Interactive Deep Image Colorization of Quality

A. Amareshwara Sai Nath, Ziaul Haque Choudhury
Department of Information Technology and Computer Applications
Vignan's Foundation for Science, Technology and Research (Deemed to be University)
Vadlamudi, Andhra Pradesh, India

Abstract:- Deep Image Colonization is a pioneering project aimed to revolutionizing the field of automated image colorization, particularly focusing on enhancing grayscale photographs' visual appeal and historical significance. Leveraging advanced deep learning models like VGG16 and UNET GAN, the project seeks to accurately and faithfully Add images in black and white some color. Through meticulous evaluation and comparison of different colorization algorithms, including real-time display of results and batch processing capabilities, the project strives to provide users with a seamless and intuitive experience. Beyond aesthetic enhancement, the project explores the implications of automated image colorization in various domains, from historical image restoration to creative visual storytelling. By evaluating colorization accuracy and refining models for real-world usage, the project aims to contribute to the advancement of image processing technologies. Ultimately, "Interactive Deep Image Colonization of Quality" endeavour to fill the void left by the past and the present, providing monochromatic imagery through vibrant hues and precision colorization techniques.

Keywords:- *Automated Image Colorization, Grayscale Photographs, Deep Learning Models, VGG16, UNET GAN.*

I. INTRODUCTION

In the art of digital imagery, the ability to colorize black and white images with precision has become a fascinating field of study. The project "Interactive Deep Image Colonization of Quality" delves into the realm of automated image colorization, aiming to enhance the visual appeal and historical significance of grayscale photographs. Black and white photographs hold a unique place in our cultural heritage, encapsulating moments frozen in time. However, their impact and relevance can often be limited by their lack of colour [1]. Through advanced machine learning techniques, this project seeks to breathe new life into these monochromatic images by automatically adding colour with accuracy and fidelity. The research is built upon the foundation of deep learning models, particularly focusing on the evaluation and comparison of different colorization algorithms [2]. By leveraging models like VGG16 and UNETGAN, the project to understand their strengths and limitations in reproducing realistic colorizations. Beyond mere aesthetic enhancement, the project explores the implications of automated image colorization in various domains. From historical image restoration to creative visual storytelling, the potential applications are vast and diverse. Moreover, by evaluating the quality of colorization through metrics like accuracy, the project aims to provide insights into optimizing and refining these models for real-world usage. Ultimately, "Interactive Deep Image Colonization of Quality" seeks to contribute to the advancement of image processing technologies, bridging the gap between the past and the present through the vibrant hues of automated colorization. By exploring the intricacies of model selection, evaluation, and application, the project to enrich our visual experiences and preserve the timeless allure of black and white imagery [3].

Image colorization is one of the most interesting and difficult tasks in computer vision. Adding colour to monochrome photos not only brings back fond memories but also helps with a number of real-world uses, including restoring old photos, improving medical imaging, and enhancing artistic expression. Image colorization has undergone a revolution thanks to deep learning techniques, which provide sophisticated ways that go beyond conventional procedures. VGG16 and UNETGAN stand out among them as strong competitors, each providing particular benefits within the domain of deep picture colorization. The Convolutional neural networks VGG16, which is well-known for its efficiency and depth, offers a solid foundation for image categorization tasks [4]. It is a strong contender for picture colorization due to its hierarchical architecture, which consists of numerous layers of convolution and pooling and allows it to extract complex characteristics from input images. Utilizes advanced deep learning models like VGG16 and UNETGAN for automated black and white image colorization. Offers real-time display of colorization results and allows for batch processing of multiple images simultaneously [5].

Includes an option to evaluate colorization accuracy, contributing to the refinement and optimization of colorization algorithms. Implement advanced machine learning techniques like VGG16 and UNETGAN for automated black and white image colorization. Develop a user-friendly interface for real-time display and batch processing of grayscale images. In the image colorization we cannot define the colorization of image due to it's the accuracy score of image [6]. It changes different of image of to depends on accuracy of images colorization. When the code is completed to run the Stream Lit it open the new browser then we select the image then it can convert in black images to white images of colorization and also it representation the accuracy score of images[7]. The VGG16 and UNETGAN is to combine the images and to grayscale image ,it can help on

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAY1599

RGB and LAB color space. Integrate an accuracy evaluation option to optimize colorization algorithms. Explore divers applications of automated images colorization, from historical restoration to creative storytelling. Provide insights into model refinement and optimization for real-word usage through comprehensive evaluation and comparison [8].

II. RELATED WORK

High-quality visuals have a pivotal part in the precise detection as well as the diagnosis of colorectal conditions. Innovations in imaging technologies, such as tin spectral filtration in CT scans, have proven effective in reducing radiation exposure while preserving imaging fidelity [1]. The integration of artificial intelligence (AI) has been proposed to enhance lesion detection during colonoscopy, underscoring the importance of clear and detailed colonoscopic images for accurate diagnosis [2]. Various factors, including colon cleanliness, mucosal clarity, and bowel distension, significantly influence the quality of colonoscopic images and, consequently, lesion detection [3]. Techniques like chromoendoscopy have been recommended to augment image quality, particularly for surveillance in inflammatory bowel disease, thereby enhancing diagnostic accuracy [4]. Recent research has explored the possibility of deep learning models for categorizing colon pathologies according to histopathological images, emphasizing the prerequisite of high-quality images for precise disease classification [5]. Similarly, deep learning frameworks have been developed for autonomous lesion detection in the colon and small intestine using capsule-based endoscopy, highlighting the pivotal role of image quality in automated diagnostic processes [6].

