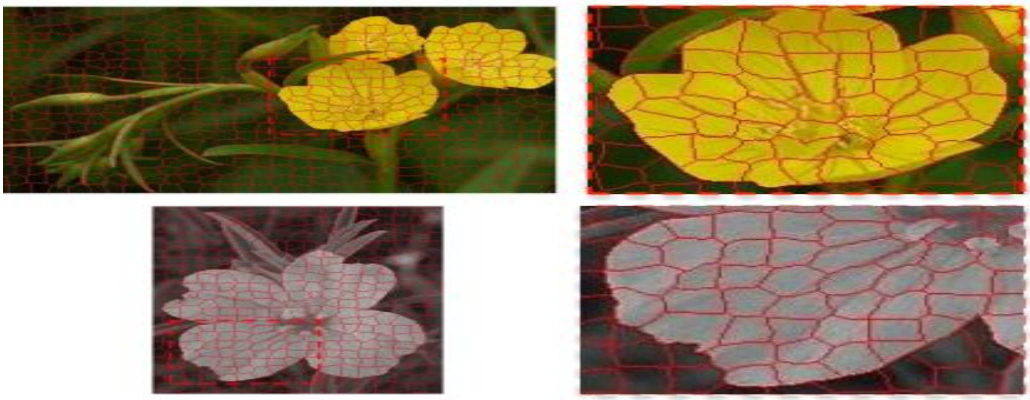

Figure (9) Super pixel segmentation results[16].

B. Feature extraction: -

The process of extracting features was carried out through three levels: low, medium, and high. Each level shows focus on a specific goal, as shown in the figure (10).

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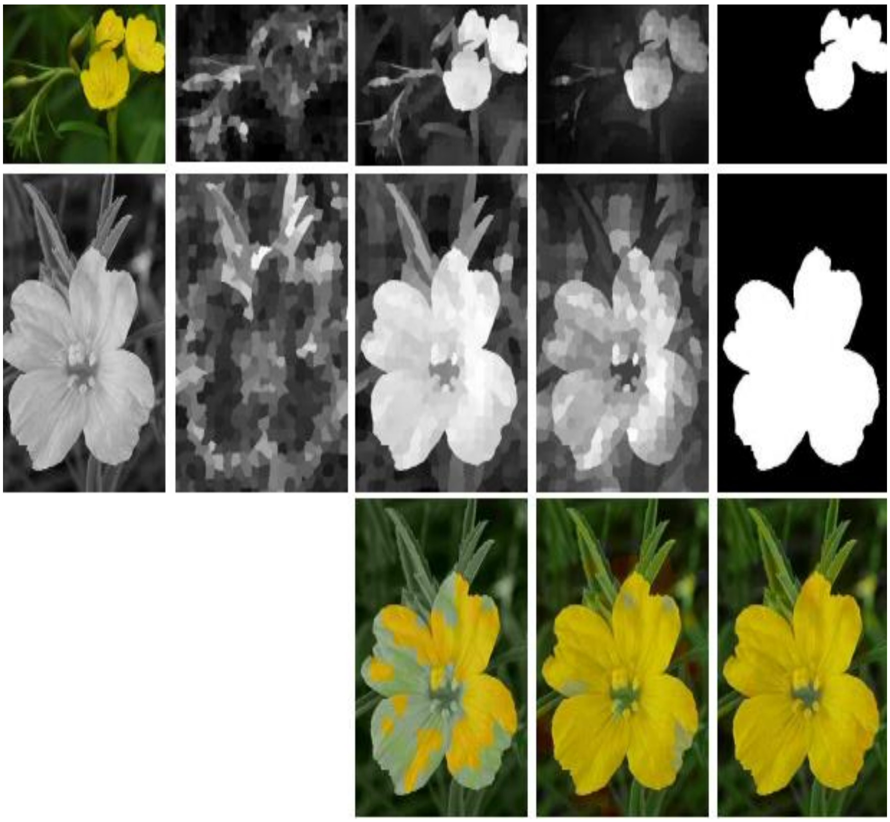

Figure (10) gray scale image, the reference image, and the feature extraction process[16] .

