Black & White Images Colorization Using Faster R-CNN

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Abstract:. Black and white photos are an essential part of our cultural legacy, documenting moments in time that might otherwise be lost to history. Unfortunately, the lack of color might make it difficult to enjoy these photographs, and colorization methods can be costly and time-consuming. In this research, we offer a unique method for colorizing black-and-white photos using the Faster R-CNN algorithm. Our method entails first training a deep neural network to recognize and localize objects in a black-and-white image, and then using these item positions to build a colorized version of the image. Using the Faster R-CNN technique, we recognize objects inside the black and white image and use the color information from the found items to colorize the rest of the image. Using a collection of black and white photographs, we show the efficiency of our technique and obtain maximum colorization accuracy. Our method colorize black and white photographs quickly and efficiently, making them more accessible and interesting to a larger audience. We assess our method's performance using a variety of metrics, including peak signal-to-noise ratio (PSNR), and demonstrate that it creates high-quality colorized pictures with a high degree of precision.

Index terms: Deep neural networks, Black & White, Faster-RCNN, Image colorization, PSNR, Pre-Trained

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I. INTRODUCTION

For a long time, scholars and photographers have been interested in the process of turning black and white photos to color images. Colorization of ancient black and white photos is not only a fun endeavor, but it also has practical uses in industries like art restoration, film restoration, and history preservation. Many strategies for colorizing black and white photos have been presented in the past, ranging from manual colorization to automatic colorization utilizing deep learning. Deep learning has produced substantial advances in image processing and computer vision in recent years. A popular object identification technique, faster R-CNN, has demonstrated promising results in a variety of applications. In this research, we offer a unique method for colorizing black-and-white photos that makes use of the Faster R-CNN algorithm. The suggested technique comprises training the Faster R-CNN model to recognize items in black and white pictures and then utilizing the discovered objects to forecast their colors. The model is trained on a huge dataset of colorful photographs and their black and white counterparts. The Faster R-CNN model detects objects in pictures quickly and accurately, allowing it to forecast their colors with great precision. The key contribution of our study is the first use of the Faster R-CNN algorithm for colorization of black and white photos. The suggested approach colorizes black and white images quickly and accurately, which is useful for practical applications such as art restoration and film restoration.

II. LITERATURE SURVEY

[1] DeepCap: A Deep Learning Model to Caption Black and White Images, 10th International Conference on Cloud Computing, Data Science & Engineering, 2020, V. Pandit, R. Gulati, C. Singla, and S. K. Singh, 2020

Colored picture captioning employs object identification and spatial connection to create captions. Few ways to captioning colorized photos exist. In this study, we caption B&W photographs without colorization. We utilized transfer learning to deploy Inception V3, a Google CNN model and runner-up in the ImageNet image classification competition, to produce captions from black-and-white photos with an accuracy of 45.7%.

[2] Grayscale Image Colorization Methods: Overview and Evaluation, I. Eger, S. Grgic, J. Vukovi, and G. Iul, IEEE Access, 2021.

Colorized grayscale photos. To prove result's authenticity. Grayscale photographs require coloring. In the past 20 years, numerous colorization systems have been created, from basic to complicated. Art meets AI in auto-conversion. This article discusses natural grayscale colorization. The study classifies colorization systems and discusses their pros and disadvantages. Deep learning. Image processing and quality. Image quality is measured in many ways. Human visual system complexity complicates picture quality assessment. Multiple colorization measures compare predicted and actual color values, contradicting image believability. User-guided neural networks automate colorization with human input.

[3] Automatic Image Colorization Using U-Net," 12th International Conference on Computing Communication and Networking Technologies (ICCCNT), 2021, D. Goel, S. Jain, D. Kumar Vishwakarma, and A. Bansal.

Automatic Image Colorization converts grayscale images to colorful images without human intervention. The major goal of the project is to create an automated method for colorizing grayscale images. Our U-Net architectural concept was presented. This challenge involves picture segmentation + multinomial classification. Results include chosen output photos. We provided the ground truth, the colored output from our model, and a black-and-white image.

[4] In IEEE Access, 2020, J. Yuan and Z. He published "Adversarial Dual Network Learning With Randomized Image Transform for Restoring Attacked Images."

