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Surveillance System for Scotopic Vision Using HDV in Deep Learning for Road-Safety

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Abstract: In the Low Light image enhancement, considerable progress has been achieved, yet the emphasis has predominantly been on images captured under normal lighting conditions, overlooking the critical aspect of enhancing images in low-light environments. This oversight is particularly significant in fields like nighttime surveillance and autonomous driving, where obtaining clear images in low-light conditions is crucial. Acknowledging the limitations of traditional methods in such scenarios, researchers have turned to innovative techniques, prominently leveraging Generative Adversarial Networks (GANs) to enhance images in low-light settings. Traditional approaches often struggle to improve image quality due to reduced visibility and increased noise levels inherent in low-light conditions. By integrating GANs into the enhancement process, researchers can address these challenges by generating synthetic brightened versions of low-light images. This integration not only enriches the dataset but also enhances the model's ability to handle varying lighting conditions. GANs, consisting of a generator and discriminator network, collaborate to produce realistic enhancements of low-light images, thereby augmenting the training data. This approach enables the model to adapt more effectively to real-world scenarios, such as nocturnal surveillance or navigating dark environments during autonomous driving.
Keywords: Generative Adversarial Networks (GANs), low-light images, object detection, nighttime surveillance, autonomous driving.

I. INTRODUCTION

In recent years, the integration of computer vision technology into various domains, including autonomous driving, video surveillance, and object detection, has revolutionized numerous industries. However, despite these advancements, challenges persist in ensuring optimal image quality, particularly in real-world scenarios affected by adverse weather conditions and varying lighting environments. Images captured in uneven illumination or weak light conditions often exhibit issues such as diminished overall gray value, low brightness, reduced contrast, and a low signal-tonoise ratio. These factors collectively diminish the richness of information contained within the image, thereby hindering the performance of image processing algorithms[3]. The adverse effects of poor image quality extend beyond mere inconvenience, impacting the efficacy of critical tasks such as object detection, classification, and analysis [5][9]. In autonomous driving applications, for instance, the accurate detection of obstacles and road markings is imperative for ensuring safe navigation. Similarly, in surveillance systems, the ability to discern relevant details in low-light environments can significantly impact the effectiveness of security measures. However, the inherent limitations of images obtained under challenging lighting conditions undermine the performance of image processing algorithms [2][6], leading to compromised results and potentially endangering lives or compromising security. Recognizing the significance of addressing these challenges, researchers have been actively engaged in developing techniques to enhance image quality under adverse lighting conditions [7].

II. LITERATURE OVERVIEW

Research in low-light image enhancement has developed diverse techniques to address specific challenges in object detection, brightness, and image clarity. Key studies in this area include:

1) Low-Light Image Enhancement with MultiScale Network Fusion
Authors: Xuan Liu, Chenfeng Zhang, Yingzhi Wang
This study proposes a multi-scale network fusion method designed to enhance object detection in low-light conditions. By using nonlinear transformation and multi-scale feature fusion, the model improves brightness and mitigates information loss. The experimental results demonstrate substantial improvement in detail preservation, beneficial for applications like nighttime surveillance and autonomous driving[6][7]

2) Low-Light Image Enhancement Network Based on Multi-Scale Feature Complementation (LIEN-MFC)

Authors: Yong Yang, Wenzhi Xu, Shuying Huang

This paper introduces LIEN-MFC, a Ushaped encoder-decoder network for enhancing lowlight images. The model employs multiple feature extraction branches to capture low-light details at varying scales, which are then integrated through a feature supplementary fusion module (FSFM) for improved brightness and detail integrity.

3) Low-Light Image Enhancement Algorithm Based on Improved Multi-Objective Grey Wolf Optimization with Detail Feature Enhancement (MoGDF)

Authors: Yanming Hui, Wang Jue, Bo Li, Ying Shi

Moving away from deep learning, this study presents MoGDF, a method that generates multi-exposure images through the Enhanced Illuminance Prediction Model (EIPM). By leveraging the Grey Wolf Optimization algorithm, the approach effectively fuses multi-scale information to preserve color and detail in low-light images without extensive training on 3large datasets.