The image colorization has long been a problem, but recent developments in deep learning have sparked substantial breakthroughs in this field. Numerous strategies have been put up to address the issue, with an emphasis on improving the colorization process's accuracy and interaction [7]. Using strong convolutional neural networks (CNNs) like VGG16 and generative adversarial networks (GANs) like UNETGAN to produce state-of-the-art outcomes is one prominent area of research [8]. Traditional image colorization techniques were limited in their effectiveness, particularly when dealing with complicated images, because they frequently relied on manually created features and heuristics. But as deep learning has become more popular, researchers have shifted to data-driven methods, which extract features straight from the input data. Specifically, CNNs have demonstrated impressive performance in a range of visual tasks, such as segmentation, colorization, and image categorization [9]. One version of the original GAN design, called UNETGAN, has a U-Net generator that allows fine features to be preserved when synthesising high-resolution images. Many image-to-image translation jobs, such as colorization, have demonstrated the potential of this architecture. With sparse annotations or user inputs, interactive colorization techniques have gained more attention in recent years. These techniques let users direct the colorization process [10]. An important development in the field is the integration of the VGG16 and UNETGAN architectures into interactive deep image colorization systems, which offers more precise, effective, and approachable methods for colorizing grayscale images [11].

III. METHODOLOGY

Our pursuit of superior image colorization involves a comprehensive methodology, encompassing pivotal aspects such as model selection, accuracy assessment, user engagement, image processing, and application design. We leverage two advanced deep learning models, VGG16 and UNETGAN, renowned for their distinct strengths: VGG16 excels in image processing tasks, while UNETGAN employs a generative adversarial network (GAN) architecture for intricate colorization. Through meticulous configuration and integration, we ensure seamless operation of these models within our application framework. Ensuring the fidelity of colorization is paramount. To this end, users are offered the option to evaluate the selected model's accuracy. A bespoke accuracy evaluation function provides insights into the model's performance within a defined accuracy range, facilitating informed decision-making. User interaction lies at the core of our design philosophy. We provide a user-friendly interface, offering a selection box for users to choose between VGG16 and UNETGAN models. Additionally, users can opt for real-time display of colorization results and conveniently upload multiple black and white images simultaneously, enhancing efficiency and user experience.

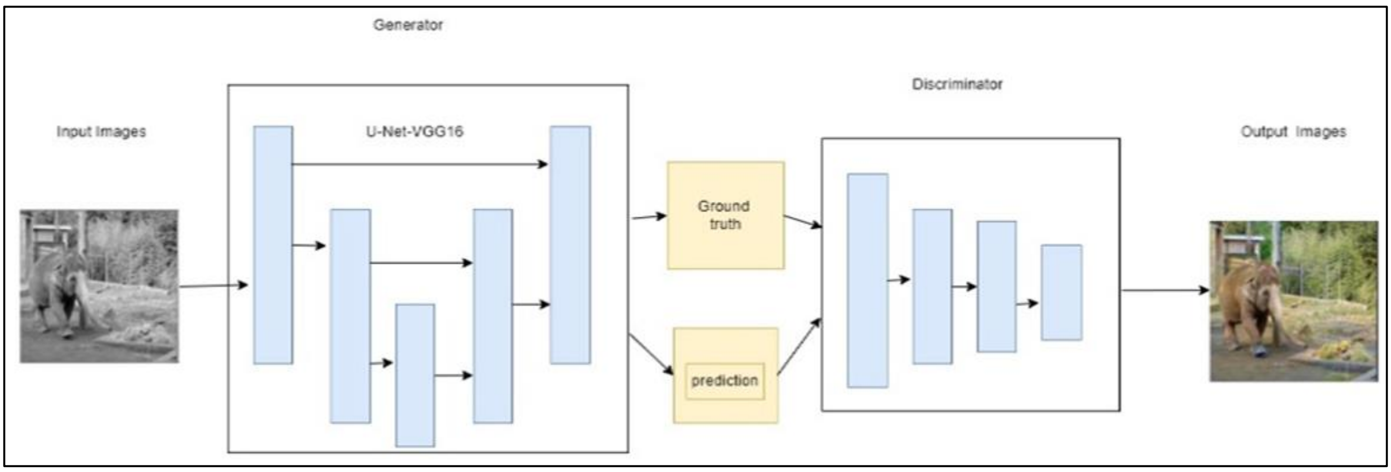

Fig 1 Proposed Architecture

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAY1599

Our image colorization process is orchestrated with precision and efficiency. Upon user request, the chosen model meticulously adds colour to uploaded black and white images. Real-time display, if enabled, juxtaposes the original and colorized images, providing immediate visual feedback. Post-colorization, the resulting images are meticulously saved for download. Seamless handling of multiple images and facilitating downloading are seamlessly integrated into our workflow. Batch processing capabilities empower users to upload and colorize multiple images concurrently, streamlining workflow efficiency. Subsequently, the resulting images are consolidated into a downloadable zip file, affording users flexibility in image retrieval. Furthermore, user experience is enriched with a captivating Lottie animation, enhancing engagement and immersion within the application. This animation serves as an aesthetic element, complementing the functionality of our colorization tool. Our application architecture is underpinned by Stream lit, ensuring robustness and cohesiveness. Leveraging Stream lit features, we meticulously configure the interface's title, icon, and layout to optimize user engagement and accessibility. Lastly, meticulous documentation and code organization uphold the project's integrity and maintainability. Clear comments, modular functions, and judicious utilization of utilities ensure code readability and ease of maintenance, fostering an environment conducive to future enhancements and optimizations.