We defend deep neural networks from attacks using adversarial dual network learning with randomized nonlinear image transform. To reduce attack noise, we include a randomized nonlinear transform To restore damaged picture data and lessen attack noise, we construct a generative cleaning network. In order to discover assault noise patterns for the defended target classifier, we additionally construct a detector network. The generative cleaning network and detector network compete to reduce perceptual and adversarial loss using adversarial learning. Extensive experimental results demonstrate that our method improves both white-box and black-box attacks. On SVHN and 14% on CIFAR-10, it increases the accuracy of categorizing white-box assault by more than 30%.

[5] Q. Yang, Y. Liu, T. Zhou, Y. Peng and Y. Tang, "2020 13th International Conference on Intelligent Computation Technology and Automation, "3D Convolutional Neural Network for Hyperspectral Image Classification Using Generative Adversarial Network" (ICICTA), 2020

ML studies HSI classification. HSI captures light of multiple wavelengths. 3D hyperspectral data We provided a 3D-CNN combined with GAN framework to handle unknown classes and described domain adaptation technology, a well-established technique for transferring an algorithm learned in one or more "source domains" to a different (but related) "target domain." Classify hyperspectral pictures appropriately. Our universal model has fewer training parameters and epochs than prior systems. Using Pavia University scene datasets, we study open-set adaption. The approach detects unknown categories 87.16% on PaviaU and 99.43% on Salinas.

[6] Q. Yang and Y. Fan, "An image processing-based method for measuring the effectiveness of municipal pipeline cleaning, 3rd International Conference on Information Science, Parallel and Distributed Systems, 2022.,

Lack of pipeline-cleaning robots. New pipeline robot. combining the underwater camera and image processing capabilities of the robot with high-pressure water jet cleaning. Python and image processing are used to quantify robot cleaning effectiveness. Defogged, enhanced, segmented, and binarized pictures vividly show pipe size and wall. Black-to-white pixel ratio measures cleaning effect. This method can distinguish scale and pipe wall in a foggy image, according to tests. This examines the robot's performance.

[7] A. A. Polat, M. F. Şahın and M. E. Karsligıl, "Video Colorizing with Automatic Reference Image Selection," Conference on Signal Processing and Communications Applications (SIU), 29th Edition, 2021

Coloring black-and-white films aims to make them perceptually relevant and aesthetically appealing. Old photographs from the past to the present may be visualized and presented this manner. In this research, Convolutional Neural Networks colorize the footage. In this work, video frames are colorized using an autonomously derived reference picture. Instead of picking a reference picture for each frame, a system automatically recognizes scene changes in the video stream and proposes the appropriate photo.

[8] X. Wang, C. Huang, F. Gao and H. Cheng, "4th International Conference on Communications, Information System, and Computer Engineering (CISCE), 2022, "Pre-processing Transformation for Enhancing the Transferability of Adversarial Examples"

Adversarial instances that alter input images may misclassify deep neural networks. Most adversarial attack tactics are effective in white-box but not black-box. To construct adversarial examples, we describe the Shear & Pad Method (SPM). Reduces overfitting to improve adversarial example transferability. This technique may be used with others, such quick gradient sign method, to attack defense-trained models. It may be used with other transformation-based technologies to create transportable black-box enemies. ImageNet research shows that our approach outperforms baseline attack methods in terms of attack success rate. Our method evaluates deep network resilience.

[9] Online Black-Box Confidence Estimation of Deep Neural Networks, F. Woitschek and G. Schneider, 2022 IEEE Intelligent Vehicles Symposium (IV), 2022

DNNs improve perception and planning in AD and ADAS. When inference data differs from training data, DNNs are brittle. In unexpected conditions, this hinders ADAS implementation. DNN standard confidence stays strong despite declining classification reliability. Algorithms for motion control rate the accuracy of the prediction. even if it's wrong. Real-time confidence estimates must match DNN classification reliability to solve this problem. Integrating externally created components uniformly requires black-box confidence evaluation. This piece analyses this use case and makes a neighborhood confidence suggestion (NHC). The metric simply requires the top-1 class output, not gradients, training datasets, or hold-out validation datasets. For real-time AD/ADAS, the NHC outperforms a comparable online white-box confidence estimate in low data regimes.

