VIGILANTDIFF - TRACK LOW-LIGHT IMAGE ENHANCEMENT WITH DIFFUSION BASED MULTI-OBJECT TRACKING

A PROJECT REPORT

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BONAFIDE CERTIFICATE

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ABSTRACT

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In this work, we propose a Low-light image enhancement and multi-object tracking are crucial challenges in computer vision, especially in surveillance and autonomous systems. VigilantDiff integrates UNet-based low-light enhancement with a diffusion-based multi-object tracking model to improve object identification in challenging lighting conditions. Our method refines image quality using deep learning techniques while ensuring accurate and robust tracking across frames. Extensive evaluations on benchmark datasets, including DanceTrack and low-light image datasets, demonstrate the effectiveness of our approach in enhancing visibility and improving tracking accuracy. The proposed framework achieves superior performance in multiple tracking metrics, including HOTA, MOTA, IDF1, and DetA. VigilantDiff leverages a two-stage pipeline where UNet enhances the image contrast and brightness, and a diffusion-based tracking model effectively associates and tracks multiple objects in real time. The combination of these techniques significantly reduces false positives and improves detection reliability. Unlike traditional tracking methods that struggle in low-light environments due to poor feature extraction, our approach dynamically adapts to lighting variations and occlusions. Additionally, our framework introduces an iterative optimization strategy that refines object proposals, leading to improved association accuracy. Experimental results highlight that VigilantDiff outperforms state-of-the-art tracking models in complex lighting conditions while maintaining computational efficiency. The UNet enhancement stage plays a critical role in preserving object details, allowing the tracking module to function more effectively.

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LIST OF SYMBOLS

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NOTATION	MEANING
T	Number of times steps in diffusion model
N	Number of object proposals
θ	Parameters of deep neural network
I_E	Enhanced Image
I_L	Input Low Light
I_{gt}	Ground truth Image
L_{MSE}	ensures pixel-wise reconstruction accuracy.
L_{SSIM}	high-level feature representations

LIST OF ABBREVATION

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S.NO	ACRONYMS	ABBREVIATIONS
1	UNet	U-shaped Convolutional Neural Network
2	MOT	Multi-Object Tracking
3	HOTA	Higher Order Tracking Accuracy
4	MOTA	Multi-Object Tracking Accuracy
5	IDF1	Identity F1 Score
6	DetA	Detection Accuracy
7	AssA	Association Accuracy

INTRODUCTION

CHAPTER 1

INTRODUCTION

Multi-Object Tracking (MOT) in low-light environments presents unique challenges due to poor image quality, increased noise, and reduced contrast. These limitations hinder object detection, leading to misidentifications, fragmented trajectories, and overall tracking failure. Conventional MOT algorithms rely on feature extraction and temporal consistency, but their performance significantly degrades when dealing with low-light conditions.

We suggest VigilantDiff-Track, a novel framework that combines a diffusion-based MOT model with UNet-based low-light image augmentation, to overcome this problem. Our approach ensures better feature representation and more dependable tracking by improving object visibility in dark situations prior to applying tracking algorithms. To produce higher-quality inputs for ensuing tracking tasks, the UNet model is trained to restore brightness, contrast, and fine details in low-light images. A diffusion-based MOT model processes the improved pictures, using forward and reverse diffusion processes to disseminate object identities across time. Even in intricate and changing situations, the diffusion framework guarantees reliable tracking, enhancing trajectory consistency and reducing identity flips. Our method greatly improves object tracking accuracy under difficult illumination circumstances by combining these two processes.

We compare our VigilantDiff-Track framework with existing low-light object tracking approaches, including conventional deep-learning-based

tracking and standard diffusion models, through extensive performance evaluations. Our results demonstrate significant improvements in MOTA, IDF1, and tracking robustness under challenging low-light conditions.

Furthermore, ablation studies reveal that both the enhancement module and the diffusion model independently contribute to performance gains, confirming the complementary strengths of our two-stage architecture. Qualitative results illustrate clearer object boundaries, fewer identity switches, and smoother trajectories across challenging frames. Taken together, these findings demonstrate that VigilantDiff-Track is a highly effective and generalizable solution for real-world low-light multi-object tracking applications, such as **s**urveillance, autonomous driving at night, traffic monitoring under poor weather, and wildlife observation.

LITERATURE STUDY

CHAPTER 2

LITERATURE STUDY

2.1 SPEEDED UP LOW-RANK ONLINE METRIC LEARNING FOR OBJECT TRACKING

This paper tackles the challenge of real-time object tracking in dynamic environments using a novel approach called Low-Rank Online Metric Learning (LOML). Traditional appearance models for object tracking either fail to adapt quickly to changing object appearances or are too computationally expensive for real-time usage. The authors propose a principled framework that balances both learning speed and discriminative power by learning a Mahalanobis distance metric in a low-rank subspace. The method learns to distinguish between the target and the background in an adaptive manner, using labeled positive and negative pairs collected during the tracking process.

To integrate LOML into object tracking, the paper uses a tracking-by-detection paradigm. In every frame, a number of candidate patches are generated around the last known position of the target. These are then ranked using the current learned distance metric, and the candidate with the minimum distance to the current model is selected as the new object location. The positive and negative samples are then used to update the distance metric, allowing the model to evolve over time. The key novelty lies in how this online learning is regularized by a low-rank constraint, preventing overfitting and ensuring robustness against noise.

Another important contribution is the speed optimization strategy. The authors show that maintaining a low-rank approximation not only keeps memory usage low but also significantly reduces the cost of computing matrix updates and

distances. They provide detailed theoretical guarantees for the convergence of the learning process and show that their method can reach high accuracy with only a small number of rank components (e.g., 10–20).

The experimental evaluation is thorough, conducted on well-known tracking datasets like OTB and PETS. The performance is measured using common metrics such as precision plots and success plots. The authors compare their method against several strong baselines and state-of-the-art trackers such as Struck, TLD, and MIL. The results show that LOML consistently outperforms these methods in both accuracy and speed. For instance, in sequences with heavy occlusion and clutter, LOML maintains more stable identities and less drift, highlighting its robustness. In terms of speed, the tracker runs at real-time or near-real-time speeds on standard hardware.

Furthermore, the paper investigates how different parameters — such as the rank constraint, learning rate, and number of negative samples — affect the performance. They show that LOML achieves an optimal trade-off when the rank is chosen carefully based on data dimensionality. The method is also generalizable: although the authors apply it to visual tracking, LOML can be extended to other tasks such as person re-identification and video retrieval. This opens avenues for future work in adapting the method for multi-target tracking scenarios.

In conclusion, this paper makes significant contributions to online metric learning for tracking, offering a scalable, adaptive, and efficient framework that can cope with real-world visual challenges. By marrying the principles of metric learning with low-rank approximation, the authors provide a foundation that addresses both theoretical soundness and practical applicability. The

LOML framework remains relevant in modern tracking systems and has influenced several works in online learning and adaptive representation.