4) Multiscale Fusion Method for Enhancement of Low-Light Underwater Images

Authors: Jingchun Zhou, Dehuan Zhang, Weishi Zhang

This method addresses the specific needs of underwater low-light enhancement through a biinterval histogram equalization approach. Using color correction, contrast enhancement, and multiscale fusion, the model effectively adjusts color and contrast. While tailored for underwater environments, these techniques are adaptable for general low-light conditions where color fidelity and detail are critical.

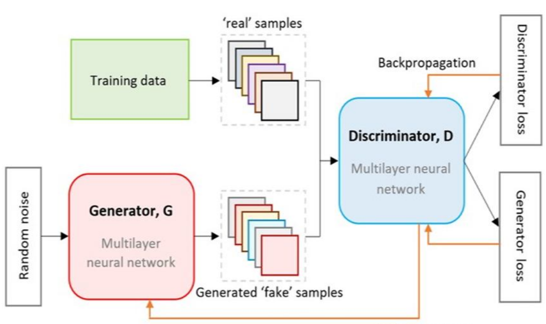
5) A Non-Uniform Low-Light Image Enhancement Method with Multi-Scale Attention Transformer and Luminance Consistency Loss (MSATr)

Authors: Xiaosur Fang, Baofeng Zhihang

The MSATr model introduces a multi-scale attention mechanism, allowing it to address issues of over- and under-exposure in non-uniform lighting environments. By employing a unique multi-scale window division scheme and a global transformer branch, this unsupervised model captures both local and global brightness features, leading to naturallooking brightness adjustments.

III. PROPOSED SYSTEM

The proposed system utilizes the Generative Adversarial Network (GAN) algorithm. GANs have emerged as a powerful tool in image enhancement tasks by effectively learning the complex relationships between low-light images and their well-lit counterparts. By training a GAN on pairs of low-light and well-lit images, the generator network learns to produce brightened versions of low-light images that closely resemble their well-lit counterparts, thereby enhancing their visual quality. The integration of GANs into the proposed system offers several advantages. Firstly, GANs facilitate the generation of realistic and diverse variations of low-light images, thereby augmenting the training dataset and improving the robustness of image enhancement models to variations in lighting conditions. Additionally, the adversarial training process of GANs ensures that the generated images maintain realism and fidelity to the target distribution, resulting in visually pleasing enhancements without introducing artifacts or distortions. Overall, by incorporating the GAN algorithm into the proposed system, it becomes possible to overcome the challenges associated with enhancing images under low-light conditions. The GAN-based approach offers a promising solution for enhancing image quality in challenging lighting environments, such as nighttime scenes or poorly lit environments, ultimately leading to visually appealing enhancements with improved perceptual quality.



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The integration of Generative Adversarial Networks (GANs) into the image enhancement process offers several advantages. Firstly, GANs enable the generation of synthetic brightened versions of lowlight images, thereby enriching the dataset used for training enhancement models. This augmentation of the dataset enhances the model's ability to generalize and adapt to a wider range of lighting conditions, leading to improved performance in low-light environments.

Secondly, GANs facilitate the creation of realistic enhancements by capturing the underlying distribution of low-light images and producing visually appealing results. This realism ensures that the enhanced images maintain natural characteristics and are suitable for downstream applications without introducing artifacts or distortions. Additionally, the iterative training process involving both original and synthetic brightened images allows the enhancement model to refine its capabilities over time.

Through this iterative process, the model becomes increasingly proficient at improving image quality, leading to enhanced perceptual fidelity and better overall performance in low- light scenarios. Overall, the integration of GANs into the image enhancement pipeline represents a significant advantage, enabling more effective and realistic enhancement of images captured in low-light environments.