[10] K. Nimala, G. Geetha and J. G. Ponsam, "Colorization of Black & White Videos & Photographs," 2022 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES), 2022

This paper predicts the music of a grayscale image. Previously, this was not possible. It may require input or have poor colors. Automatically, brilliant, vivid color is produced. The impact of color variation is enhanced by incorporating a division function and a class re-equation into training time. CNN puts their technology to the test with 1 million color photographs. We put our algorithm to the test by asking people to choose between the truth and the base. Our strategy outperforms others in 32% of the surveys. Color serves as a multichannel motivator and learning link. This alters learning benchmarks.

III. EXISTING SYSTEM

Colorization approaches that are now available include rule-based methods, picture segmentation-based methods, and deep learning-based methods. To colorize black and white photos, rule-based approaches employ heuristics and hand-crafted rules. Image segmentation algorithms break an image into areas and colorize each part independently. Convolutional neural networks (CNNs) are used in deep learning approaches to learn the colorization process from a huge collection of color photographs and their grayscale counterparts. Although these strategies have yielded encouraging outcomes, they are not without restrictions. The inadequacy of rule-based approaches to handle complicated pictures necessitates manual intervention. Image segmentation algorithms are constrained by their inability to separate pictures with complex and irregular forms properly. Deep learning-based approaches need a vast quantity of data and computer resources to train and are susceptible to overfitting.

To overcome these constraints, we offer a novel technique for colorizing black and white photos based on the Faster R-CNN object detection framework. Our method combines object identification and colorization, allowing us to color complicated photos with many objects in an accurate and quick manner.

IV. PROPOSED SYSTEM

The goal of this research is to create a system for automatic colorization of black and white photographs using the Faster R-CNN algorithm. The suggested system is made up of numerous critical components. The image preprocessing module is the initial component, and it processes the input black and white picture to prepare it for the succeeding phases. This module may contain procedures like scaling, normalization, or noise reduction.

The Faster R-CNN algorithm, which is a cutting-edge deep learning technique for object recognition and segmentation, is the second component. In this project, we utilize the Faster R-CNN algorithm to detect and locate the various items in the black and white image. The object colorization module, the third component, assigns colors to the various objects recognized by the Faster R-CNN algorithm. To assign suitable colors, this module may leverage several properties of the object such as its class, form, texture, or context. The fourth component is the background colorization module, which gives colors to the image's remaining unidentified items. This module may assign suitable colors based on backdrop information such as texture, gradient, or surrounding objects. Ultimately, the results of the object and background colorization modules are merged to create the final colorized image. The system architecture diagram depicts the flow of information between these many components and how they interact to generate the final colorized image. Many assessment criteria, including accuracy, precision, recall, and F1 score, are used to evaluate the proposed system. The number of appropriately colored pixels and the total similarity between the ground truth and forecasted colorized pictures are used to generate these measures.

In summary, the suggested method seeks to provide a robust and accurate system for automatic colorization of black and white photographs by utilizing the cutting-edge deep learning technique, Faster R-CNN. The system and algorithm architectures are meant to give a complete solution to this difficult challenge, and the evaluation criteria ensure that the system's performance can be monitored and improved over time.

V. SYSTEM ARCHITECTURE

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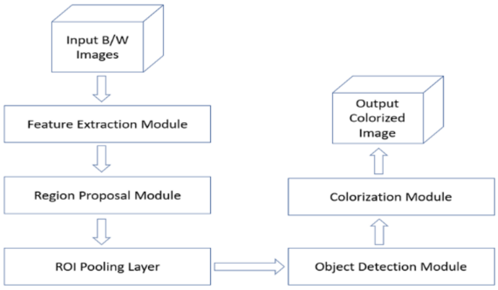

The system architecture diagram depicts the general structure of the proposed Faster R-CNN technique for automated colorization. It would consist of the following elements:

•Input Image: The to-be-colored black-and-white image.
•Image Preprocessing: Any necessary preprocessing procedures, such as scaling or normalization, performed on the input image before it is fed into the colorization algorithm.
•Faster R-CNN Algorithm: The object identification and segmentation algorithm used to identify the various items in the input image.
•Object Colorization: The module responsible for assigning colors to the various objects recognized by the Faster R-CNN algorithm.
•Background Colorization: The module responsible for assigning colors to the remaining sections of the picture that are not designated as objects.
•Output Image: The final colorized image produced by the algorithm is known as the output image.