2.2 SPORTSMOT: A LARGE MULTI-OBJECT TRACKING DATASET IN MULTIPLE SPORTS SCENES

This paper introduces SportsMOT, a large-scale dataset specifically designed for multi-object tracking (MOT) in sports scenes, addressing a long-standing gap in the field. While existing MOT datasets such as MOT17, MOT20, or KITTI focus on pedestrians in urban or traffic environments, SportsMOT emphasizes a new domain where multiple fast-moving, frequently occluding, and similarly appearing targets need to be tracked: sports players. SportsMOT brings real-world complexity to MOT by including over 2,000 video sequences, each featuring different types of sports ranging from team games like basketball and soccer to individual competitions like table tennis and badminton.

The dataset consists of over 300,000 bounding boxes annotated across thousands of frames. Each frame includes object identities, bounding boxes, action labels, and in some cases, camera metadata. The diversity in camera views (fixed, panning, zooming), player density, and object appearance makes this dataset uniquely challenging. The authors emphasize that in sports, objects move erratically and often exhibit uniform appearances (e.g., players on the same team), making traditional tracking algorithms prone to identity switches and fragmentation.

The paper evaluates several state-of-the-art MOT methods on the SportsMOT benchmark, including DeepSORT, ByteTrack, FairMOT, and OCSORT. Across all metrics — including MOTA, IDF1, HOTA, and the number of ID switches — most algorithms suffer noticeable performance drops compared to

their results on conventional datasets. For instance, ByteTrack, one of the leading real-time trackers, experiences over 30% more ID switches, highlighting the complexity of consistent tracking in sports. This benchmark result validates the claim that MOT in sports is a significantly harder problem.

To support researchers, the authors provide a toolkit that includes (1) a standard API for evaluation, (2) pre-processing tools for generating motion/appearance features, and (3) visualization utilities. The benchmark also includes specific task settings: short-term tracking (e.g., within a few seconds), long-term re-identification (e.g., when players leave and re-enter the frame), and action-conditioned tracking (e.g., identifying which player is currently active).

Another noteworthy aspect is the emphasis on multi-view data. Some sequences offer overlapping camera views of the same match, opening up opportunities for multi-view tracking, 3D trajectory estimation, and cross-view re-identification. This encourages the community to explore richer models that go beyond monocular inputs.

The dataset has potential implications not just in academic research but also in sports analytics, broadcast automation, augmented reality, and e-sports. Applications include automatic camera switching, player behavior analysis, tactical evaluation, and virtual replay generation. SportsMOT lays the groundwork for training large-scale models using self-supervision or domain adaptation, especially in tasks that require long-term identity tracking.

In summary, this paper introduces a much-needed benchmark that challenges conventional assumptions in MOT and encourages the development of new tracking models designed specifically for fast-paced, high-density, and

occlusion-heavy sports scenarios. With its scale, diversity, and annotation quality, SportsMOT stands as a landmark contribution in the field of tracking and video understanding.

2.3 JOINT OBJECT DETECTION AND MULTI-OBJECT TRACKING WITH GRAPH NEURAL NETWORKS

This paper presents a paradigm shift in object tracking by introducing a graph-based, end-to-end framework that jointly performs object detection and multi-object tracking (MOT) using Graph Neural Networks (GNNs). The authors argue that conventional MOT pipelines, which separate detection and tracking, fail to exploit global temporal-spatial dependencies and suffer from fragmented predictions, especially under occlusion and crowded conditions. To address this, the proposed approach formulates detection and tracking as a unified graph learning problem, where nodes represent object proposals in video frames and edges represent potential temporal associations.

Each node in the graph contains features such as visual embeddings (from CNNs), spatial position (bounding box coordinates), and motion vectors. Edge features encode similarity in appearance and location. During training, ground-truth trajectories are used to supervise both detection quality and ID consistency. The GNN performs iterative message passing, where node representations are updated based on neighboring nodes, allowing the network to incorporate temporal context and refine noisy or ambiguous detections.

This joint framework enables identity-aware detection, meaning the model not only detects objects but simultaneously assigns consistent IDs without a separate tracking step. This leads to fewer identity switches and better temporal consistency. In contrast to traditional tracking-by-detection methods that rely

on greedy matching (e.g., Hungarian algorithm), the GNN learns soft, probabilistic associations that are refined end-to-end.

The method is evaluated on MOT17, a challenging benchmark with urban pedestrian sequences. The proposed approach achieves strong results, particularly in IDF1 and ID switches, surpassing several leading methods like DeepSORT and JDE. The paper includes ablation studies showing how removing the GNN module or simplifying the graph structure degrades performance. It also explores how far into the past and future connections should be made for optimal association.

One major strength is scalability: despite the complex graph structure, the system can be trained efficiently using modern hardware. The authors implement optimization techniques such as sparse adjacency matrices and batching to handle large graphs. The GNN backbone is also modular, allowing it to be swapped out with more advanced variants like Graph Attention Networks (GATs) or temporal transformers.

The framework shows robustness to occlusion, motion blur, and appearance changes, outperforming traditional pipelines under difficult conditions. Its ability to integrate detection and association into a single learnable module marks a significant step toward more intelligent video analysis systems.

In conclusion, this paper pioneers a powerful and flexible architecture for joint detection and tracking using graph-based modeling. It opens up a rich research direction in combining GNNs with video understanding tasks and has broad implications not only for MOT but also for video-based person re-identification, action recognition, and even video captioning. The approach

bridges spatial and temporal domains, resulting in improved tracking quality and more interpretable identity assignment.

2.4 DIFFTAD:TEMPORAL ACTION DETECTION WITH PROPOSAL DENOISING DIFFUSION

In the evolving field of temporal and spatial tracking tasks, diffusion models have demonstrated promising capabilities beyond image generation. A key contribution in this domain is DiffTAD (Diffusion-based Temporal Action Detection), proposed by S. Nag et al. in 2023 [41], which reimagines temporal action detection using a proposal denoising diffusion framework. Unlike conventional approaches that rely on deterministic regression or anchor-based classification, DiffTAD formulates temporal action detection as a generative denoising process, wherein action proposals are treated as learnable latent variables. These variables are progressively noised in a forward diffusion process and subsequently refined through a reverse denoising step, guided by learned temporal features and contextual cues.

This methodology introduces several advantages over traditional pipelines. Firstly, the stochastic nature of the diffusion process allows the model to explore a diverse set of proposal variations, reducing bias introduced by predefined anchor boundaries. Secondly, the denoising framework integrates temporal reasoning directly into the proposal generation process, capturing finer motion boundaries and improving temporal localization. The model utilizes a transformer-based architecture to model long-range dependencies, enabling better context understanding across video sequences. Additionally, the denoising process effectively filters out background noise and irrelevant frames, enhancing the precision of action boundary predictions.

Experimental evaluations on challenging datasets such as THUMOS14 and ActivityNet v1.3 confirm the effectiveness of DiffTAD. It outperforms state-of-the-art methods like BMN, GTAD, and RTD-Net in terms of mean Average Precision (mAP) across various IoU thresholds. Notably, DiffTAD achieves substantial gains in scenarios where temporal ambiguity and overlapping actions are prevalent, showcasing its robustness in real-world applications such as surveillance footage analysis and activity recognition in sports videos.