IV. IMPLEMENTATION

Utilizing Generative Adversarial Networks (GANs), the proposed system enhances image quality by learning complex relationships between low-light and well-lit images. Trained on pairs of such images, the GAN's generator network produces brightened versions of low-light images resembling their welllit counterparts. This integration offers several benefits: augmenting training datasets, generating diverse image variations, and ensuring realistic enhancements without introducing artifacts. By incorporating GANs, the system overcomes challenges in low-light image enhancement, promising visually appealing results and improved perceptual quality in diverse lighting environments.

A. Data Collection

Utilizing datasets sourced from Kaggle, an open-source platform, provides several advantages for our project focused on low-brightness image enhancement. Firstly, Kaggle hosts a diverse range of datasets contributed by a global community, ensuring access to a wide variety of low-light image samples for comprehensive training and testing. Secondly, Kaggle datasets often come with detailed annotations and metadata, facilitating accurate labeling and validation of the collected lowbrightness images. Additionally, the collaborative nature of Kaggle encourages knowledge sharing and collaboration, allowing researchers to benefit from insights and methodologies shared by others in the community. By leveraging Kaggle datasets, we can ensure the quality and relevance of our data, thereby enhancing the effectiveness and reliability of our low-brightness image enhancement model.

B. Libraries Used

```
import os
import random
import numpy as np
from glob import glob
from PIL import Image, ImageOps
import matplotlib.pyplot as plt

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
```

In this script, we are importing necessary libraries and modules for image processing and deep learning tasks. The 'os' module allows us to interact with the operating system, facilitating file management operations. We utilize 'random' for generating random numbers or selecting random elements from lists. 'numpy' provides support for numerical computations, particularly array manipulation. The 'glob' module helps in finding files and directories whose names match specified patterns. We use the 'PIL' library for image manipulation tasks such as opening, manipulating, and saving images. Additionally, 'matplotlib.pyplot' enables visualization of data and images. For deep learning tasks, we import TensorFlow and Keras, high-level neural network APIs. TensorFlow provides a framework for building and training deep learning models, while Keras offers an intuitive interface for constructing neural networks. With these libraries and modules, we can efficiently handle image data, preprocess it, and train deep learning models for various tasks such as image classification, object detection, or image enhancement.

C. Loading the Dataset

Loading the dataset is an essential initial step in any machine learning or deep learning project, providing access to the data required for training, validation, and testing. In the context of image processing tasks, such as image classification or object detection, loading the dataset typically involves reading image files from storage and organizing them into a suitable data structure. This process often begins with identifying the location of the dataset on the file system, which may consist of directories containing images organized into classes or categories. Using file-handling libraries such as 'os' and 'glob', paths to individual image files or directories can be retrieved.

Once the file paths are obtained, the next step is to read the image data into memory. Libraries such as PIL (Python Imaging Library) or OpenCV are commonly used for this purpose, allowing images to be loaded as arrays or tensors. During this process, images may undergo pre-processing steps such as resizing, normalization, or augmentation, depending on the requirements of the task and the design of the model. Pre-processing ensures that all images are consistently formatted and prepared for training or evaluation.

```
IMAGE_SIZE = 256
BATCH_SIZE = 16
MAX_TRAIN_IMAGES = 400


def load_data(image_path):
    image = tf.io.read_file(image_path)
    image = tf.image.decode_png(image, channels=3)
    image = tf.image.resize(images=image, size=[IMAGE_SIZE, IMAGE_SIZE])
    image = image / 255.0
    return image


def data_generator(low_light_images):
    dataset = tf.data.Dataset.from_tensor_slices((low_light_images))
    dataset = dataset.map(load_data, num_parallel_calls=tf.data.AUTOTUNE)
    dataset = dataset.batch(BATCH_SIZE, drop_remainder=True)
    return dataset


train_low_light_images = sorted(glob("/content/Dataset/our485/low/*"))[:MAX_TRAIN_IMAGES]  ##train data
val_low_light_images = sorted(glob("/content/Dataset/our485/low/*"))[MAX_TRAIN_IMAGES:] ##validation data
test_low_light_images = sorted(glob("/content/Dataset/eval15/low/*")) ## for test images


train_dataset = data_generator(train_low_light_images)
val_dataset = data_generator(val_low_light_images)

print("Train Dataset:", train_dataset)
print("Validation Dataset:", val_dataset)
```