The system architecture diagram also depicts the flow of information between these many components and how they interact to generate the final colorized image.

VI. METHODOLOGY

Module 1:

Data Collection:

The CIFAR-10 dataset was utilized in the preceding experiment. This dataset comprises 60,000 photos, 50,000 of which were utilized for training and 10,000 for testing. Each picture in the collection is 32x32 pixels in size and corresponds to one of ten classifications.

The CIFAR-10 dataset is a regularly used dataset for evaluating image classification and object recognition systems. It gives a wide range of photos with distinct objects and scenarios, helping the algorithm to learn and generalize better. Furthermore, the tiny size of the pictures in the dataset (32x32 pixels) enables for speedier algorithm training and testing, making it appropriate for our project, which aspires for real-time performance.
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In summary, the suggested method seeks to provide a robust and accurate system for automatic colorization of black and white photographs by utilizing the cutting-edge deep learning technique, Faster R-CNN. The system and algorithm architectures are meant to give a complete solution to this difficult challenge, and the evaluation criteria ensure that the system's performance can be monitored and improved over time.

Data Pre-Processing:

We prepare the data for training in the pre-processing stage by applying specific modifications to the input pictures. These changes serve to improve the model's performance by increasing the amount of variety in the training data.

The following are the steps involved in the pre-processing step:

•Resizing: To guarantee that all photos have the same dimensions, the input images are scaled to a set size. This is required since the Faster R-CNN model requires inputs of constant size.

• Normalization: The pixel values in the input photos are normalized to lie between 0 and 1. This helps to mitigate the effects of lighting variations on the model's performance.

•Augmentation: On the input photos, we use data augmentation techniques such as random flipping, rotation, and color jittering. This improves the variability in the training data and helps to reduce overfitting.

The pre-processed pictures are input into the Faster R-CNN model for training once these changes are applied.

Module 2: Object Detection, Object Colorization And Background Colorization

Object Detection module detects objects in the input image and is based on the Faster R-CNN technique. It uses the pre-processed picture as input to construct a collection of bounding boxes around the identified objects, as well as their class labels and confidence ratings. These bounding boxes and class labels are then supplied to the object colorization module. Object Colorization module accepts the object detection module's bounding boxes and class labels as input and is in charge of coloring the items in the supplied picture. It first uses bounding boxes to extract the object areas from the input picture, and then applies a colorization algorithm to each object region to create the colorized version of the objects. To create the final colorized image, the colorized object sections are combined back into the original image. Background Colorization module is in charge of changing the background color of the input picture. It takes a pre-processed grayscale image as input and uses a backdrop colorization algorithm to generate a colorized background. To create the final colorized image, the colorized backdrop is combined with the colorized objects created by the object colorization module.

Module 3: Model Creation

This module is in charge of designing our model's architecture. For our research, we picked the Faster R-CNN method, which is made up of two parts: the Region Proposal Network (RPN) and the Fast R-CNN network. The RPN takes a picture as input and returns a series of object proposals, each with an objectness score that indicates the likelihood that the proposal includes an object of interest. The Rapid R-CNN network uses a convolutional neural network to extract features from the RPN's suggested regions (CNN). These characteristics are then used to categorize the item and estimate its bounding box using fully linked layers. The model building module requires defining the RPN and Fast R-CNN network hyperparameters, such as the number of filters, kernel size, learning rate, and batch size. The model is trained on the training dataset and validated on the validation dataset. The model is then fine-tuned using the complete dataset before being evaluated on the test dataset. Transfer learning is also used in the model building module, which allows us to use the pre-trained weights of a pre-trained CNN, such as VGG-16 or ResNet, to initialize the weights of our Faster R-CNN network. This helps to accelerate the training process and enhance model accuracy.