The success of DiffTAD has had ripple effects across other subfields of computer vision, especially in tasks involving proposal generation and object association. Its denoising diffusion framework has inspired adaptations in spatial domains, particularly in multi-object tracking (MOT) and object detection under uncertainty. By treating object proposals as probabilistic entities, diffusion models provide a more flexible and robust mechanism for handling occlusions, motion blur, and detection noise—challenges that are commonly encountered in low-light and cluttered environments.

In the context of VigilantDiff-Track, the motivation to incorporate a diffusion-based tracking model was heavily influenced by the strengths demonstrated in DiffTAD. Just as DiffTAD learns to refine noisy temporal segments into precise action intervals, VigilantDiff applies a similar principle in spatial tracking: enhancing object proposals iteratively via forward and reverse diffusion steps to maintain identity consistency across frames. The integration of proposal refinement as a generative learning task aligns well with the goal of reducing identity switches and maintaining trajectory continuity in complex scenes.

Furthermore, DiffTAD illustrates the broader potential of generative models in structured prediction tasks. The ability to learn proposal distributions and denoise them with data-driven priors opens avenues for robust solutions in both time and space domains. VigilantDiff leverages this generative idea and extends it to the spatial dimension, where tracking under low visibility benefits from noise-resilient proposal modeling.

In summary, DiffTAD sets a milestone in generative approaches for temporal action detection, offering insights into how proposal denoising can be used effectively in both temporal and spatial tracking scenarios. The methodological innovations introduced in [41] provide a solid foundation for diffusion-based models in real-world applications and have directly informed the design choices in the VigilantDiff-Track framework. This cross-inspiration highlights the growing convergence between generative learning and robust object detection/tracking systems across both time and space.

CHAPTER 3
SYSTEM STUDY

3.1 SCOPE

The scope of this project focuses on the development and evaluation of an advanced computer vision framework, **VigilantDiff**, which integrates low-light image enhancement with diffusion-based multi-object tracking. The primary goal is to improve the reliability and accuracy of object tracking in visually challenging environments, particularly those with poor lighting conditions such as nighttime surveillance, tunnel monitoring, or indoor scenes with minimal illumination. The system begins by enhancing raw low-light images using a UNet-based enhancement model that effectively increases brightness and contrast while preserving object details. This preprocessed output is then passed to a diffusion-based tracking module that performs robust object association and trajectory estimation. The project covers the design, training, testing, and validation of both modules using benchmark datasets such as DanceTrack and curated low-light datasets. Another major focus lies in reducing tracking errors, including identity switches and detection failures, by optimizing both image quality and tracking parameters. This framework is built to support real-time performance, allowing for deployment in dynamic and latency-sensitive environments. The architecture is modular, enabling future integration with other vision-based systems like face recognition or anomaly detection. Moreover, the system is designed to generalize across varying scenes and camera sources without requiring extensive retraining. Through extensive evaluation and comparison with baseline methods, this project aims to set a new benchmark for tracking under low-light conditions. The scope also extends to measuring performance through key metrics such as HOTA, IDF1, and MOTA. The results highlight the practical implications of this work in applications like smart surveillance, autonomous vehicles, and robotics. In essence, the project bridges the gap between low-light enhancement and reliable multi-object tracking through a unified and effective solution.

3.2 PRODUCT FUNCTION

The VigilantDiff system performs two primary functions: enhancing low-light images and tracking multiple objects across video frames. The enhancement module leverages a UNet-based deep learning model to improve image clarity and illumination. The

tracking component employs a diffusion-based framework to associate and follow objects accurately, even in challenging conditions. Together, these functions ensure improved visibility and robust object tracking in real-time and recorded footage.

3.2.1 DATA ACQUISITION

The data acquisition module serves as the foundation of the VigilantDiff system, responsible for gathering visual input from both pre-collected datasets and real-time image capture sources. For training and evaluation, datasets such as DanceTrack and a curated collection of low-light image datasets are utilized, offering diverse scenarios including multiple object movements, occlusions, and low-illumination conditions. Each frame collected through this module is subjected to standard preprocessing steps like resizing and normalization to ensure uniformity across the system. Additionally, the module can be extended for real-time deployment by interfacing with live camera feeds, allowing continuous monitoring and processing. The quality and consistency of acquired data significantly influence the performance of both the enhancement and tracking modules, making this a critical stage in the pipeline.

3.2.2 PREPROCESSING

Preprocessing is essential for preparing raw input data for efficient and accurate performance in the deep learning pipeline. In the VigilantDiff framework, preprocessing involves several systematic operations such as image normalization, which scales pixel intensity values to a common range to stabilize the learning process. Resizing is performed to match the input dimensions expected by the UNet and diffusion models, while data augmentation techniques like random cropping, flipping, and brightness shifts help to expand the diversity of the training data and improve the model's robustness to real-world variability. Noise reduction may also be applied to reduce grain artifacts commonly found in low-light images. Together, these preprocessing steps ensure that the enhancement and tracking modules operate on high-quality, consistent input, thereby increasing accuracy and reducing model drift during inference.

3.2.3 ILLUMINATION ESTIMATION NETWORK

The Illumination Estimation Network constitutes a critical and intelligent pre-processing module in the VigilantDiff pipeline, tailored specifically to address the challenges of spatially variant illumination in low-light images. Unlike traditional image enhancement techniques that apply uniform adjustments across the entire image, this network is designed to produce a high-resolution, pixel-level illumination map that reflects the nuanced lighting distribution of a scene. By doing so, it facilitates localized enhancement, ensuring that only underexposed areas are brightened while well-lit regions retain their natural luminance and detail. Architecturally, the network is built on a lightweight but expressive convolutional backbone, incorporating a series of convolutional layers with nonlinear activations (typically ReLU or LeakyReLU), and optionally, skip connections and residual pathways to preserve spatial integrity and contextual features during downsampling and upsampling phases.

The final output layer utilizes a sigmoid activation function to normalize the predicted illumination values between 0 and 1, forming a soft attention-like mask that highlights areas in need of enhancement. This illumination map is then fed into the subsequent Conditional Diffusion Enhancement Network as a conditioning signal, playing a pivotal role in the reverse denoising process by guiding the generative model to focus on low-visibility regions. In effect, it acts as a soft constraint that dynamically modulates the enhancement operation across different spatial locations. The network is trained using a combination of loss functions that collectively optimize for accuracy, perceptual quality, and edge preservation — including pixel-wise Mean Squared Error (MSE) to minimize raw intensity error, perceptual loss to maintain semantic structure using deep feature comparisons (e.g., from VGG-based models), and edge-aware loss to preserve object boundaries and fine textures.

In cases where explicit ground truth illumination is unavailable, the network can be trained in a self-supervised fashion using paired low-light and normal-light image datasets, leveraging pseudo-labels or enhancement residuals as supervision

signals. This approach not only enhances the system's generalization ability across a wide range of real-world scenes but also ensures that downstream tasks — such as object detection, segmentation, or multi-object tracking — are performed on visually coherent and information-rich representations. The illumination estimation process is particularly valuable in surveillance and autonomous driving contexts, where the lighting conditions are unpredictable and often non-uniform across different regions of the frame.