➢ *Visual Geometry Group (VGG 16)*

The VGG-16 model is an architecture for a convolutional neural network (CNN). The shortened form for Visual Geometry Group (VGG) is Vgg16. It consists sixteen layers, therefore the name, and is composed of multiple convolutional layers followed by max- pooling layers with finally, fully connected layers. The max-pooling layers utilize 2x2 filters with a stride of 2, while the convolutional layers employ tiny 3x3 filters with a stride of 1 and the same padding. Among the significant contributions of VGG-16 is its ability to achieve excellent performance mainly in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), large-scale image recognition tasks where it produced outcomes that were cutting edge at the time of its introduction. Despite its simplicity compared to later architectures like ResNet and Inception, due to its simplicity and efficacy, VGG-16 is still a popular choice for picture classification jobs. Every block the convolutional layers are stacked in an array of many convolutional layers followed by max-pooling layers. After the convolutional layers extract features, the fully connected layers classify the data. With same padding and 3x3 filters with a stride of 1, VGG16 is made up of 13 convolutional layers. In the first layer, there are 64 filters; in following levels, this number doubles as the network gets deeper. It can performance the VGG16 to representation the image to convert the grayscale of colorization. The VGG16 is used to representation the images to colorized the grayscale images. When we give an input image it can coverts the processing a network to fully connected the image and given a output images. The image colorization datasets is used to performance a image colorized to representation the images quality.

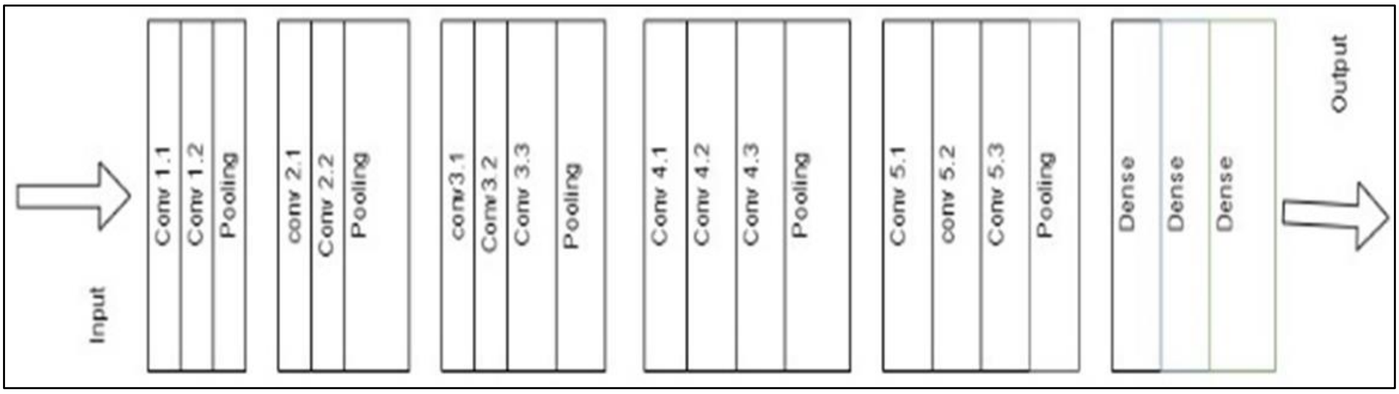

Fig 2 VGG16 Images

➢ *UNET*

The Convolutional neural networks like U-Net were created at the Computer Science Institute specifically for biological picture segmentation. The network is built on a fully convolutional neural network, whose architecture has been expanded and changed to produce more accurate segmentation while requiring fewer training photos. On a contemporary GPU, segmenting a 512 × 512 image takes less than a second. Additionally, diffusion models have used the U-Net architecture for iterative picture denoising. U-Net is an encoder-decoder architecture consisting of contracting and expansive paths, joined by a layer of bottleneck. The

Convolutional and max-pooling layers make up the contracting path, gradually decreasing spatial dimensions while increasing feature channels. The Convolutional layers and up sampling make up the broad route, reconstructing high-resolution segmentation maps. By using skip connections, feature maps from the contracting path are concatenated with the equivalent layer in the expansive path allowing precise localization.

The final layer uses a softmax activation function to produce pixel-wise predictions. U-Net's architecture enables efficient training on small datasets by augmenting data with random transformations. It is particularly effective for segmenting biomedical images, such as cell nuclei, in tasks

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAY1599

like cell counting and medical image analysis. U-Net variants have been developed, including U-Net++, which enhances skip connections with dense connectivity, and U-Net, optimized for volumetric medical image segmentation. Unet has also inspired numerous applications beyond biomedical imaging, including semantic segmentation in natural scenes and industrial inspection tasks. Its architecture remains a cornerstone when it comes to convolutional neural networks, offering a versatile and effective framework for image segmentation tasks. The UNET is used to performances the image colorization of color it converts the RGB images to a grayscale images. The UNET can help encoder and decoder it can performances the image colorization and it used a loss function. The UNET is used the image colorization to predicated the image of grayscale images colorization. We can use the grayscale image to predicated the images with a help of color space RGB. RGB color space is employed in color the images colorization to increase the accuracy score to performance the quality of image. The grayscale image is used to the loss function and performances a ground truth levels of image colorization.