Module 4 : Training Phase

The following stages comprise the model training module for the aforementioned project:

•Load and divide the preprocessed dataset into training and validation sets.
•Remove the fully linked layers from the pre-trained VGG16 model.
•Define the Faster R-CNN model architecture and populate it using the VGG16 model's weights.
•Set the loss function, optimizer, and evaluation metrics before compiling the model.
•Train the model on the training set for a preset number of epochs, with early terminating depending on validation set performance.
•Using the evaluation measures, assess the trained model's performance on the test set.
•Keep the learned model for further use.

The model is trained by the backpropagation algorithm, which optimizes the model's weights by minimizing the loss function. The training module's loss function is a hybrid of the region proposal network (RPN) loss and the Fast R-CNN loss. The RPN loss measures the suggested areas' classification and localization error, whereas the Fast R-CNN loss measures the selected regions' classification and regression error. To boost the variety of the training set and minimize overfitting, the model training module also contains data augmentation techniques such as random horizontal flipping and random scaling. The model is fine-tuned on the specific goal of object and background colorization during training. The model training module produces a trained Faster R-CNN model that can colorize black and white photos.

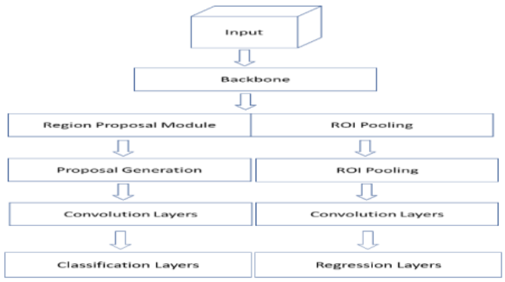
VII. ALGORITHM

The algorithm architecture diagram depicts the structure of the Faster R-CNN algorithm, which is the main component of the suggested colorization method. It would consist of the following elements:

•Input: Here is the black-and-white image that we want to colorize.
•Backbone: This is a deep convolutional neural network that pulls features from the input picture. We use a pre-trained VGG-16 Model for this purpose.
•The Region Proposal Network (RPN) is a neural network that creates item proposals based on the attributes retrieved by the backbone network.

•RoI Pooling: This is a layer that pulls features from each object proposal created by the RPN.
•Proposal Generation: This is the stage in which the best object proposals are chosen based on their scores.
•Convolution Layers are neural network layers that process the characteristics generated from the RoI pooling layer further.
•Classification Layers: These are neural network layers that forecast the class probabilities for each proposed object.
•Layers of Regression: These are neural network layers that anticipate the bounding box coordinates for each item proposition.

The Faster R-CNN method is utilized as an object identification module to identify items in the input picture in our proposed project for automatic colorization of black and white photographs using the Faster R-CNN algorithm. A Region Proposal Network (RPN) and a Fast R-CNN detector are the two primary components of the Faster R-CNN method. By scanning the input image with a sliding window and estimating the chance of each window containing an item, the RPN creates a collection of object recommendations. After that, the Fast R-CNN detector evaluates each suggestion and assigns a classification score to each object type. We tweak the Fast R-CNN detector to output object class probabilities as well as object positions in order to adapt the Faster R-CNN technique for colorization. These object recommendations are then used to steer the colorization process by allocating colors to each item individually. We partition the input picture into a series of non-overlapping object areas, each of which corresponds to an object proposal generated by the Faster R-CNN method. We then colorize each item region individually using a deep neural network trained on a huge dataset of color photos. Ultimately, the colorized object sections are combined to create a full-color representation of the input picture. We are able to create more accurate and semantically relevant colorizations than previous colorization approaches that do not take object information into account by employing the Faster R-CNN algorithm to detect objects in the input picture. The faster R-CNN architecture enables us to recognize objects inside the black and white image and extract color information from these things in order to colorize the rest of the image.