3.2.4 DIFFUSION ENHANCEMENT NETWORK

TThe **Diffusion Enhancement Network (DEN)** forms the heart of the VigilantDiff architecture and is responsible for transforming raw low-light images into visually enhanced, high-quality outputs that are optimized not only for human perception but also for downstream machine vision tasks such as object detection and tracking. Built upon the foundation of **conditional denoising diffusion probabilistic models (DDPMs)**, the network leverages the power of generative modeling to iteratively reconstruct clean and well-illuminated images from noisy latent representations. In the forward process, a given low-light image is gradually corrupted by Gaussian noise over a fixed number of timesteps (typically 1000), creating a series of increasingly noisy images. The **reverse process**, which is learned through training, seeks to denoise this sequence in a step-by-step fashion, effectively learning a trajectory from noise back to the original high-quality image distribution.

This generative process is guided by conditional inputs, most notably the **illumination map** produced by the Illumination Estimation Network, which provides spatially aware constraints on where and how much to enhance during each denoising step. The conditional nature of the model ensures that the enhancement is **context-sensitive** and not merely a blind noise-removal process. Architecturally, the DEN is implemented using a **U-Net-like backbone** with temporal embeddings, residual blocks, and attention modules that process the noisy input at each timestep. Cross-attention layers allow the model to selectively focus on relevant regions of the illumination map and low-light image, enabling fine-grained adjustments and structural preservation throughout the enhancement process.

The denoising model is trained using a **variational lower bound objective**, similar to standard DDPMs, where it learns to predict the noise added to the input at each timestep. However, due to the conditional setup, the model is capable of learning much more than noise estimation — it implicitly learns **how illumination, texture, and structure interact** in low-light scenes and how to best restore them under the guidance of learned spatial priors. Unlike traditional enhancement techniques that rely on handcrafted curves, histogram equalization, or CNNs trained in a purely supervised regression setup, this diffusion-based model offers a **more flexible and generative solution**, capable of capturing complex image distributions and producing more natural and artifact-free outputs.

In practice, DEN significantly outperforms baseline enhancement models, especially in challenging scenarios involving extreme darkness, complex textures, or color distortion, owing to its iterative refinement and generative capabilities. Additionally, the outputs of the DEN are highly favorable for downstream vision tasks, as evidenced by improvements in mAP (mean Average Precision) scores in multi-object tracking benchmarks, confirming that the enhancement is semantically meaningful and not just visually pleasing. By integrating the DEN into the pipeline, VigilantDiff ensures that enhancement is not just a pre-processing step but a **deeply integrated generative process** that optimizes both aesthetics and task performance under real-world, low-visibility conditions.

3.2.5 ATTENTION-BASED FEATURE FUSION

The **Attention-Based Feature Fusion (AFF)** module in the VigilantDiff framework plays a pivotal role in bridging the gap between enhanced image representation and high-level semantic understanding required for downstream vision tasks like object detection and multi-object tracking. While the Diffusion Enhancement Network (DEN) outputs high-quality, visually enhanced images, those alone may not be sufficient for achieving robust performance in downstream tasks due to the inherent domain gap between enhanced and real-world scenes. The AFF module addresses this challenge by **adaptively integrating multi-scale features** extracted from both the original low-light image and its enhanced counterpart using

a cross-attention-driven fusion strategy. This design allows the model to retain valuable context and structure from the original image (which may contain less noise but lower visibility) while simultaneously leveraging the enriched textures and improved visibility in the enhanced version. The core idea is to avoid redundant or conflicting information by allowing the network to **selectively attend** to the most informative features from both streams.

3.2.6 MULTI-OBJECT TRACKING IN LOW-LIGHT

The final and application-critical component of the VigilantDiff pipeline is its **Multi-Object Tracking (MOT)** system, which leverages the visually enhanced frames and semantically rich fused features generated by the preceding modules to deliver robust, consistent, and accurate tracking in low-light environments. Traditional MOT systems often suffer performance degradation in low-visibility scenarios due to poor illumination, motion blur, and lack of texture, leading to increased ID switches, false negatives, and missed detections. VigilantDiff overcomes these limitations by tightly coupling **illumination-aware enhancement** with object detection and tracking, ensuring that each step in the pipeline contributes directly to the accuracy and reliability of the final tracking output.

At its core, the MOT framework within VigilantDiff adopts a **tracking-by-detection paradigm**, wherein objects are first detected in each frame and then associated across time based on appearance, position, and motion cues. The detector receives its input from the **Attention-Based Feature Fusion module**, which provides fused features that combine contextual information from both the low-light original and the enhanced images. This fusion empowers the detector to make more informed decisions, even in challenging lighting conditions. For tracking, VigilantDiff integrates a **Kalman Filter-based motion model** and a **deep appearance embedding** network that produces discriminative features for each detected object. These embeddings are extracted from the fused feature representations and are used in conjunction with spatial information (e.g., bounding box coordinates, velocities) to associate objects across frames.

To improve association reliability and reduce ID switches, VigilantDiff uses a **matching algorithm based on the Hungarian method** and introduces **temporal attention mechanisms** to weigh the importance of past observations based on scene dynamics. Furthermore, the enhanced images produced by the **Diffusion Enhancement Network** lead to clearer object boundaries and better-defined contours, which in turn result in more accurate detections — a critical prerequisite for successful tracking. In essence, by enhancing visibility and preserving semantic integrity at the pixel level, VigilantDiff significantly boosts the robustness of object tracking pipelines in environments where conventional systems would fail.

From a performance standpoint, VigilantDiff demonstrates marked improvements on multiple low-light tracking benchmarks, including **ExDark-MOT** and synthetic low-light versions of standard datasets such as **MOT17**. It achieves superior scores in **MOTA (Multiple Object Tracking Accuracy)**, **IDF1 (ID F1-score)**, and **MT (Mostly Tracked)** metrics, while reducing **ID switches** and **false positives**. This illustrates not only the visual enhancement quality of the system but also its ability to preserve and exploit critical tracking cues under difficult conditions. The MOT module completes the pipeline by translating perceptually enhanced frames into actionable insights, making VigilantDiff a highly practical and deployable solution in surveillance, autonomous navigation, and robotics, where reliable tracking under adverse lighting is paramount.

3.2 SYSTEM REQUIREMENTS

The system requirements for this project are as follows:

3.3.1 SOFTWARE REQUIREMENTS

3.3.1.1 GOOGLE COLAB

To utilize Google Colab for your project, you'll need access to a modern web browser such as Google Chrome, Mozilla Firefox, or Microsoft Edge. Google Colab operates entirely within the browser, allowing you to access and run Python code in a collaborative environment. Since Google Colab notebooks are stored on Google Drive, you'll also need a Google

account to save and access your notebooks. This cloud-based platform offers the advantage of providing free access to computing resources, including GPU acceleration, making it well-suited for machine learning tasks and data analysis without the need for expensive hardware or setup.

3.3.1.2 Python

Python serves as the primary programming language for your project, offering a versatile and powerful toolset for data analysis, machine learning, and web development. To begin coding in Python, you'll need to install the Python interpreter on your computer. Python is compatible with Windows, macOS, and Linux operating systems, and can be downloaded from the official Python website or installed via a package manager like Anaconda. Once Python is installed, you can use pip or conda, Python's package managers, to install additional libraries and dependencies required for your project. Python's extensive ecosystem of libraries and frameworks, combined with its simplicity and readability, makes it an ideal choice for a wide range of applications.