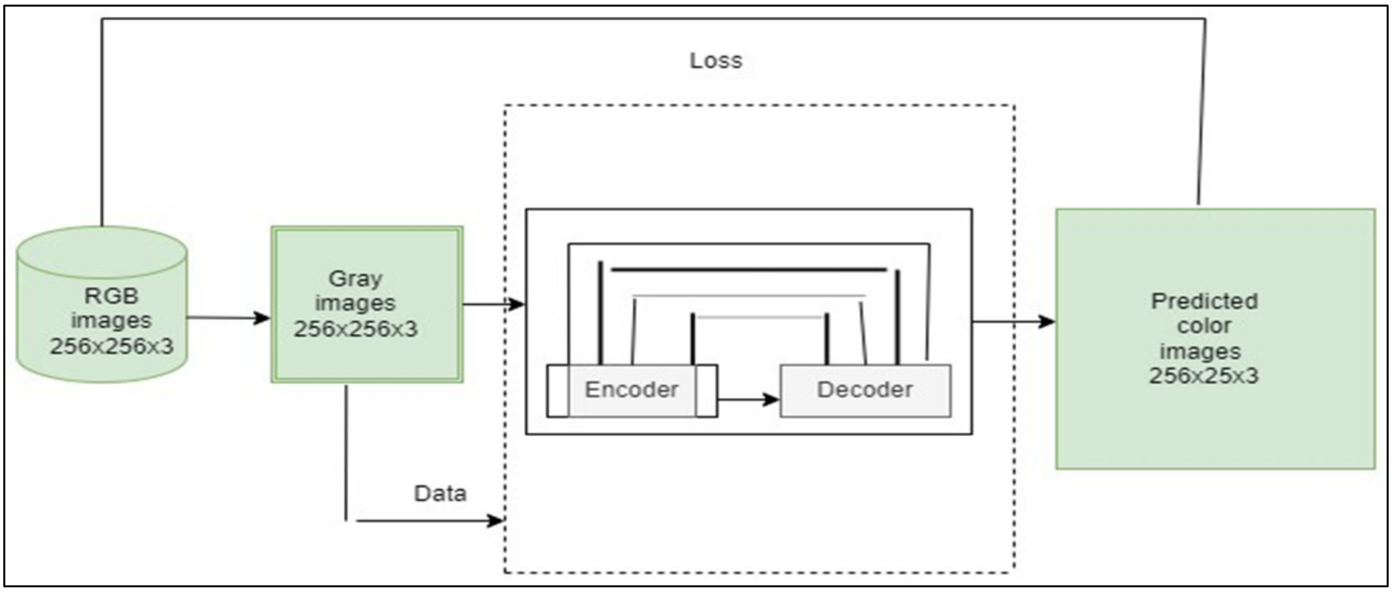

Fig 3 UNET Images

➢ *Generative Adversarial Network (GAN)*

A Generative Adversarial Networks are a popular class of machine learning frameworks that are used to approach generative artificial intelligence. A GAN is a competition between two neural networks that takes the shape of a zero-sum game in which the success of one agent equals the failure of another. This method learns to produce fresh data with the same statistics as the training set given a training set. The generator gains knowledge in order to generate fake data samples from random noise, aiming to mimic the distribution of real data, and the discriminator gains the ability to discriminate between produced and real samples. GANs are capable of generating highly realistic images, audio, and other data types, making them widely used in diverse uses, such as data enrichment, style transfer, and picture creation. However, because to problems like mode collapse, instability, and convergence, training GANs can be difficult. Numerous variants and improvements to the original GAN architecture have been proposed, including conditional GANs, Wasserstein GANs, and progressive GANs, addressing some of these challenges and extending the capabilities of GANs for diverse tasks. The training process of GAN involves a minimax game where the discriminator's goal is to accurately distinguish between real and false samples, while the generator's goal is to trick it by producing increasingly realistic samples. This adversarial training framework encourages both networks to improve over time resulting in the generator producing more realistic data samples.