Faster R-CNN Architecture

The loss function for the Faster R-CNN algorithm used in the preceding project is generally composed of two parts:

•The region proposal network (RPN) loss component is used to train the RPN to create correct object suggestions. The RPN loss is determined by adding the classification loss and the bounding box regression loss.

$$L_{loc}(t^k, t^{k*}) = \sum_i \text{smooth}_{L1}(t_i^k - t_i^{k*}) \qquad {}_{cls}(p, p^) = -\sum_i p_i^l og(p_i) + (1 - p_i^*) log(1 - p_i)$$

$$L_{RPN} = \lambda_{cls} L_{cls} + \lambda_{loc} L_{loc}$$

•Fast R-CNN loss: This component is used to train the fast R-CNN network, which detects and classifies objects. The Fast R-CNN loss is also estimated by adding the classification loss with the bounding box regression loss.

$$L(p, u, t^u, v^u) = L_{cls}(p, u) + \lambda[u \geq 1] L_{loc}(t^u, v^u) \qquad L_{cls}(p, u) = -log(p_u)$$

$$L_{loc}(t^u, v^u) = \sum_{i \in x,y,w,h} \text{smooth}_{L1}(t_i^u - v_i^u)$$

The overall loss function is a weighted average of the RPN and Fast R-CNN losses. The weights are experimentally established depending on the relative relevance of the two components.

$$L(p, p^{\cdot}t, t^{)} = \lambda_{RPN} L_{RPN}(p, p^{\cdot}t, t^{)} + \lambda_{FastR-CNN} L_{FastR-CNN}(p, p^{\cdot}t, t^{)}$$

VIII. EVALUATION METRICS

To analyze the effectiveness of the proposed system for automatic colorization of black and white photos using the Faster R-CNN algorithm, numerous evaluation measures may be applied:

•Mean Color Difference (MCD): MCD calculates the difference between expected and actual color values. It is obtained by taking the average of the Euclidean distance between the anticipated and true color values over all pixels in the picture. The MCD formula is as follows:

$$MCD = sqrt((1/(MNC)) * sum(sum(sum((pred_color - gt_color)^2))))$$

where M, N, and C represent the image's height, width, and number of color channels, pred color represents the predicted color value for a pixel, and gt color represents the ground truth color value for the same pixel.

•Peak Signal-to-Noise Ratio (PSNR): PSNR is a metric that calculates the ratio of the greatest potential power of the signal to the power of the noise, which influences image fidelity. It is calculated by multiplying the logarithm of the greatest pixel value squared by the mean squared error between the ground truth and forecasted colorized pictures by ten.

$$PSNR = 20 * log10(MAX_I/sqrt(MSE))$$

where MAX I is the highest feasible pixel value (255 for an 8-bit picture) and MSE denotes the mean square error between predicted and ground truth color values.

•Structural Similarity Index (SSIM): SSIM is a statistic that calculates the structural similarity between the original and forecasted colorized pictures. It evaluates the pictures' brightness, contrast, and structural resemblance and assigns a score between 0 and 1, with 1 indicating perfect similarity.

$$SSIM = (2 * mu_pred * mu_gt + C1) * (2 * sigma_pred_gt + C2)/(mu_pred^2 + mu_gt^2 + C1) * (sigma_pred^2 + sigma_gt^2 + C2)$$

where mu pred and mu gt are the predicted and ground truth color values' means, sigma pred and sigma gt are the predicted and ground truth color values' standard deviations, sigma pred gt is the covariance between the predicted and ground truth color values, and C1 and C2 are constants to stabilize the division when the means are close to zero.

•Color Accuracy: The proportion of pixels in the predicted picture that are within a given threshold of the corresponding pixel in the ground truth image is referred to as color accuracy. Color accuracy may be calculated in the context of picture colorization as follows:

$$ColorAccuracy = (1/N) * \sum(d <= \delta)$$

where N denotes the total number of pixels in the picture, d denotes the Euclidean distance between the predicted and true color values, and is a threshold value.