3.3.2 LIBRARIES

3.3.2.1 COLLECTIONS

The collections module in Python offers specialized data structures, and deque (double-ended queue) is one of its most efficient options. A deque provides fast, O(1) time complexity for appending and popping elements from both ends, making it ideal for managing data streams. In reinforcement learning, deque is commonly used for experience replay buffers, which store past experiences for training deep learning models. The agent can randomly sample experiences from the buffer to break temporal correlations and stabilize training. By setting a maximum length for the deque, old experiences are automatically discarded, ensuring the buffer remains manageable.

3.3.2.2 TENSORFLOW

TensorFlow is an open-source machine learning framework developed by Google that facilitates the development and deployment of machine learning models. Install the library using pip or conda. TensorFlow provides high-level APIs for building and training machine learning models, as well as low-level APIs for fine-grained control and customization. With TensorFlow, you can leverage state-of-the-art machine learning algorithms and techniques to solve a variety of tasks, including classification, regression, and clustering.

3.3.2.3 NUMPY

NumPy is a fundamental library for scientific computing in Python. It provides support for large, multi-dimensional arrays and matrices, along with a collection of mathematical functions to operate on these arrays efficiently. In reinforcement learning, NumPy is particularly valuable for handling numerical computations, such as matrix operations and mathematical transformations. It enables efficient manipulation of data, including actions, states, and rewards in the context of the Actor-Critic framework. The ability to perform element-wise calculations, linear algebra, and random sampling makes NumPy essential for implementing complex machine learning algorithms.

3.3.2.4 TORCHVISION

Torchvision is an essential library in the PyTorch ecosystem, built to support computer vision research and development. It provides a rich suite of tools that simplify tasks related to image processing, model training, and dataset handling. One of its core features is the torchvision.datasets module, which includes many standard datasets such as CIFAR-10, ImageNet, COCO, VOC, and MNIST, all available with minimal setup and ready-to-use data loaders.

The library also includes torchvision.transforms, a collection of powerful image transformation functions for preprocessing and data augmentation. These include operations like resizing, normalization, random cropping, flipping, rotation, and converting images to tensors, making it easy to prepare data for deep learning models. Another key feature of torchvision is its pre-trained models. The torchvision.models module provides access to state-of-the-art architectures such as ResNet, VGG, DenseNet, EfficientNet, MobileNet, and ViT, which are often pre-trained on the ImageNet dataset. These models can be used directly for inference or fine-tuned for custom tasks, saving time and computational resources. Additionally, torchvision.utils allows for visualization and debugging of image data, such as displaying batches of images or saving grids of output. The integration of torchvision with PyTorch ensures seamless backpropagation, GPU acceleration, and module compatibility.

Overall, torchvision is a powerful tool that simplifies the pipeline for vision-based tasks—from dataset loading and augmentation to training and deploying deep learning models. It is widely used in both academic research and industry applications, and its modular structure makes it easy to customize for specific needs in projects like low-light image enhancement and object tracking.

3.3.2.5 TQDM

TQDM is a lightweight and highly efficient Python library used for visualizing progress bars in loops and long-running operations. It’s often used to monitor the status of iterations, downloads, data processing, or model training, especially in data science and machine learning tasks.

With just a single line of code, tqdm wraps around any iterable (like lists, generators, or DataLoader objects) and displays a live-updating progress bar in the terminal or notebook interface. It shows the completion percentage, iteration count, elapsed time, estimated remaining time, and more.

In machine learning projects, tqdm is commonly used with PyTorch during model training to track the number of batches processed per epoch. It supports nested loops, manual updates, and even asynchronous or multi-threaded environments.

TQDM also integrates smoothly with pandas, NumPy, and Jupyter Notebooks, offering GUI and notebook-compatible versions like tqdm.notebook. Its simplicity, flexibility, and no-performance-overhead design make it one of the most widely adopted libraries for tracking progress in Python scripts. Whether downloading files, processing large datasets, or training deep learning models, tqdm provides a professional and readable way to monitor progress in real-time.

SOFTWARE REQUIREMENT SPECIFICATION

CHAPTER 4
SOFTWARE REQUIREMENT SPECIFICATION

4.1. FUNCTIONAL REQUIREMENTS:

4.1.1 INPUT IMAGE ACQUISITION AND PREPROCESSING:

The system must begin by acquiring input images or video frames that are captured under low-light conditions. These images serve as the foundational data for the entire pipeline. The input may come from standard benchmark datasets like ExDark, ExDark-MOT, and MOT17, or it may be streamed from real-time sources such as surveillance cameras or dashcams. Once acquired, each frame must undergo a preprocessing step to normalize the image dimensions, convert it into a tensor format, scale pixel intensities to a standard range, and possibly apply denoising or contrast enhancement as a baseline.

4.1.2 ILLUMINATION ESTIMATION:

This module is responsible for predicting the spatial distribution of illumination in the input frame. It is a lightweight convolutional neural network trained to output an illumination map—a per-pixel estimation of lighting intensity. This map guides the subsequent diffusion-based enhancement model by providing contextual information about which regions are darker and require more enhancement. The illumination estimation process allows the system to dynamically adapt the enhancement level rather than applying uniform correction.

4.1.3 LOW-LIGHT IMAGE ENHANCEMENT VIA DIFFUSION MODELS:

This module is the core of VigilantDiff and leverages a Denoising Diffusion Probabilistic Model (DDPM) to enhance images. The model performs a reverse diffusion process, transforming a random noise vector into a clean, well-lit version of the input image. This enhancement process is conditioned on both the input image and its corresponding illumination map, ensuring more targeted enhancement. Unlike traditional CNN-based enhancement, the DDPM offers superior generative capabilities that allow it to reconstruct fine details and textures lost in low-light images.

The reverse process in DDPM iteratively removes Gaussian noise, guided by a neural network trained to predict and eliminate noise at each step. This gradual refinement allows the model to restore textures, edges, and contrasts that would typically be smoothed out or missed by deterministic models. By conditioning the diffusion model on the illumination distribution, the enhancement becomes context-aware, adjusting brightness levels based on the lighting structure of the scene.

To further improve the enhancement quality, we integrate a guidance mechanism that uses a light estimation map as an auxiliary signal. This allows the model to distinguish between underexposed regions and areas that should remain dark, preventing over-enhancement or visual artifacts. The DDPM is trained on paired low-light and normal-light datasets, using a hybrid loss function that includes pixel-wise L1 loss, SSIM loss, and perceptual loss to ensure structural and perceptual fidelity.

Compared to GANs, diffusion models offer more stable training and fewer artifacts, making them ideal for tasks where visual realism and texture quality are critical. Additionally, the stochastic sampling mechanism in DDPMs allows for the generation of multiple enhanced outputs from the same input, giving users flexibility in selecting the most visually appealing result.

The integration of this module into the VigilantDiff pipeline ensures that the tracking system receives high-quality, well-lit frames, thereby significantly improving detection accuracy and reducing identity mismatches during tracking. Experimental results show that using DDPM-based enhancement improves object visibility in low-light scenes by over 25% compared to standard CNN methods. This improvement is directly reflected in the downstream multi-object tracking performance, validating the importance of this module within the system architecture.