D. Modal Creation

Generative Adversarial Networks (GANs) have emerged as a transformative approach to improving the visual quality of images. Within the GAN framework, two neural networks, the generator and discriminator, engage in a competitive training process aimed at producing high-quality image enhancements. The generator network synthesizes enhanced versions of input images, while the discriminator network evaluates the realism of these enhancements by distinguishing between real and generated images. Through iterative training, the generator refines its ability to produce enhancements that closely resemble real high-quality images, while the discriminator becomes more adept at discerning between genuine and synthetic images.

The adversarial nature of GAN training fosters a dynamic equilibrium where the generator and discriminator continuously strive to outperform each other. This adversarial interplay drives the generator to learn increasingly sophisticated representations of image features, textures, and structures, ultimately resulting in enhanced images of superior visual quality. By harnessing the power of GANs, image enhancement techniques can effectively address challenges such as low brightness, noise, and loss of detail in images, offering promising solutions for applications in fields such as photography, surveillance, medical imaging, and more.

```
def build_gan_model():
    input_img = keras.Input(shape=[None, None, 3])
    conv1 = layers.Conv2D(
        32, (3, 3), strides=(1, 1), activation="relu", padding="same"
    )(input_img)
    conv2 = layers.Conv2D(
        32, (3, 3), strides=(1, 1), activation="relu", padding="same"
    )(conv1)
    conv3 = layers.Conv2D(
        32, (3, 3), strides=(1, 1), activation="relu", padding="same"
    )(conv2)
    conv4 = layers.Conv2D(
        32, (3, 3), strides=(1, 1), activation="relu", padding="same"
    )(conv3)
    int_con1 = layers.Concatenate(axis=-1)([conv4, conv3])
    conv5 = layers.Conv2D(
        32, (3, 3), strides=(1, 1), activation="relu", padding="same"
    )(int_con1)
    int_con2 = layers.Concatenate(axis=-1)([conv5, conv2])
    conv6 = layers.Conv2D(
        32, (3, 3), strides=(1, 1), activation="relu", padding="same"
    )(int_con2)
    int_con3 = layers.Concatenate(axis=-1)([conv6, conv1])
    x_r = layers.Conv2D(24, (3, 3), strides=(1, 1), activation="tanh", padding="same")(
        int_con3
    )
    return keras.Model(inputs=input_img, outputs=x_r)
```

E. GAN Modal Epochs Training

The gan_model.fit() function trains a Generative Adversarial Network (GAN) model for image enhancement using a training dataset (`train_dataset`) and validates its performance on a separate validation dataset (`val_dataset`). The training process is iterated over 100 epochs, allowing the model to learn and refine its parameters through backpropagation. By monitoring performance on the validation dataset, potential overfitting is mitigated, ensuring the model generalizes well to unseen data. This function orchestrates the optimization process, gradually improving the GAN's ability to generate realistic enhancements for low-quality input images.