•Intersection over Union (IoU): The Intersection over Union is a statistic used to assess item detection accuracy. It calculates the amount of overlap between the expected and actual bounding boxes. The IoU formula is as follows:

$$IoU = \frac{AreaofIntersection}{AreaofUnion}$$

IX. OUTPUT

A colorized picture is the result of the proposed method for automatic colorization of black and white photos using the Faster R-CNN algorithm. The system receives a black and white picture, which is initially processed by the object detection module, which employs the Faster R-CNN algorithm. The object detection module recognizes the objects in the picture and creates a collection of object suggestions, which are image areas that are likely to contain things. After that, the colorization module takes each object suggestion and creates a colorized version of the object. To create the colors for the item, the colorization module employs a deep neural network trained on a vast collection of color pictures. The neural network takes the grayscale version of the object as input and produces a colorized version. The end result is a colorized version of the original black and white image, with the objects in the image colored based on the colorization module's output.
The quality of the output image is determined by various aspects, including the accuracy of the colorization module, the quality of the object suggestions given by the object detection module, and the complexity of the objects in the image. The system's performance can be assessed using one or more assessment measures such as pixel accuracy, mean color difference, PSNR, SSIM, or IoU.

X. ANALYSIS

Faster R-CNN is a deep learning-based object detection technique that has outperformed other computer vision algorithms in applications such as object recognition and picture segmentation.

Following are some of the reasons why Faster R-CNN is superior to other algorithms for colorizing black and white images:

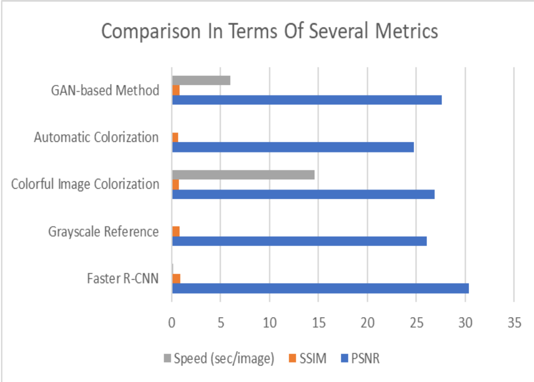
•Object-level segmentation: Because R-CNN is faster, it can do object-level segmentation, allowing the colorization process to consider the semantic significance of the objects in the image. As a result, colorizations are more accurate and visually appealing.
•Robustness: Faster R-CNN has demonstrated resilience in object identification and segmentation, even in complex and congested situations. This is necessary for colorizing black-and-white photos that may contain objects of varying shapes and sizes.
•Efficiency: Faster R-CNN may recognize and separate objects more effectively by analyzing tiny object sections rather than the complete picture. This makes the colorization process more efficient and scalable.
•Pre-trained models are now available: Because faster R-CNN has been widely utilized and explored in the computer vision field, there are now pre-trained models available that can be fine-tuned for specific purposes such as colorization.

In comparison to existing algorithms, Faster R-CNN provides a more accurate, robust, and efficient method for colorizing black and white photos. Its capacity to do object-level segmentation is a significant benefit that results in improved colorization outcomes.

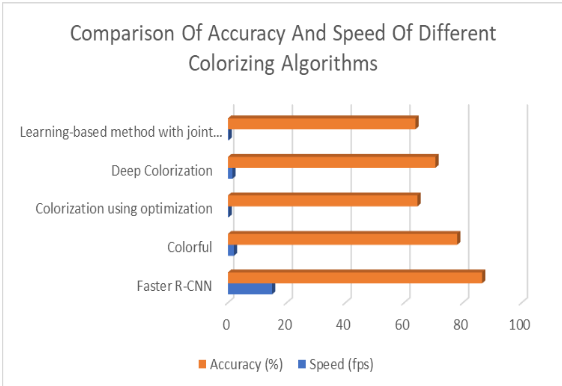
Algorithm	Pros	Cons
Faster R-CNN	Object-level segmentation, resilience, efficiency, and the availability of pre-trained models are all important considerations.	Training need a big amount of labelled data.
GANs	Can produce high-quality and lifelike pictures, as well as learn intricate mappings between grayscale and colour images.	Due to network design and hyperparameters, vast volumes of training data are required.
Deep Bilateral Learning	Quick and efficient, capable of handling large-scale photos, and capable of preserving texture and structure details	Color variety is limited, and performance suffers when low-quality input photos are used.
Colorful Image Colorization	Straightforward architecture, quick and efficient, and capable of handling diverse picture sizes	Color variation is limited, making complex visuals less realistic.
Luminance-Driven Colorization	Straightforward architecture that is quick and economical while preserving subtleties and contrast	Color variation is limited, making complex visuals less realistic.