3- Deep learning method

Deep learning is considered one of the most important coloring techniques in the current era because of its power in giving results that bring the colored image closer to the realistic image, as well as reducing the percentage of human intervention in the coloring process to the lowest possible level [17][18]. Coloring using deep learning depends on building neural networks and training these networks on a set of images and dealing with different weights to reach a state of balance within the network, where can get the best results by adding more layers to the network as well as adding more images during the training phase[43][46]. There are many Colorization methods using deep learning:-

A- Convolutional Neural Networks (CNNs):

Neural networks are the basis of many deep learning-based colorization techniques. It consists of multiple layers of convolutional, pooling, and fully connected layers that learn how to extract features from input images[19]. CNNs can be used for comprehensive coloring tasks, given that the network autonomously forecasts the chromatic data pertinent to each individual pixel within the image, many papers proposed the usage of CNN in the coloring process which provided varying results in terms of approximating the accuracy of the coloring result to reality[44]. Many studies have performed the coloring process using CNN, and among these studies is an academic paper that uses VGC-16, which is a special type of CNN coloring method used to color gray scale images. CGC-16 is a multi-convolutional block [20]. Each segment of the structure encompasses two or three convolutional strata, succeeded by a ReLu (Rectified Linear Unit) layer, and culminating with a layer dedicated to batch normalization. Figure (11)

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and (12) show how the VGC-16 work study achieved a score of 6.8069 according to the RMSE scale, which is a high percentage when compared to the previous studies that were discussed.

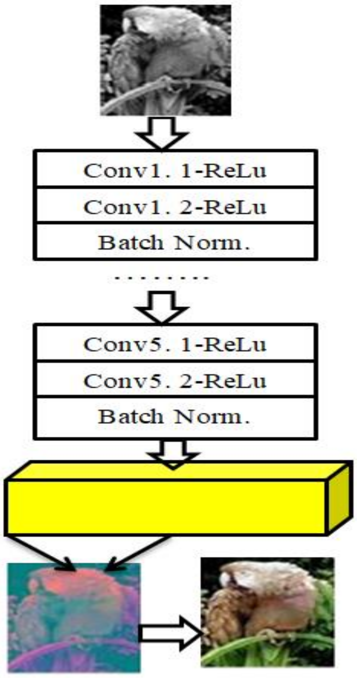

Figure (11) Architecture of the CGC-16 model [20].

a-gray **b-colored** **c-ground truth**

Figure (12) Fully automatic colorization results on Image Net[20].

Figure (13) shows the results obtained after performing the rebalancing:-

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a-no rebalance b-rebalance c-ground truth

Figure (13): The final result of balanced and unbalanced coloring[20].

Table (2) also shows a comparison between the results obtained from different methods

Table (2) results obtained by comparing some studies [20]

model	RMSE	Write down
Search1	8.8907	4.3
Search2	7.277	3.5
Search3	6.54868	3.3
CGC-16	6.8069	4.5

A convolutional neural network can be used to colorize old and heritage images. It was used to colorize ancient images of Nepal[21]. The convolutional neural network was trained using Inception-ResnetV2 by collecting image samples through back propagation over the pattern in RGB. Images for the database were obtained from various sources, including the Internet. Some of these sources are Vintage Nepal, also from the Library and Archeology Department of Nepal, cultural heritage blogs, and Getty Images. Table (3) shows the most important points about the data set used in this research:

Table (3) Shows the different types of images[21].

Data set	Culture	Heritage	History	Total
Test (gray scale)	44	65	41	150
Train (RGB)	305	350	315	970

Image pre-processing was carried out, in which images were randomly captured for both color images and grayscale images, and then the size was changed to 256 x 256, and then the RGB model was changed to the CIE three-channel model, which is L*a* b (*a*b) refers to two components of color, the other (L) refers to luminance, and this model can be used to eventually predict colors. Figure (14) shows a group of images taken from the group of images used in the testing process

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Figure(14) Some samples in dataset[21].