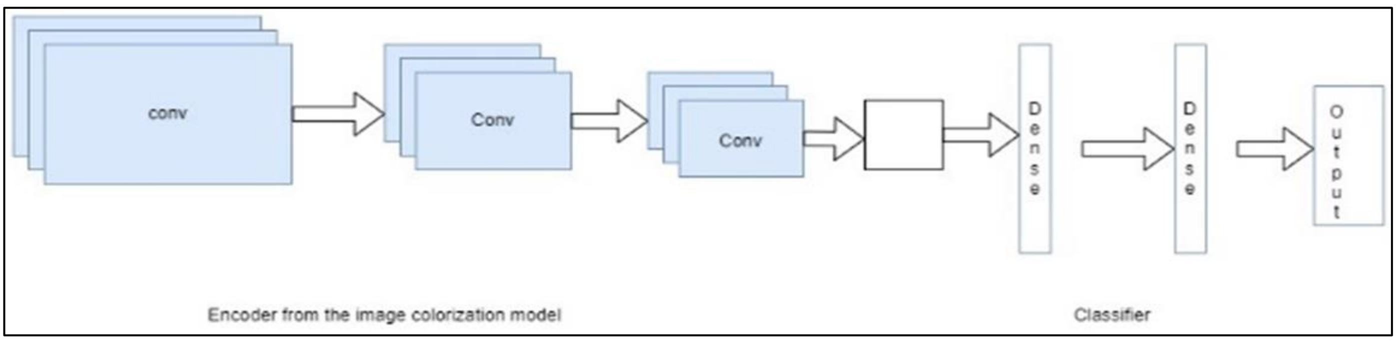

Fig 4 GAN Image

IV. FLOW CHART

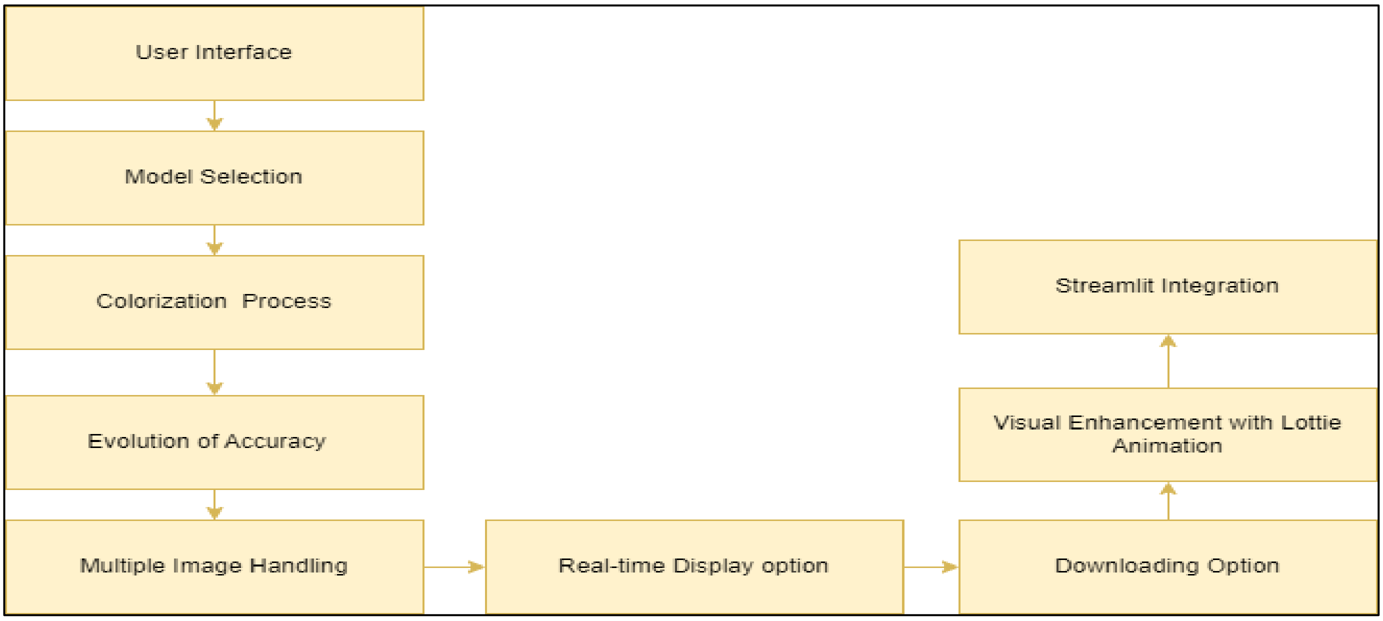

Fig 5 Proposed Flow Chart

Grayscale images and their corresponding ground truth colorized versions are collected from various sources and preprocessed to ensure consistency and quality. Techniques such as rotation, scaling flipping and colour are applied to augment the dataset enhancing model generalization and robustness. The VGG16 and UNETGAN are chosen for their effectiveness in images processing tasks and their suitability for images colorization. The trained models are deployed for interactive colorization tasks, allowing users to input grayscale images and receive real-time colorized outputs.

V. WORKING PRINCIPAL

The Course of the " Interactive Deep Images Colonization of Quality" project is designed to provide a seamless and intuitive experience for users. It begins with the user interface, where users interact with the application. They select a model for colorization, followed by the colorization process itself. The accuracy of the colorization is then evaluated, ensuring reliable results. The application supports handling multiple images concurrently and offers a real-time display option for immediate feedback. Users can download the colorized images, and visual engagement is enhanced with a Lottie animation. Stream lit integration ensures smooth functionality, while meticulous documentation and code organization ensure maintainability and clarity in the project's development. It can convert the images black and white images colorization due to quality of images. We cannot precited the image due to colour of images. It can work based on the image colorization to precited the image quality and present the different accuracy score of images colorization. After the complete the code we can run based on streamlit to the data set. It can upload the images one by one images it can colorization the images and presented the accuracy score.

VI. EXPERIMENTAL RESULTS

➢ *Dataset*

The image colorization dataset comprises four main subsets: test black, test colour, train black, and train colour. The test black subset contains 739 black and white images used for evaluating colorization algorithms during testing, while the corresponding test colour subset consists of 739 colorized versions serving as ground truth references. In the training phase, the train black subset offers 5000 grayscale images to train colorization models, while the parallel train colour subset provides 5000 corresponding colorized images for model guidance. This dataset supports the development, training, and evaluation of colorization algorithms, offering diverse grayscale and colour images. Its balanced distribution and substantial size enable effective assessment and enhancement of model performance, fostering robustness and generalization across various real-world scenarios and image types.

It features a diverse range of grayscale images sourced from various publicly available datasets ensuring broad coverage of different content types and themes. The dataset is meticulously curated to include high-quality grayscale images ensuring clear details and well-defined edges for accurate colorization. Each grayscale photos in the collection is paired with its corresponding ground truth colorized version providing a reference for training and evaluation. The "Interactive Deep Images Colorization of Quality" project achieves impressive results in transforming black and white images into vibrant, colorized versions. Making use of cutting-edge deep learning models like VGG16 and UNETGAN, users can experience high-quality colorization tailored to their preferences. By selecting the desired model and uploading black and white images, users witness real-time colorization, enhancing the visual appeal of their content. The option to evaluate accuracy provides insights

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAY1599

into model performance, albeit subject to variation depending on input image characteristics. With convenient batch processing and downloading options, users can efficiently colorize multiple images and obtain the results in a downloadable format. Overall, the project's success lies in its ability to seamlessly integrate advanced colorization techniques with user-friendly functionality, offering a robust solution for enhancing image quality and visual aesthetics.