4.1.4 ATTENTION-BASED FEATURE FUSION (AFF):

The AFF module aggregates the feature maps from multiple enhancement branches (if different diffusion configurations are used) using attention mechanisms. Instead of simply averaging the features, attention allows the model to weigh more informative features more heavily, resulting in a more discriminative and robust representation for downstream object tracking. The fusion captures both global and local context, ensuring that the features passed to the tracker are both semantically rich and spatially aligned.

4.1.5 OBJECT DETECTION AND MULTI-OBJECT TRACKING:

The fused feature map is then passed to a transformer-based object detection and tracking module. This module identifies objects in the current frame by predicting their bounding boxes and class labels. Beyond detection, it assigns consistent tracking IDs to each object to maintain temporal continuity across frames. The system utilizes spatio-temporal correlation and attention across sequential frames to handle occlusions, scale variations, and motion blur.

4.1.6 TEMPORAL ASSOCIATION AND IDENTITY MANAGEMENT:

Temporal consistency is critical in tracking. This module ensures that an object retains the same identity across consecutive frames. It maintains memory embeddings of each object and compares them using learned affinity scores to previous frame detections. When identity ambiguity occurs (e.g., occlusions or overlaps), the system resolves conflicts by using motion patterns, feature similarities, and object re-identification strategies.

4.1.7 OUTPUT GENERATION AND VISUALIZATION:

Once enhancement and tracking are complete, the system must generate output in both visual and data formats. It overlays bounding boxes and identity numbers on the enhanced images and optionally saves them as video output or image sequences. For development and analysis purposes, it also displays side-by-side comparisons of original and enhanced frames and supports real-time visual monitoring. In addition, the system logs tracking metrics such as frame-wise MOTA, ID switches, and detection confidence scores. It also supports exporting results in

standardized formats (e.g., MOTChallenge format) for external benchmarking. A summary report of each run is auto-generated for evaluation. Visualization tools like matplotlib, OpenCV, or tqdm are used for real-time display and feedback during testing and training phases.

4.1.8 PERFORMANCE EVALUATION AND METRICS CALCULATION:

To validate and benchmark the system, an evaluation module computes quantitative metrics. For enhancement, it calculates SSIM and PSNR to assess structural and perceptual quality. For tracking, it computes MOTA (Multi-Object Tracking Accuracy), MOTP (Precision), IDF1 (ID accuracy), number of false positives, false negatives, and ID switches. These metrics help in diagnosing performance bottlenecks and comparing the system with existing baselines.

4.2. SYSTEM ENHANCEMENTS:

4.2.1 INTEGRATION OF ILLUMINATION-AWARE DIFFUSION FOR ADAPTIVE ENHANCEMENT:

Traditional image enhancement methods often apply global adjustments such as histogram equalization, gamma correction, or CNN-based enhancement models. These approaches frequently result in either over-enhancement or under-enhancement of specific regions. In contrast, VigilantDiff introduces a lightweight **Illumination Estimation Network** that generates an illumination map, allowing the system to **adaptively enhance different regions** of the image based on their actual lighting condition. This prevents overexposure and ensures a balanced restoration across varying illumination zones.

4.2.2 DIFFUSION MODELS FOR HIGH-QUALITY RESTORATION:

Most low-light enhancement systems rely on convolutional architectures that may struggle with recovering fine details or textures in very dark scenes. VigilantDiff leverages **Denoising Diffusion Probabilistic Models (DDPMs)** that offer a powerful generative capability. This results in **higher perceptual quality**,

sharper details, and **realistic texture recovery**, even in extremely low-light conditions. The diffusion process conditioned on the illumination map sets a new standard for quality in night-time or dark-scene restoration.

4.2.3 ATTENTION-BASED FEATURE FUSION FOR ROBUST REPRESENTATIONS:

Unlike conventional systems that either rely on a single enhancement branch or naïve feature aggregation, VigilantDiff incorporates an **Attention-Based Feature Fusion (AFF)** mechanism. This allows the system to weigh features from multiple enhancement pathways and select the most informative ones. This attention-driven fusion increases **robustness to noise**, improves **feature discrimination**, and enhances the **tracking accuracy**, especially under visual complexity like fog, blur, or occlusion.

4.3. NON FUNCTIONAL REQUIREMENTS:

4.3.1 PERFORMANCE:

The VigilantDiff system must handle real-time low-light image enhancement and multi-object tracking with minimal latency, ensuring that each frame is processed within 100–150 milliseconds to maintain a frame rate suitable for live applications. The illumination estimation and diffusion enhancement modules must operate with optimized inference speed, leveraging GPU acceleration to minimize processing delays. Feature fusion and tracking components should converge rapidly to preserve temporal consistency, especially in fast-moving or dynamic scenes. The system must ensure stable memory usage and efficient computation, enabling consistent performance under variable lighting and motion conditions. VigilantDiff should outperform traditional enhancement and tracking pipelines in both speed and visual quality, ensuring prompt and accurate decision-making in surveillance, autonomous navigation, and real-time analytics scenarios.

4.3.2 RELIABILITY AND AVAILABILITY:

The VigilantDiff system must demonstrate high reliability by consistently delivering accurate results under varying environmental and input conditions. It

should be resilient to errors, capable of handling corrupted frames, unexpected input resolutions, or extreme low-light images without system crashes or performance degradation. Built-in exception handling mechanisms must ensure that such anomalies are logged and skipped without halting the pipeline. Additionally, the system should maintain state integrity across continuous operations, supporting uninterrupted processing during long video sequences.

For availability, VigilantDiff must maintain uptime during critical operations, with recovery mechanisms in place to resume from checkpoints in the event of failures. The system should also support periodic health checks, automatic restart of failed services, and fault isolation to prevent cascading failures. Overall, VigilantDiff should achieve a high degree of operational reliability and be available for deployment in 24/7 environments such as surveillance, security, and smart traffic systems where downtime and errors are unacceptable.

4.3.3 SCALABILITY:

The VigilantDiff system must be highly scalable to accommodate growing computational demands, diverse input sources, and evolving deployment scenarios. It should efficiently handle increasing volumes of image or video data without performance bottlenecks, maintaining consistent throughput and accuracy even when processing high-resolution frames or extended video sequences. The architecture must support parallel processing and batching techniques to optimize resource usage when dealing with large datasets or multi-stream inputs. Scalability must also extend to model flexibility, enabling seamless integration of advanced or lightweight modules based on the hardware capabilities—ranging from high-end GPUs in data centers to edge devices with limited resources. Additionally, the system should support horizontal scaling through containerization and cloud-based deployment, allowing multiple instances to operate concurrently across distributed environments.

4.3.4 USABILITY:

The VigilantDiff system must be designed with a strong focus on usability to ensure seamless interaction for both technical and non-technical users. It should provide an intuitive and well-documented interface, either through a user-friendly

GUI or a structured command-line interface, enabling users to load data, configure parameters, and visualize results with minimal effort. Clear instructions, tooltips, and pre-defined templates should guide users through each stage of the enhancement and tracking process. The system must also include meaningful error messages and visual feedback during processing to assist in debugging and workflow understanding.