The pre-processing process was carried out, where images were taken randomly for both color images and grayscale images, after which the size was changed to 256 x 256, and then the RGB model was changed to the three-channel model from CIE, which is L*a*b(. *a*b) they refer to two color components, the other (L) refers to luminance, and this model can be used to predict color in the end. The network model consists of four main components Encoder unit ,Global Feature Extractor ,Fusion Layer and Decoder Unit. The results MSE, PSNR and model accuracy were obtained as 6.08%, 34.65 as well as 75.23% respectively by running the model. It showed general acceptability of the images resulting from the user study, in contrast to the display of training results, where 41.71% showed a normal rating while evaluating the coloring results as shown in figures (15,16).

Figure (15) Results from testing model[21].

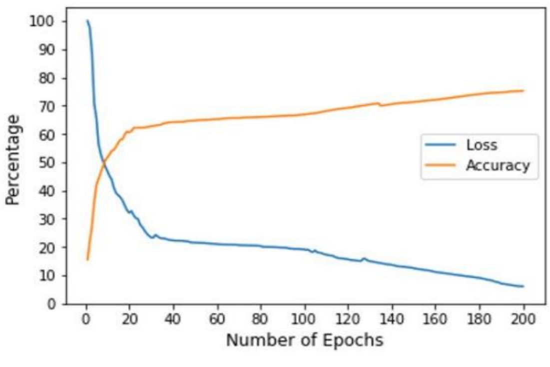

Figure (16) The MSE loss [21].

B- GANs (Generative Adversarial Networks):

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GANs consist of a generative network and a discriminative network that compete with each other during training [22]. In coloring tasks, the generator network creates colored copies of the grayscale image. This coloring process is an initial coloring stage that can be modified by changing parameters after it reaches the discriminator. At the same time, the discriminator seeks to distinguish between colored images. The original ones and those manufactured by the generator, where the realism of the color produced by the generator is judged by comparing it to copies of images on which the discriminator is trained. This competitive training helps to reach a coloring process that is as close to reality as possible. This algorithm is also characterized by the ability to form any model according to need. For example, it is possible to use more than one generator or more than one feature to produce a coloring model[48], and it has many types:

1. **Vanilla GAN:** The foundational architecture of the Generative Adversarial Network (GAN) algorithm, introduced by Ian Good fellow et al. in 2014, comprises a generator and a discriminator. These components engage in a competitive dynamic throughout the training phase[11].
2. **DCGAN (Deep Convolutional GAN):** This model uses deep convolutional neural networks to generate images. It is known for its ability to produce higher quality and more realistic images[23].
3. **CGAN (Conditional GAN):** This model extends GAN by adding additional information to both the generator and the discriminator. The generator is provided with extra information to control the generated samples and produce targeted outputs[24].
4. **WGAN (Wasserstein GAN):** WGAN aims to address the instability issues in other GAN training by using a loss function based on the Wasserstein distance between the real and generated distributions[23][25].
5. **Cycle GAN:** This model is used for image-to-image translation between two domains without the need for paired training data. It employs cyclic consistency to train two cycle-consistent generators for achieving domain-to-domain transformations[26].

Many studies have applied this algorithm in different fields, including colorization of images and videos. The process of increasing the realistic of the coloring results is done in different ways, such as using two discriminators to make the color generation process by the generator more accurate[49]. This is one way to develop an algorithm GAN to reach the highest level of accuracy in obtaining color and to solve the problem of color intersection between homogeneous regions that previous studies have suffered from, where limits can be obtained [27]. Clear separation between the components of the image resulting from the coloring process. The color space consisting of the luminance channel and the color channel was used. The algorithm structure consists of one generator and two discriminators, as shown in the figure (17,18)