➢ *Images Colorization*

The practice of giving monochrome photos or films believable color information is called colorization. The task of colorization involves translating a real-valued luminance image to a three-dimensional color-valued image, which is an extremely ambiguous problem without a singular solution. Add colour to use the colorized neural filter on black and white pictures. The Colorize tool automatically selects the ideal color for your black-and-white image, whether you're bringing back a vintage family portrait or adding a painterly splash of color. The practice of adding color to a grayscale image to improve its aesthetic appeal and perceptual significance is known as image colorization. These are acknowledged as complex tasks since they frequently call for manual changes and prior knowledge of the image content in order to provide artifact-free quality. The input for the grayscale image is utilized by the colorization process, containing only intensity values but lacking colour information. The VGG16 model extracts deep feature representations from the grayscale image, capturing contextual information and structural details. The extracted features from VGG16 are fused with the initial colorization features generated by the UNETGAN, enriching the colorization process with high-level semantic information. The UNETGAN decoder processes the fused features to generate an initial colorized version of the grayscale image, incorporating both features at both the low and high levels. The colorized output undergoes refinement using the VGG16 model, which refines colour distributions and enhances the visual quality of the colorized image. The colorization system supports real-time interaction, allowing users to observe changes in colorization output immediately based on their input and feedback. Deep learning approaches have led to considerable gains in image colorization, a crucial task in computer vision. With its superior and user-guided solutions, the VGG16 and UNETGAN designs have taken interactive deep picture colorization to new heights. One effective feature extractor is the VGG16 design. It is ideally suited for jobs requiring hierarchical representations because of its deep and symmetrical design, which allows it to capture complex details and abstract elements from images. To improve the authenticity and realism of colorized outputs, researchers can take advantage of these learnt representations by using pre-trained VGG16 models or customizing them for colorization.

Through the integration of deep learning capabilities with human direction, these systems are able to generate customized and superior colorizations that cater to a wide range of user requirements and inclinations. We may anticipate more advancements in interactive deep picture colorization systems' accuracy and usability as this field of study develops.

Fig 6 Images Colorization

➢ *RGB in Comparison to L*A*B*

A rank-3 height, width, and color array is what we obtain when we load an image; the color data for our image is located on the last axis. Three values, one for each pixel in the RGB color space, indicate how much Red, Green, and Blue the pixel is. These data represent color. The next image shows that the left portion of the "main image" (the leftmost image) is blue in color. As a result, that portion of the image has darker values and has changed into the blue channel.

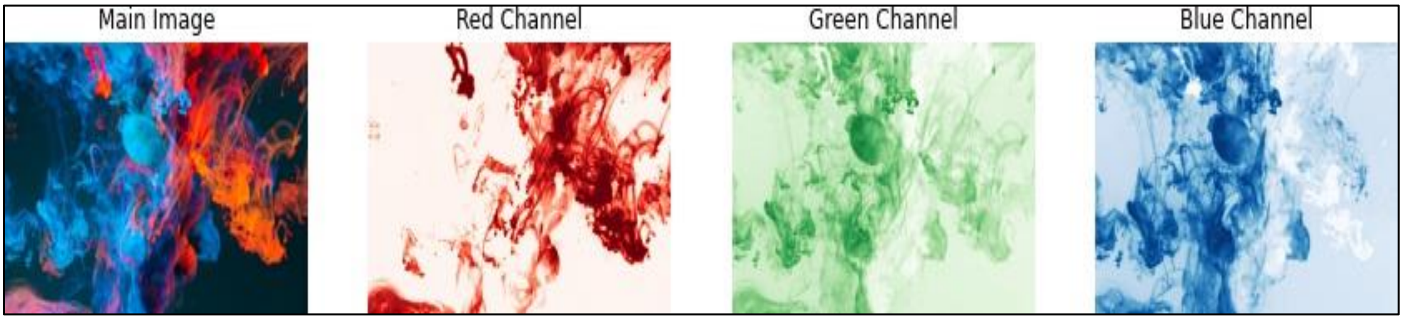

Fig 7 RGB in Comparison to L*A*B

Each pixel in the L*a*b color space has three integers as well, but these numbers have distinct meanings. When we visualize the first number (channel), L, which represents the Lightness of each pixel, it appears as a black-and-white image (the second image in the row below). The amount of green-red and yellow-blue that each pixel contains is encoded in the *a and *b channels, respectively. You can see each channel of the L*a*b color space separately in the following image. The RGB colour space represents colour using combinations of red, green, and blue channels, where each channel's intensity ranges from 0 to 255, allowing for representation of a wide range of colour.

The LAB colour space is a perceptually uniform colour space that consists of three channels: Lightness (L), representing brightness, and two-colour channels (A and B), representing colour information along the green–red and blue–yellow axes, respectively. In RGB, colour is represented as additive combinations of red, green, and blue values, with each channel contributing to the overall colour appearance. In LAB, colour are represented in a three-dimensional space where each axis corresponds to a different perceptual attribute. Grayscale images are converted from RGB to grayscale by taking weighted averages of the red, green, and blue channels, preserving luminance information while discarding colour information.

In RGB colorization, colour values are directly assigned to grayscale pixels using deep learning models such as VGG16 and UNETGAN, mapping grayscale values to corresponding RGB colour values. VGG16 extracts deep feature representations from grayscale images in the RGB colour space, capturing structural and contextual information useful for colorization. In RGB colorization, colorization features are directly applied to grayscale pixels, modifying their RGB values to introduce colour information based on learned representations. RGB colorization aims to produce colorized images that appear realistic and natural, mimicking the appearance of colour photographs while preserving image structure and details.