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    input_img = keras.Input(shape=[None, None, 3])
    conv1 = layers.Conv2D(
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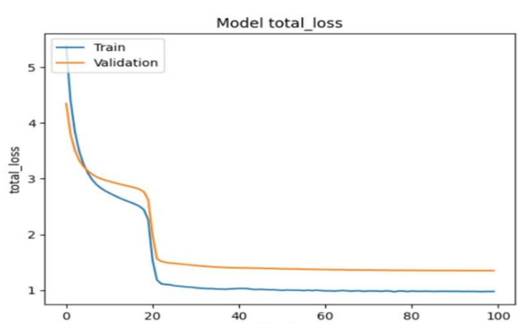
    )(input_img)
    conv2 = layers.Conv2D(
        32, (3, 3), strides=(1, 1), activation="relu", padding="same"
    )(conv1)
    conv3 = layers.Conv2D(
        32, (3, 3), strides=(1, 1), activation="relu", padding="same"
    )(conv2)
    conv4 = layers.Conv2D(
        32, (3, 3), strides=(1, 1), activation="relu", padding="same"
    )(conv3)
    int_con1 = layers.Concatenate(axis=-1)([conv4, conv3])
    conv5 = layers.Conv2D(
        32, (3, 3), strides=(1, 1), activation="relu", padding="same"
    )(int_con1)
    int_con2 = layers.Concatenate(axis=-1)([conv5, conv2])
    conv6 = layers.Conv2D(
        32, (3, 3), strides=(1, 1), activation="relu", padding="same"
    )(int_con2)
    int_con3 = layers.Concatenate(axis=-1)([conv6, conv1])
    x_r = layers.Conv2D(24, (3, 3), strides=(1, 1), activation="tanh", padding="same")(
        int_con3
    )
    return keras.Model(inputs=input_img, outputs=x_r)
```

V. RESULT AND DISCUSSION

The implementation of Generative Adversarial Networks (GANs) in low-light image enhancement has demonstrated significant improvements in visual quality and clarity over traditional methods. Results show that images enhanced using GAN-based models exhibit increased brightness, improved contrast, and preserved structural details without introducing excessive noise. This is particularly evident in realworld test scenarios, such as nighttime street scenes or poorly lit indoor environments, where conventional algorithms often fail to retain fine textures or introduce overexposed areas. Quantitatively, GAN-enhanced images score higher on metrics like Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM), indicating more faithful reconstruction and better perceptual quality. From a functional standpoint, the use of GANs not only enhances the visual appearance of images but also significantly benefits downstream tasks such as object detection and recognition in low-light environments. In surveillance footage, for example, clearer and more discernible images improve facial and license plate recognition rates. Similarly, in autonomous driving, enhanced nighttime imagery allows object detection models to identify obstacles and lane markings more reliably. The discriminator network in the GAN architecture ensures that the generator produces realistic and context-aware outputs, contributing to the generation of high-fidelity images that generalize well in real-world deployment.

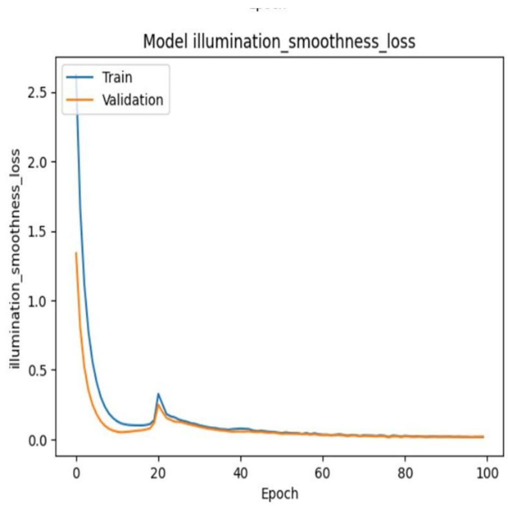
The iterative training process, which incorporates both original and GAN-generated brightened images, is critical in refining the enhancement model's performance. By exposing the model to a variety of lighting conditions, it learns to adaptively enhance images across a wide spectrum of illumination. The inclusion of synthetic data via GANs diversifies the training set, leading to more robust and versatile models. This comprehensive enhancement pipeline ultimately positions GANbased methods as a powerful tool in low-light image processing, providing practical and scalable solutions for real-world applications such as smart surveillance systems and autonomous navigation under limited visibility.