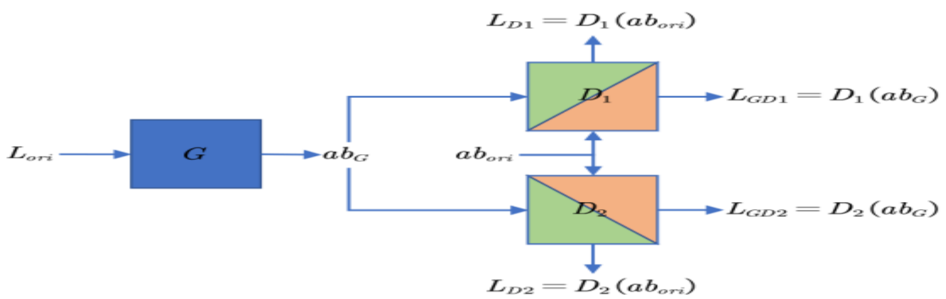

Figure (17) architecture of the system with two discriminators [27].

The generator generates a coloring of the grayscale image with something close to the natural image, and then comes the role of the discriminator, which gives a decision whether this coloring is close to the realistic image or not. The loss function is updated every time and the weights are adjusted until a state is reached in which the discriminator is deceived, and here the process of training the network takes place.

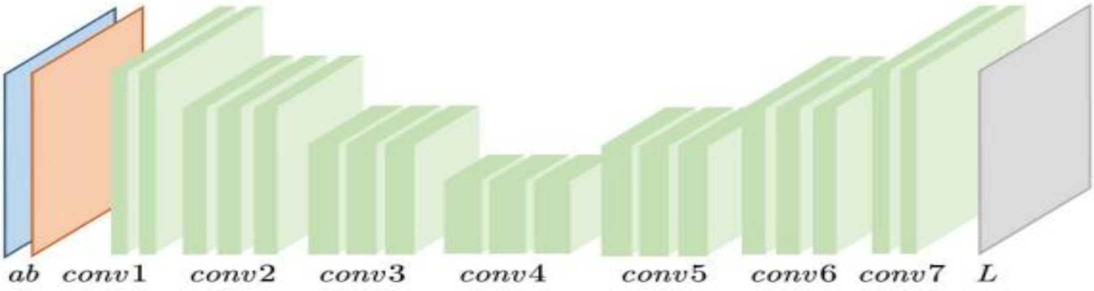

Figure (18) Discriminator network [27].

Figure (19) shows the loss function of the discriminator.

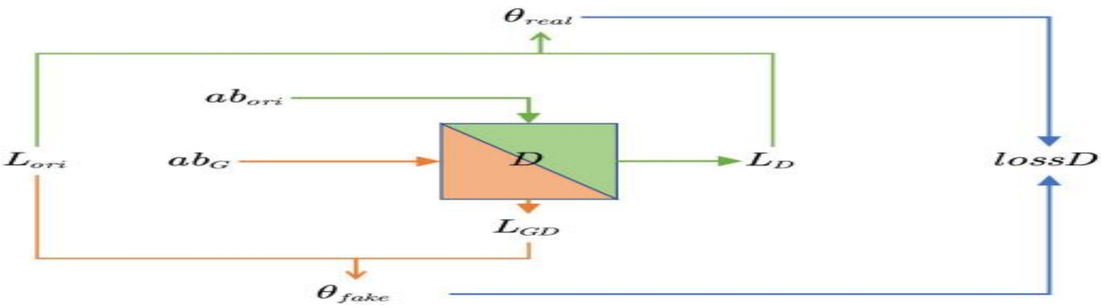

Figure (19) Discriminator loss [27]

Image Net was used where Dataset 12,000 images for training and 1,200 images for testing. In addition, 2688 images from (Sift-Flow) were used as an additional image test set. When you enter images into the form, they are resized to 256*256. Table (4) and figure (20) show some of the results obtained from applying the algorithm and comparing them with some other studies: -

Table (4) Quantitative evaluation [27].