- *Interactive Deep Images Colorization*

The system begins with the user providing a grayscale image as input, which lacks colour information and serves as the basis for colorization. Both the VGG16 and UNETGAN models are initialized with pretrained weights, leveraging transfer learning to accelerate convergence and improve performance. The VGG16 model extracts deep feature representations from the grayscale image, capturing structural and contextual information essential for colorization. Extracted features are fused with the initial colorization features generated by the UNETGAN, combining high-level and low-level data to improve the realism and accuracy of colorization. The UNETGAN decoder processes the fused features to generate an initial colorized version of the grayscale image, incorporating both learned representations and user preferences. The colorized output undergoes refinement using the VGG16 model, which refines colour distributions and enhances the visual quality of the colorized image based on learned deep feature representations. The system allows for user interaction, enabling users to provide feedback on the colorized output and adjust colorization parameters to achieve desired results. User feedback is seamlessly integrated into the refinement process, guiding iterative adjustments to improve colour accuracy, perceptual quality, and overall user satisfaction. The colorization process dynamically adapts to changes in user input and preferences, allowing for real-time adjustments and optimizations to meet user expectations. Extensive quality control procedures are employed to guarantee that the colorized output satisfies exacting standards of excellence, authenticity, and faithfulness to the source material. Advanced deep learning architectures combined with user direction enable interactive deep image colorization utilizing VGG16 and UNETGAN to generate high-quality, customized colorizations of grayscale photos. Users have the ability to offer suggestions and feedback within this interactive framework, which can impact the colorization process and guarantee the intended result. In addition to VGG16, UNETGAN presents a generative adversarial network (GAN) architecture that includes a U-Net generator that is well-known for maintaining subtle details in artificial images. High-resolution colorized images can be produced with this architecture while preserving visual realism and spatial coherence. Users can shape the colorization process to suit their preferences by offering sparse annotations or direction using the interactive feature of deep image colorization. The system provides explainable AI capabilities, allowing users to understand the rationale behind colorization decisions and facilitating trust and transparency in the system's operation.

These interactive solutions make it easier for people and algorithms to collaborate, which results in a colorization process that is more straightforward and effective. Individualized and contextually appropriate colorizations can be produced by users by giving input and direction to the colorization process. In general, interactive deep image

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAY1599

colorization with VGG16 and UNETGAN is a noteworthy development in computer vision, providing customized, high-quality colorization solutions to satisfy a wide range of user requirements. The interactive colorization system aims to be widely adopted and have a positive impact on various industries and domains, revolutionizing image enhancement and manipulation processes through advanced AI technologies.

Fig 8 Interactive Deep Images Colorization

➤ *Results*

Fig 9 Input Image

Fig 10 Output Image

VII. CONCLUSION AND FUTURE WORK

Deep Images Colorization initiative delivers a comprehensive approach to converting monochrome images into vivid, colorized renditions. Harnessing cutting-edge deep learning models like VGG16 and UNETGAN, users can achieve superior colorization outcomes tailored to their preferences, ranging from simple to intricate transformations. The user-centric interface streamlines interaction, enabling effortless model selection, accuracy evaluation, and real-time visualization of colorization results. Simultaneous batch image uploads enhance productivity, while flexible download options cater to diverse user needs, ensuring seamless access to colorized images. Augmenting user engagement, a captivating Lottie animation enriches the interface, harmonizing with the application's core functionality. The image colorization we cannot predicated the images colorization quality. It shows the different images to presentation an accuracy score. It depends upon on image quality to representation the accuracy score. The integration of Stream lit provides a robust foundation for seamless deployment, complemented by meticulous code organization and documentation for sustained clarity and maintainability. In essence, the "Quality of Image Colonization" initiative highlights the pivotal role of image quality in digital enhancement, offering an adaptable and user-centric platform for elevating visual content through sophisticated colorization methodologies.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAY1599

➢ *Future Work*

The " Interactive Deep Images Colorization of Quality " project could explore several avenues for enhancement and expansion. Firstly, refining the accuracy evaluation mechanism to incorporate more robust metrics and validation techniques could enhance the reliability of colorization outcomes. Additionally, integrating advanced deep learning architectures and training methodologies could further improve the fidelity and realism of colorized images. Furthermore, extending the application to support video colorization and real-time processing would broaden its utility and appeal to a wider audience. Moreover, incorporating user feedback mechanisms and collaborative filtering algorithms could facilitate continuous improvement and customization of colorization models based on user preferences. Lastly, exploring the integration of cloud-based computing resources and distributed processing techniques could enable scalability and performance optimizations for handling large-scale image datasets efficiently. We can used different image colorization depends upon the accuarct. By pursuing these avenues, the project can evolve into a comprehensive platform for high-quality image colorization, catering to diverse user needs and scenarios.