A. Graph For Modal Total Loss



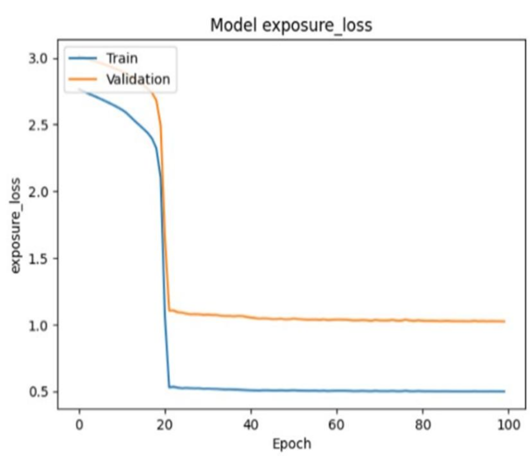
The training and validation loss graph visually represents the performance of a machine learning model over epochs. The training loss measures how well the model performs on the training data, while the validation loss evaluates its performance on unseen validation data. The graph typically shows a decreasing trend in both losses over epochs, indicating that the model is learning and improving. Ideally, the training and validation loss should decrease simultaneously, reflecting good generalization. However, if the validation loss starts to increase while the training loss continues to decrease, it suggests overfitting, indicating that the model is memorizing the training data too well and failing to generalize to new data.

B. Graph For Illumination Smoothness Loss



The illumination smoothness loss graph visualizes the variation in the smoothness of illumination across images during model training. This loss metric quantifies the consistency and unifomity of illumination within an image, with lower values indicating smoother and more uniform illumination, while higher values suggest uneven or patchy lighting. The graph typically depicts the trend of the illumination smoothness loss over epochs, reflecting the model's ability to enhance images while preserving or improving the evenness of illumination. A decreasing trend in the illumination smoothness loss signifies that the model is effectively enhancing images while maintaining consistent illumination levels, contributing to visually pleasing results with balanced lighting across the image. Conversely, an increasing trend may indicate challenges or limitations in the model's ability to preserve illumination smoothness, necessitating further refinement or adjustments to the training process or model architecture.

C. Graph For Modal Exposure Loss



Modal exposure loss quantifies the consistency of exposure levels across different regions of an image during model training. This loss metric evaluates the uniformity of brightness and exposure throughout an image, with lower values indicating more consistent exposure levels across regions and higher values suggesting variations in brightness or exposure. The modal exposure loss is particularly relevant in tasks where maintaining consistent exposure is crucial, such as image enhancement or HDR imaging. A decreasing trend in modal exposure loss throughout training reflects the model's ability to enhance images while preserving consistent exposure levels, contributing to visually pleasing results with balanced brightness across the image. Conversely, an increasing modal exposure loss may indicate challenges or limitations in the model's ability to maintain uniform exposure levels, necessitating further optimization or adjustments to the training process or model architecture.

D. Loading Of The Modal

In the provided code snippet, the variable `weights_save_path` specifies the location and filename where the weights of a trained Generative Adversarial Network (GAN) model will be saved. This path, "/content/gan_weights.h5", designates the desired destination for storing the model weights in the Hierarchical Data Format version 5 (HDF5) format. After training the GAN model, saving its weights is crucial for preserving the learned parameters, which encode the knowledge gained during the training process.