Methods	Image Net		
	PSNR	SSIM	LPIPS
Search1	26.453	0.969	0.146
GAN	26.875	0.967	0.148
DDGAN	26.528	0.971	0.136

Methods	Sift flow		
	PSNR	SSIM	LPIPS
Search1	26.216	0.966	0.154
GAN	26.553	0.966	0.151
DDGAN	26.081	0.969	0.142

The following figure shows a group of images and a comparison of the coloring results from the proposed method with results from other methods:-

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Figure (20) some coloring results and a comparison between different methods[27]

Another example of using technology GAN is the use of the principle of what is known as the hyper column [28] which is taken from neuroscience, where all information at all levels and levels is exploited to obtain a completely automated image for coloring. The data was trained using the VGG19 model, which trained data from Image Net and the DIV2K database. The results showed that a result of 21.3795 was achieved according to the PSNR scale. This result is considered a good result compared to previous studies that used other staining methods. Adding the Hyper Column principle with the GAN algorithm gave a better result than several methods, as shown in table (5)

Table (5) Evaluation results [28].

Algorithm	PSNR
Search1	22.1949
Search2	22.1232
Search3	21.5156
Search4	21.3795
Search5	21.2248
Search6	21.0773
Search7	20.8710
Search8	17.9634
Proposed	22.5248

Colorization process in training and testing phases can be explained in figures (21, 22)

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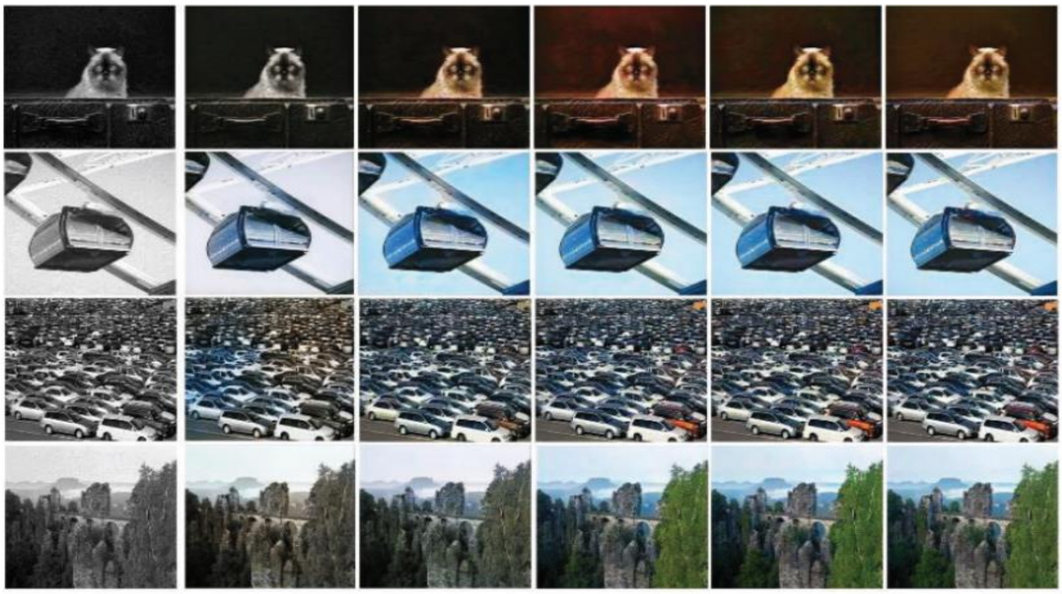

Figure (21) Colorization in training phase[28].

Figure (22) colorization in testing phase[28].

Two methods have been combined to implement the coloring process, namely CGAN and U-Net. This is done initially using CGAN technology to generate a color image from a gray audio input, and then the output of this process is used as an encoded input to the U-NET architecture [29]. This study accomplished the task in several steps start the grayscale image preprocessing and noise removal process as shown in figure (23).

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Figure (23) Examples of images from the database [29].