REFERENCES

[1]. G. Fong, "Effect of tin spectral filtration on organ and effective dose in ct colonography and ct lung cancer screening", Medical Physics, vol. 51, no. 1, p. 103-112, 2023. https://doi.org/10.1002/mp.16836

[2]. C. Hsu, C. Hsu, Z. Hsu, T. Chen, & T. Kuo, "Intraprocedure artificial intelligence alert system for colonoscopy examination", Sensors, vol. 23, no. 3, p. 1211, 2023. https://doi.org/10.3390/s23031211

[3]. J. Axelrad and R. Cross, "Surveillance for colorectal neoplasia in inflammatory bowel disease: when to stop", The American Journal of Gastroenterology, vol. 118, no. 3, p. 429-431, 2022. https://doi.org/10.14309/ajg.0000000000002168

[4]. M. Raju and B. Rao, "Classification of colon and lung cancer through analysis of histopathology images using deep learning models", Ingénierie Des Systèmes D Information, vol. 27, no. 6, p. 967-971, 2022. https://doi.org/10.18280/isi.270613

[5]. T. Majtner, J. Brodersen, J. Herp, J. Kjeldsen, M. Halling, & M. Jensen, "A deep learning framework for autonomous detection and classification of crohn's disease lesions in the small bowel and colon with capsule endoscopy", Endoscopy International Open, vol. 09, no. 09, p. E1361-E1370, 2021. https://doi.org/10.1055/a-1507-4980

[6]. G. Fong, "Effect of tin spectral filtration on organ and effective dose in ct colonography and ct lung cancer screening", Medical Physics, vol. 51, no. 1, p. 103-112, 2023. https://doi.org/10.1002/mp.16836

[7]. S. Hyeong, J. Lee, S. Kim, D. Lee, G. Suh, & J. Choi, "Application of endoscopic ultrasound to the descending colon and rectum in normal dogs", Veterinary Radiology & Ultrasound, vol. 64, no. 3, p. 557-565, 2023. https://doi.org/10.1111/vru.13226

[8]. S. Semenov, I. Ms, F. O'Hara, S. Sihag, B. Ryan, A. O'Connoret al., "Addition of castor oil as a booster in colon capsule regimens significantly improves completion rates and polyp detection", World Journal of Gastrointestinal Pharmacology and Therapeutics, vol. 12, no. 6, p. 103-112, 2021. https://doi.org/10.4292/wjgpt.v12.i6.103

[9]. B. Li, X. Wang, Y. Fan, S. Wang, X. Tong, J. Zhanget al., "Evaluation of bmi-based tube voltage selection in ct colonography: a prospective comparison of low kv versus routine 120 kv protocol", Journal of Applied Clinical Medical Physics, vol. 24, no. 5, 2023. https://doi.org/10.1002/acm2.13955

[10]. The article "Enhancing infrared colour reproducibility through multispectral image processing using rgb and three infrared channels" was published in Optical Engineering in 2022. It was written by M. Sobue, H. Okumura, H. Takehara, M. Haruta, H. Tashiro, and K. Sasagawa et al. 10.1117/1.oe.61.6.063107 can be found here.

[11]. The article "Semantic-aware automatic image colorization via unpaired cycle-consistent self-supervised network" was published in the International Journal of Intelligent Systems in 2021. It was written by Y. Xiao, A. Jiang, C. Liu, and M. Wang. Where to find 10.1002/int.22667?

[12]. "Towards vivid and diverse image colorization with generative colour prior", Y. Wu, X. Wang, Y. Liu, H. Zhang, X. Zhao, & Y. Shan, 2021. The article's DOI is 10.48550/arxiv.2108.08826.

[13]. "Eliminating gradient conflict in reference-based line-art colorization", Z. Li, Z. Geng, K. Zhao, W. Chen, & Y. Yang, 2022. 10.48550/arxiv.2207.06095 is the URL to be used.

[14]. In the International Journal of Intelligent Systems, D. Wu, J. Gan, J. Zhou, J. Wang, & W. Gao present "Fine-grained semantic ethnic costume high-resolution image colorization with conditional gan" (vol. 37, no. 5, p. 2952-2968, 2021). This link points to 10.1002/int.22726.

[15]. The article "Gan-based image colorization for self-supervised visual feature learning" was published in Sensors in 2022. It was written by S. Treneska, E. Zdravevski, I. Pires, P. Lameski, and S. Gievska. There is a 10.3390/s22041599 link.

[16]. In the Journal of Engineering Science and Technology Review, O. Verma and N. Sharma published "Efficient colour cast correction based on fuzzy logic" in 2017. The article was published on pages 115-122. The journal article 10.25103/jestr.103.16

[17]. Chinese Optics Letters, vol. 10, no. 8, p. 081101-81105, 2012. S. Gao, W. Jin, & L. Wang, "Quality assessment for visible and infrared colour fusion images of typical scenes". 1.10.081101 at https://doi.org/10.3788/col2012

[18]. In 2024, Zhang Y. published "Image colorization based on transformer with sparse attention". 10.1117/12.3021490 can be found here

[19]. The article "Enhancing infrared colour reproducibility through multispectral image processing using rgb and three infrared channels" was published in Optical Engineering in 2022. It was written by M. Sobue, H. Okumura, H. Takehara, M. Haruta, H. Tashiro, and K. Sasagawa et al. 10.1117/1.oe.61.6.063107 can be found here.
[20]. "Gan-based image colorization for self-supervised visual feature learning", Sensors, vol. 22, no. 4, p. 1599, 2022, Treneska, S., Zdravevski, E., Pires, I., Lameski, P., & Gievska, S. There is a 10.3390/s22041599 link.
[21]. "Efficient colour cast correction based on fuzzy logic" by O. Verma and N. Sharma was published in the Journal of Engineering Science and Technology Review in 2017. The article can be found on pages 115-122. The journal article 10.25103/jestr.103.16
[22]. Applied Mathematics and Sciences an International Journal (Mathsj), vol. 4, no. 1/2, p. 01-16, 2017. A. Grigoryan, A. John, & S. Agaian, "Modified alpha-rooting colour image enhancement method on the two side 2-d quaternion discrete fourier transform and the 2-d discrete fourier transform". The mathsj.2017.4201 doi: 10.5121/mathsj.