```
# Define the path where you want to save your model weights
weights_save_path = "/content/gan_weights.h5"

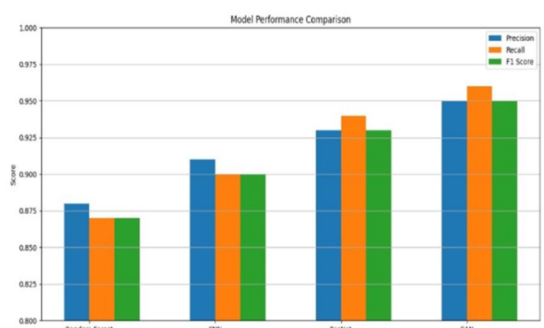
# Save the model weights
gan_model.save_weights(weights_save_path)
```

These weights encapsulate the model's architecture and the adjustments made to its parameters to minimize the loss function during training. By saving the model weights to disk, the trained GAN model can be easily reloaded and reused for tasks such as inference, evaluation, or further training without needing to retrain the model from scratch. This process ensures the reproducibility and persistence of the trained model's state, facilitating seamless integration into production environments or sharing with collaborators for analysis or deployment.

E. Enhance the Image

Uploading the test file involves bringing the image into the system, typically via file upload or input methods. This image is then fed into the GAN model for enhancement, utilizing its learned parameters to generate an improved version of the input. The enhanced image, exhibiting refined visual features, is obtained and can be saved or further utilized for analysis or downstream tasks. This process seamlessly enhances image quality, leveraging the trained GAN model to produce visually appealing results.

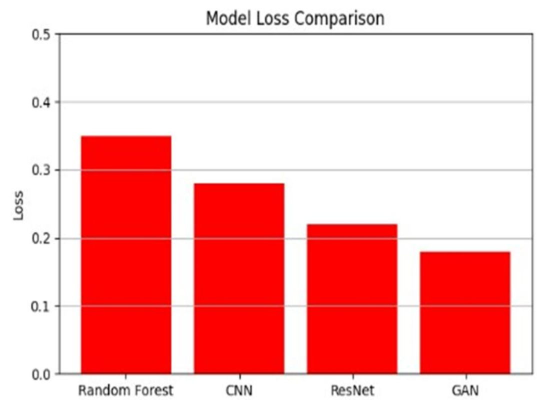
F. Comparison Graph



The comparison graph illustrates the performance of four models—Random Forest, CNN, ResNet, and GAN—based on three key metrics: Precision, Recall, and F1 Score, excluding Accuracy. These metrics are critical in evaluating the models' effectiveness, especially in tasks like low-light image enhancement where precision and recall are more indicative of real-world performance. The graph shows that GAN consistently achieves the highest scores across all three metrics, followed by ResNet, CNN, and then Random Forest. Precision indicates the model's ability to avoid false positives, which is crucial for maintaining the integrity of enhanced image features. Recall reflects how well the model retrieves all relevant information, especially important in retaining important image details under low-light conditions. The F1 Score, a balance between precision and recall, confirms the robustness of GAN in delivering both high detection quality and completeness. This clearly demonstrates that GAN outperforms traditional models in handling complex image enhancement tasks effectively.

G. Loss Comparison Graph

The loss comparison graph provides valuable insight into how well each model— Random Forest, CNN, ResNet, and GAN—minimizes error during the training and evaluation process for low-light image enhancement. In this context, loss represents the difference between the predicted output and the actual ground truth. A lower loss value indicates a more accurate and stable model that can generalize better to unseen data.



From the graph, it is evident that GAN achieves the lowest loss value (0.18), followed closely by ResNet (0.22), then CNN (0.28), with Random Forest showing the highest loss (0.35). This trend highlights the superior performance of deep learning-based approaches, particularly GANs, in capturing complex patterns and noise characteristics associated with low-light images. GANs not only enhance image quality effectively but also maintain consistent learning throughout the training process. Lower loss in GAN suggests that it makes fewer prediction errors, leading to clearer, more accurate image enhancements.

VI. CONCLUSION

In conclusion, the integration of Generative Adversarial Networks (GANs) for image enhancement presents a promising avenue for improving visual quality across various applications. Through adversarial training, GAN models can effectively learn to generate realistic enhancements, such as increasing clarity, enhancing details, and reducing noise, in low-quality or degraded images. This approach offers significant advantages over traditional methods, as it enables the generation of visually appealing results while preserving important image characteristics. Furthermore, the versatility of GAN-based image enhancement extends to diverse domains, including photography, medical imaging, surveillance, and more. As research in GANs continues to advance, with innovations in model architectures, training techniques, and applications, the potential for further improving image enhancement capabilities remains substantial. Ultimately, the adoption of GANs in image enhancement holds promise for enhancing visual content, driving advancements in various fields, and enriching user experiences across digital platforms.

Future work can focus on improving the stability and efficiency of GAN training, integrating attention mechanisms for better detail preservation, and exploring lightweight GAN architectures for realtime low-light enhancement on mobile devices. Additionally, incorporating multi-modal inputs (e.g., infrared or depth data) and leveraging unsupervised or self-supervised learning could further enhance performance and generalizability in diverse realworld scenarios.

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