Determine the appropriate architecture for each of the two models used and the function of each will be illustrated in figure (24). The training process on grayscale images and their corresponding color images Adjusting the elements of the model that control the accuracy and diversity of the results, such as the batch size and the loss function. By merging the two models and creating a main model that performs the training and testing process. The working mechanism of this model can be illustrated through the figure (24):-

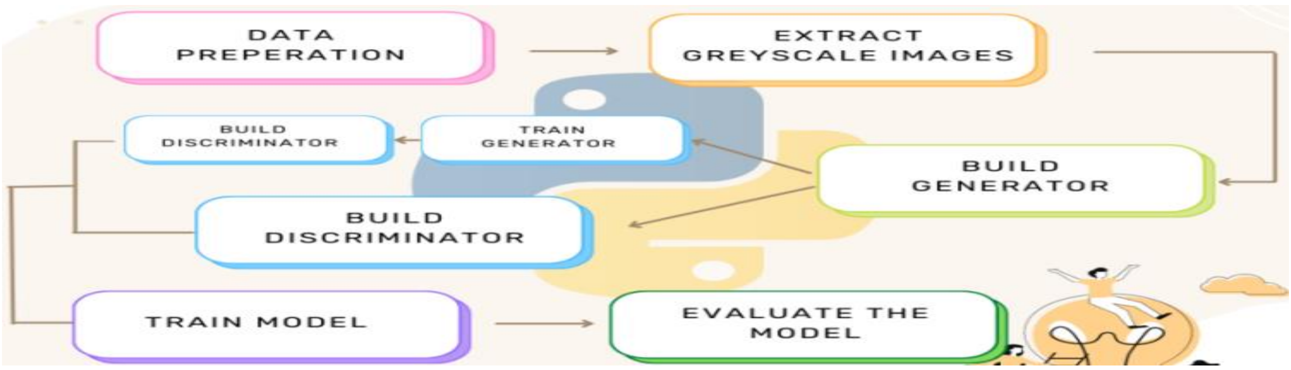
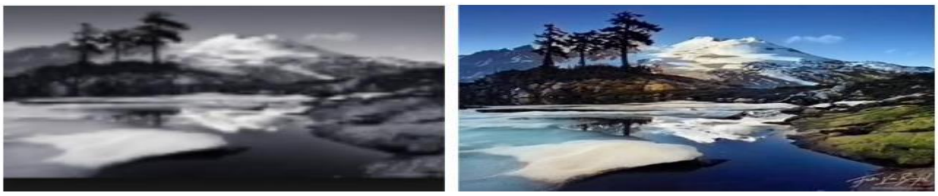


Figure (24) shows how the model works in terms of data processing, data flow, and building the generator and discriminator parts of the network[29].

This study showed outstanding results and high accuracy in twinning gray scale input images. The process of testing the accuracy of the results is done By combining two models and creating a main model that performs the training and testing process, this study showed outstanding results and high accuracy in twinning the input gray scale images as shown in figure (25).



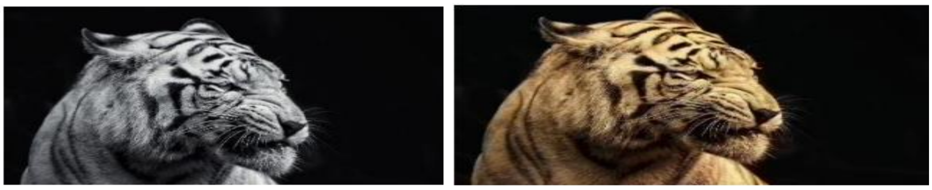


Figure (25): coloring results [29].

One of the applications of coloring is coloring aerial photographs of terrain, called SAR, which are gray scale images that are colorized. MC-GAN technology was used to colorize this type of gray scale images. Due to its nature, it suffers from two main problems: noise and the lack of a clear gray scale [30]. MC-GAN technology is proposed to address these issues through coloring. The use of a cycle-consistent generative adversarial network in the above-mentioned research is an advantage for terrain images. MC-GAN was tested on SEN1-2 dataset.The MC-GAN algorithm was applied to two terrain classes in landscaped areas and rural areas as shown in figures (26, 27). This method is distinguished by the fact that it deals with the vector mask principle, which other methods of GAN algorithms do not deal with. The table below shows the results obtained using the research method. Compared to other methods for both landscape and rural terrain: -