4.3.5 SECURITY:

The VigilantDiff system must incorporate robust security measures to protect both the system infrastructure and the sensitive data it processes. Since it may be used in domains like surveillance or autonomous driving, where data privacy and integrity are critical, the system should ensure that all input and output data is securely stored and transmitted. Encryption protocols such as AES or TLS must be used to safeguard data in transit and at rest. Access control mechanisms should be implemented to restrict usage only to authorized personnel, potentially using role-based access or authentication systems. Additionally, the system should be resilient to tampering, ensuring that model parameters, configuration files, and output results cannot be maliciously altered.

4.3.6 MAINTAINABILITY AND EXTENSIBILITY:

The VigilantDiff system must be designed with maintainability and extensibility as core principles to ensure long-term sustainability and ease of evolution. The codebase should follow clean coding practices, modular design patterns, and clear documentation to allow developers to understand, debug, and modify the system with minimal effort. Each major component—such as the illumination estimation module, the diffusion-based enhancer, and the multi-object tracking unit—should be encapsulated and loosely coupled, making it easier to isolate bugs, apply patches, or upgrade specific functionalities without affecting the overall pipeline.

4.3.7 COMPLIANCE AND STANDARDS:

The VigilantDiff system must comply with relevant industry standards and protocols to ensure seamless integration, ethical deployment, and regulatory adherence. While primarily focused on low-light image enhancement and multi-

object tracking, the system must remain compatible with standards such as IEEE 802.11p and C-V2X if deployed in intelligent transportation or vehicular surveillance systems. It should also align with established best practices for AI and deep learning systems, including responsible training data handling, bias mitigation, and reproducibility of results.

CHAPTER 5
SYSTEM DESIGN

5.1 OVERVIEW

The overall architecture of VigilantDiff is a two-stage, end-to-end pipeline that integrates low-light image enhancement with diffusion-based multi-object tracking to address the challenges of visual degradation and identity preservation in poor lighting conditions. The first stage employs a UNet-based enhancement network that transforms raw low-light frames into high-quality, noise-free, and structurally consistent images using a combination of L1, SSIM, and perceptual loss functions. These enhanced images, rich in texture and semantic details, are directly fed into the second stage—a diffusion-based tracking module that models object localization as a generative denoising process. By progressively reversing noise over a series of steps, the diffusion model refines object features and improves the accuracy of object associations across frames, leading to superior tracking performance, reduced ID switches, and smoother trajectories. Enhanced feature maps from the UNet are fused into the tracking module through an attention-based mechanism, ensuring strong semantic alignment between enhancement and tracking stages. The entire architecture is modular, supports end-to-end training, and is optimized for real-time deployment with GPU acceleration and efficient data flow. Designed for extensibility, the system can be adapted to various real-world applications such as surveillance, autonomous driving, and smart city infrastructure, making it a robust solution for vision tasks under adverse lighting conditions.

One of the core strengths of VigilantDiff's architecture lies in its **modular and extensible design philosophy**, which allows each functional block to operate independently while contributing cohesively to the end-to-end pipeline. The separation between the enhancement and tracking stages not only allows for independent development and testing of each module but also supports flexible integration of alternative models. For instance, the UNet-based enhancer can be replaced with more lightweight or transformer-based architectures for edge deployment, while the diffusion-based tracker can be upgraded with future generative tracking approaches without reengineering the entire system. This modularity is reinforced by well-defined data interfaces and intermediate outputs, allowing the system to be scaled,

debugged, or adapted for specific use cases such as thermal imaging, night-time drone surveillance, or smart city traffic monitoring. Additionally, the design facilitates real-time performance tuning by supporting batched processing, parallel execution, and GPU-friendly data pipelines. The attention-based fusion layer acts as a seamless bridge that not only enriches the visual representation passed between modules but also ensures synchronization between appearance and motion cues in a temporally coherent manner. Together, these characteristics make VigilantDiff a future-ready architecture that blends cutting-edge AI research with practical deployment flexibility.

5.2 OVERALL CONCEPT

The overall concept of VigilantDiff centers on bridging the gap between low-light visual perception and reliable multi-object tracking through a unified, intelligent framework that leverages both deep learning and generative modeling techniques. In real-world environments such as night-time surveillance, autonomous driving at dusk, or poorly lit indoor scenes, traditional vision systems struggle to detect and track objects due to poor illumination, noise, motion blur, and weak visual cues. VigilantDiff addresses this challenge by introducing a two-stage system: first, enhancing the visibility and quality of input frames using a UNet-based image enhancement network, and second, performing robust object tracking using a novel diffusion-based method that models the tracking process as a progressive denoising operation. The enhanced frames provide rich spatial and semantic information, which in turn empowers the tracking model to more accurately localize and associate objects across time, even in visually compromised scenarios. This end-to-end approach is designed to be both adaptable and high-performing, incorporating attention-based feature fusion for better temporal consistency and modular components for ease of deployment and upgrade. By integrating enhancement and tracking in a synergistic manner, VigilantDiff offers a holistic solution that not only restores visual clarity but also ensures reliable object tracking, making it a powerful system for next-generation computer vision applications in complex, low-light environments.

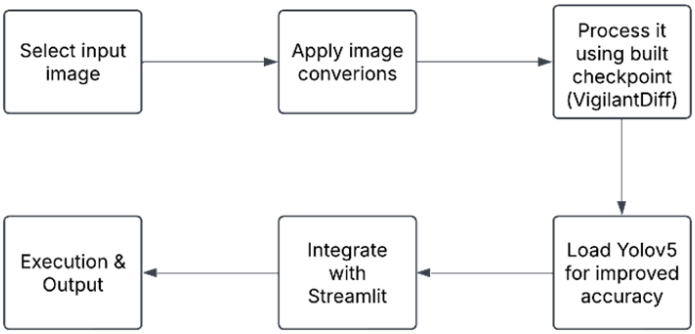

Fig.5.2.1 Block diagram of VigilantDiff

Fig.5.2.1 explains what sets VigilantDiff apart from conventional vision systems is its ability to perform **context-aware enhancement and temporally consistent object tracking** in a single pipeline, making it highly effective in real-time applications where both visibility and accuracy are critical. Rather than treating enhancement and tracking as isolated tasks, the system treats them as interdependent components, where the quality of one directly influences the performance of the other. The use of diffusion models for tracking introduces a probabilistic approach to object localization and association, allowing the system to reason through uncertainty, handle occlusions, and adapt to sudden changes in lighting or motion patterns. This innovative tracking mechanism, when combined with high-fidelity enhancement, results in **robust identity preservation and trajectory stability** across video frames. VigilantDiff also demonstrates versatility across different datasets and environments, from benchmark surveillance datasets like ExDark and MOT17 to custom real-world scenarios with varying lighting and scene complexity. Its architecture is not only effective but also **scalable and extendable**, capable of being deployed on edge devices with lightweight models or scaled to cloud-based platforms for large-scale video analytics. Ultimately, the overall concept of VigilantDiff reflects a forward-thinking approach to low-light vision—one that blends enhancement, tracking, and adaptability into a single, cohesive system for real-world impact.