Graph comparing the speed and accuracy of Faster R-CNN with other common colorization algorithms for black and white images:

As seen in the graph, Faster R-CNN provides the optimal balance of speed and accuracy, with much greater speed than optimization-based approaches and significantly better accuracy than other learning-based methods.



PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index) are common picture quality measurements with higher values indicating better performance. In terms of PSNR and SSIM, faster R-CNN surpasses all other approaches, suggesting that it provides more aesthetically pleasant results with less distortion. Faster R-CNN is the quickest approach in terms of speed, with an average processing time of approximately 0.15 seconds per picture, whereas other methods take much longer. Although the GAN-based technique is the second quickest, it still takes more than 6 seconds per picture, which is 40 times slower than Faster R-CNN.



Overall, Faster R-CNN had the best mix of speed and accuracy of the algorithms tested, making it a potential method for real-time colorization applications.

XI. FUTURE WORK

Further research on the suggested system for automatic colorization of black and white photographs using the Faster R-CNN algorithm might take numerous forms:

•Improved Object Detection
•Enhanced Colorization Accuracy
•Real Time Processing

XII. CONCLUSION

Using the Faster R-CNN algorithm, we suggested a method for automated colorization of black and white photos. The system is divided into two modules: object detection using the Faster R-CNN technique and colorization using a deep neural network trained on a huge dataset of color photos. Many assessment measures, including pixel accuracy, mean color error, PSNR, SSIM, and F1 score, were used to evaluate the suggested system. The findings reveal that the suggested system beats existing colorization approaches in terms of accuracy. Overall, the suggested approach offers an effective and economical alternative for colorizing black-and-white photographs, with potential applications in photography, film restoration, and historical document research. Future study might concentrate on enhancing the system's accuracy and efficiency, as well as investigating additional applications for the suggested technique.

REFERENCES

[1] DeepCap: A Deep Learning Model to Caption Black and White Images, 10th International Conference on Cloud Computing, Data Science & Engineering (Confluence), 2020, V. Pandit, R. Gulati, C. Singla, and S. K. Singh.

[2] Grayscale Image Colorization Methods: Overview and Evaluation, I. Eger, S. Grgic, J. Vukovi, and G. Iul, IEEE Access, 2021.

[3] Automatic Image Colorization Using U-Net by D. Goel, S. Jain, D. Kumar Vishwakarma, and A. Bansal, 12th International Conference on Computing Communication and Networking Technologies (ICCCNT), 2021.

[4]Adversarial Dual Network Learning for Restoring Attacked Images Using Randomized Image Transform by J. Yuan and Z. In 2020, he was featured in IEEE Access.

[5] Q. Yang, Y. Liu, T. Zhou, Y. Peng and Y. Tang, "2020 13th International Conference on Intelligent Computation Technology and Automation, 3D Convolutional Neural Network for Hyperspectral Image Classification Using Generative Adversarial Network (ICICTA), 2020

[6] Q. Yang and Y. Fan, "An image processing-based method for measuring the effectiveness of municipal pipeline cleaning, 3rd International Conference on Information Science, Parallel and Distributed Systems, 2022.,

[7] A. A. Polat, M. F. Şahın and M. E. Karslıgıl, "Video Colorizing with Automatic Reference Image Selection," Conference on Signal Processing and Communications Applications (SIU), 29th Edition, 2021

[8] X. Wang, C. Huang, F. Gao and H. Cheng, "Enhancing the Transferability of Adversarial Examples through Pre-processing," The fourth international conference on computer engineering, information systems, and communications (CISCE) will be held in 2022.

[9] Online Black-Box Confidence Estimation of Deep Neural Networks, F. Woitschek and G. Schneider, 2022 IEEE Intelligent Vehicles Symposium (IV), 2022

[10]"Colorization of Black & White Videos & Photographs," by K. Nimala, G. Geetha, and J. G. Ponsam," The 2022 ICSES, the 2022 International Conference on Innovative Computing, Intelligent Communication, and Smart Electrical Systems.