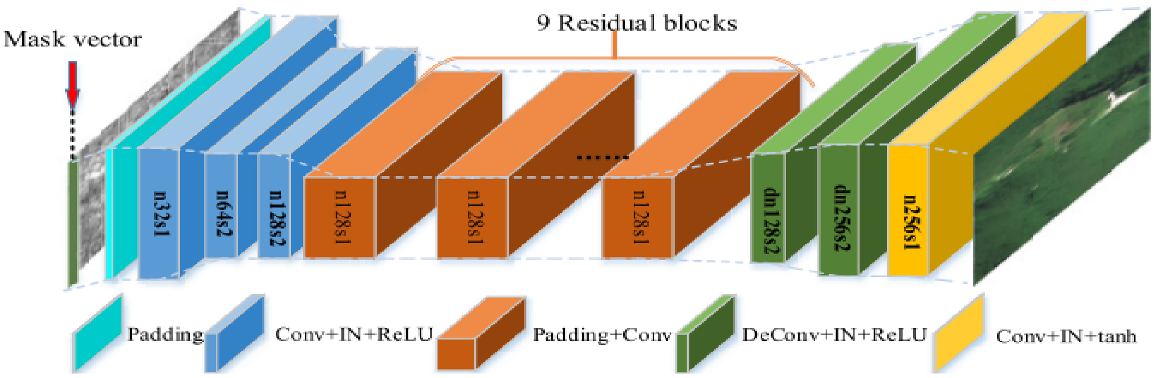


Figure (26) Structure of two generators [30].

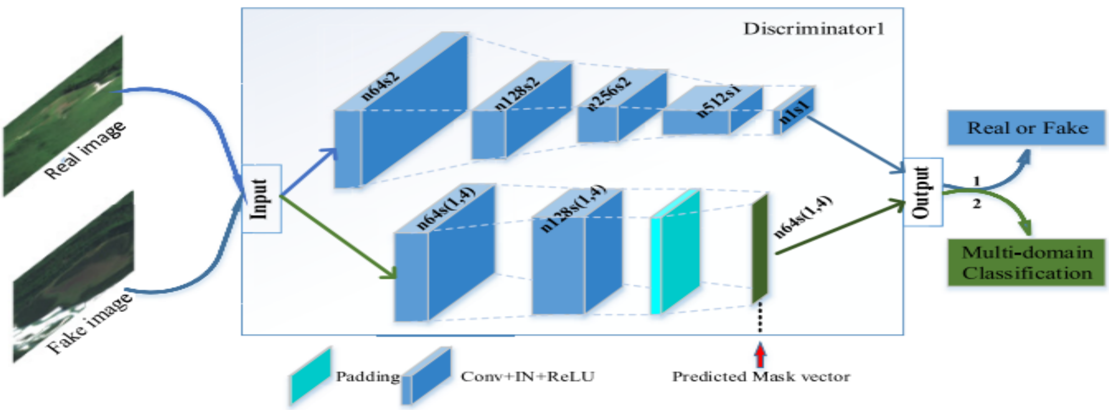


Figure (27) Structure of two discriminators [30].

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Table (6) shows a set of distinctive results of the proposed technique compared with other techniques and using different accuracy measures: -

Table (6) Quantitative results between MC-GAN , Cycle-GAN and Pix 2 Pix[30].

region	paired	method	PSNR	SSIM	COSIN	FID
Neutral landscape	Y	Pix2 pix	23.345	0.471	0.950	86.015
	N	Cycle GAN	16.403	0.326	0.817	104.629
	N	M-C GAN	19.132	0.419	0.882	95.901
Urban rural integration	Y	Pix2p ix	16.350	0.187	0.907	172.793
	N	Cycle GAN	12.055	0.092	0.785	147.646
	N	M-C GAN	14.066	0.117	0.853	136.725

4-Attribute-based method

Attribute-based coloring is a technique used in data visualization and information design to assign colors to data points or objects based on their attributes or properties. Instead of using random or arbitrary colors, attribute-based coloring aims to use color as a meaningful visual encoding to represent specific data characteristics [47]. The process of attribute-based coloring involves selecting a set of attributes or variables that are relevant to the data being represented. These attributes can be quantitative (such as numerical values) or qualitative (such as categories or labels). Each attribute is then associated with a specific color or a color palette [31].Here are a few examples of attribute-based coloring:

1- Categorical Coloring: If you have categorical data, you can assign different colors to each category.
2- Sequential Coloring: Sequential coloring is used when you have ordered or sequential data. It involves using a gradient or a sequential color scheme to represent a range of values.
3- Diverging Coloring: Diverging coloring is suitable for data with a distinct midpoint or a critical value. It involves using two contrasting colors to represent values above and below the midpoint.
4- Heatmap Coloring: Heat maps are often used to visualize matrices or tables with color-coded cells.

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Sometimes a specific color system can be used as a determinant of color qualities and generate a color model based on a reference image such as the color system (YCbCr) [32] which can be used in the process of coloring a gray-scale image. This color space model consists of three channels, one for the gray scale image and two other channels representing the color direction. This model completes its task by selecting both the gray scale image and the reference image, and then the reference image is converted into a system (YCbCr) and then the transformation of the grayscale image into three layers is achieved after it goes through several transformation, comparison, and tracking operations between the pixels of the gray scale image and the pixels of the modified reference image. Table (7) summarizing the advantages and limitations of the coloring methods mentioned in the above researches.

Table (7) comparison of essential methods

Method	Positives	limitation
Scribble Method	-The scribble coloring method gives the user freedom in the process of specifying the color to be added to the image area, and the image area also has greater color customization [33]. -The scribble coloring method is characterized by being a simple method that does not require complex mathematical operations.	- Because it is done manually, it requires more time than other coloring methods - Since it does not include any automatic coloring methods, it does not give accurate results when compared with other methods [34].
Example method	- Choosing a reference image as a color reference is important, especially in cases where the color needs to be chosen and applied according to the user's desire [35]. The coloring method using the example is also considered more accurate than the scribbling method, especially with care in choosing the reference image	- Relying on a reference image in this way may make it limited in some cases Within the color range of the reference image and makes it more limited Failure to carefully choose the reference image may cause problems with the color image [36]
Deep learning	-The method that requires the least human intervention to accomplish the coloring [37]. -The results of this method, especially new technologies, are excellent, enjoyable, and attractive to the viewer also Its reliance on training the model on a database makes it more comprehensive. [38].	-Depending on deep learning techniques for training, large databases must be provided, and sometimes these rules can be generated if they are not available. Sometimes we need a specific type of data for training, which is difficult to provide. Likewise, deep learning models are considered more complex than other coloring models because they use mathematical principles whether It was one or more mathematical methods to achieve coloring [39] [40] [41].

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3. Conclusion

In this paper, a general overview of the coloring methods for coloring gray scale images will be touched on, where the coloring methods dividing into three methods in terms of the most human intervention to the least, and in terms of the least accuracy to the most. So started by giving a summary of the coloring method based on scribbling, which depends on scribbling the colors that are distributed to specific areas in the image, and then the color is distributed and spread to the neighboring areas, that is, the neighboring pixels, according to the amount of light intensity in the gray scale image, on which the amount of color distribution in the colored image is based, and noticed Through the previous studies that presented, this method is easy to use, but it does not give excellent results, meaning that the resulting color is not close to the truth. Then discussed the coloring method based on the reference example, that is, there are gray scale images, and there must be one or more reference images that are considered a coloring reference that can be used to distribute the color on the target image. touched on previous research papers that referred to, which used this method in coloring and had results. Acceptable, but it suffered from the control of the reference image as a determinant of the coloring mechanism, so great effort must be made in the process of selecting the reference images. also touched on coloring methods based on deep learning, which are the most widely used and most innovative methods, as artificial intelligence techniques and their algorithms are introduced into coloring images. have explained through the research to which previously referred the use of the method CNN and GAN has given this The methods produced excellent results by bringing the resulting image closer to reality, and the results of the algorithm were GAN the best, most realistic and accurate results. Hope that this research will be a useful gesture for the research community so that there is hope for producing a wonderful research product related to image processing.

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