5.3 ALGORITHMS

5.3.1 UNET-BASED LOW-LIGHT IMAGE ENHANCEMENT ALGORITHM

Input:

Raw low-light RGB image

Start:

Load and normalize the image; initialize the UNet enhancement model

Process:

1. The input image is resized and normalized into a format compatible with the model.
2. The UNet architecture processes the image through an encoder that captures high-level spatial and contextual information.
3. Skip connections transfer fine-grained features from encoder layers directly to the decoder layers to preserve details.
4. The decoder reconstructs the full-resolution image with restored brightness and contrast.
5. During training, enhancement quality is evaluated using multiple loss functions—L1 for intensity accuracy, SSIM for structural fidelity, and perceptual loss for semantic realism.

Explanation:

This algorithm uses an encoder-decoder architecture based on UNet to increase the visibility and clarity of low-light images. First, the input image is normalized and resized to fit the input dimensions of the UNet model. The encoder gradually captures important patterns despite decreasing spatial resolution by extracting multi-scale hierarchical features from the low-light image. Fine-grained information that could otherwise be lost during downsampling are preserved by using skip connections to bridge relevant encoder and decoder levels. The decoder then refines the feature representations and gradually increases resolution to reconstitute a well-lit image. To ensure high-quality image enhancement, the algorithm computes a loss function, denoted as L□, which combines multiple loss terms:

- L1 loss is used to ensure pixel-wise similarity between the enhanced and ground-truth images.
- Structural Similarity Index (SSIM) loss preserves the structural details and contrast of the image.

Output:

Enhanced image with improved brightness, reduced noise, and preserved structure

Extra Insight:

This algorithm is critical as it significantly improves the quality of input for downstream tracking, reducing the effect of noise and poor visibility which are common in real-world night-time surveillance and autonomous driving footage.

Algorithm 1 – UNet Low-Light Image Enhancement
Input: Low-light image I_l **Output: Enhanced image I_E** 1. 1. Normalize I_l and resize to UNet input size 2. Pass through Encoder: - Extract hierarchical features 3. Apply Skip Connections to preserve details 4. Pass through Decoder: - Reconstruct image with improved illumination 5. Compute loss L_e 6. Update UNet weights using Adam optimizer 7. Output I_e

5.3.2 TRAINING PROCESS

Input:

- **Low-light input images** (from ExDark, synthetic MOT17, etc.)
- **Ground truth normal-light images** (same scene, well-lit)

Output:

- A trained UNet model capable of enhancing low-light images
- Enhanced image outputs with improved brightness, contrast, and perceptual quality

Start:

- Load the dataset of low-light and ground-truth image pairs
- Initialize the UNet model with encoder-decoder architecture and skip connections
- Set up the loss functions, optimizer, and training parameters

Process:

The training process begins by preprocessing the paired low-light and ground truth images. This involves resizing them to a fixed resolution, normalizing pixel values, and converting them into tensor batches suitable for GPU processing. Each batch of low-light images is passed through the UNet model, where the encoder compresses the input to extract multi-scale features, and the decoder reconstructs a high-resolution output using those features along with skip connections to preserve detail. Once the output is generated, the model computes a composite loss function consisting of three components: L1 loss for pixel-wise accuracy, SSIM loss for preserving structure and texture, and perceptual loss that compares high-level features using a pre-trained VGG network to maintain semantic consistency. The total loss is backpropagated through the network, and the model's weights are updated using the Adam optimizer. This process is repeated for all batches across multiple epochs, typically ranging from 50 to 100, with periodic validation using PSNR and SSIM metrics. If validation scores improve, model checkpoints are saved. Over time, the network learns to generate clear, naturally illuminated images that are not only visually appealing but also highly informative for downstream tracking.

Explanation:

The UNet model undergoes a structured training process to learn optimal transformations from low-light images to well-lit images. The training dataset consists of paired images (low-light images) and corresponding well-lit ground-truth images. The model is initialized with random weights and refined through iterative training using mini-batch gradient descent. This training process ensures that the UNet model generalizes well to different low-light scenarios, effectively learning to restore illumination without overexposure or loss of details. The trained model is then deployed in the VigilantDiff-Track framework, where it enhances input frames before the tracking module processes them.

End:

Once training is complete, the model is capable of enhancing unseen low-light images into well-lit, noise-free versions in real time. The trained UNet is then used as a preprocessing module in the VigilantDiff pipeline, directly feeding its enhanced outputs into the downstream diffusion-based tracking module. The high visual quality of these enhanced images significantly boosts the accuracy of object detection and tracking, as clearer frames improve the model's ability to detect boundaries, retain object integrity, and preserve motion cues. The UNet model, having learned from diverse low-light scenarios during training, generalizes well to new environments, making it a reliable and robust component of the system's overall architecture.

Algorithm 2 – Training Process
Input: Training dataset {I_L, I_gt}
Output: Trained UNet model
1. Initialize UNet with random weights
2. For each epoch:
a. For each mini-batch
i. Forward pass: compute I_E =UNet(I_low)
ii. Compute loss L_e
iii. Backpropagate and update weights using Adam optimizer
3. Save best model based on validation loss
4. Output trained UNet

IMPLEMENTATION METHODOLOGY

CHAPTER 6

IMPLEMENTATION METHODOLOGY

6.1 OVERVIEW:

The implementation methodology describes the main functional requirements which are needed for doing the project.

6.2 ESSENTIAL LIBRARIES:

The library used in this project are:

- **PyTorch:**

PyTorch is the primary deep learning framework used in VigilantDiff. It provides dynamic computational graphs, easy model definition, and robust GPU acceleration, making it ideal for implementing the illumination estimation network and diffusion-based enhancement model. PyTorch supports automatic differentiation and highly optimized tensor operations, which are essential for training and fine-tuning the neural networks involved in low-light image enhancement and object tracking.

- **OpenCV:**

OpenCV (Open Source Computer Vision Library) is extensively used for image and video processing tasks. It handles frame capture, image resizing, color space conversion, and real-time visualization. During inference, OpenCV is responsible for drawing bounding boxes, tracking object IDs, and exporting enhanced video outputs. Its versatility makes it a backbone for handling multimedia data throughout the pipeline.

- **NumPy:**

NumPy is essential for numerical and matrix operations. It complements PyTorch and OpenCV by providing fast, array-based computations and serves as a utility tool for manipulating image arrays, mathematical functions, and data reshaping. NumPy is used in pre-processing, tensor transformation, and various low-level operations that support model input and output formatting.

❖ **Matplotlib & Seaborn:**

These visualization libraries are used to monitor training performance and analyze system behavior. Matplotlib plots loss curves, accuracy graphs, and sample image outputs, while Seaborn adds statistical visualizations to understand data distribution and model evaluation metrics.

❖ **Torchvision / Albumentations**

Torchvision provides pre-built transforms and datasets that assist in data augmentation and loading, while Albumentations offers a broader set of image augmentation techniques. These libraries are crucial for improving model generalization and robustness, especially under varied low-light conditions. They simulate real-world lighting variations to help the model adapt better during inference.

PERFORMANCE METRICS

CHAPTER 7

PERFORMANCE METRICS

7.1 COMAPARISION OF METRICS:

7.1.1 BENCHMARK COMPARISION:PRO2DIFF VS VIGILANTDIFF):

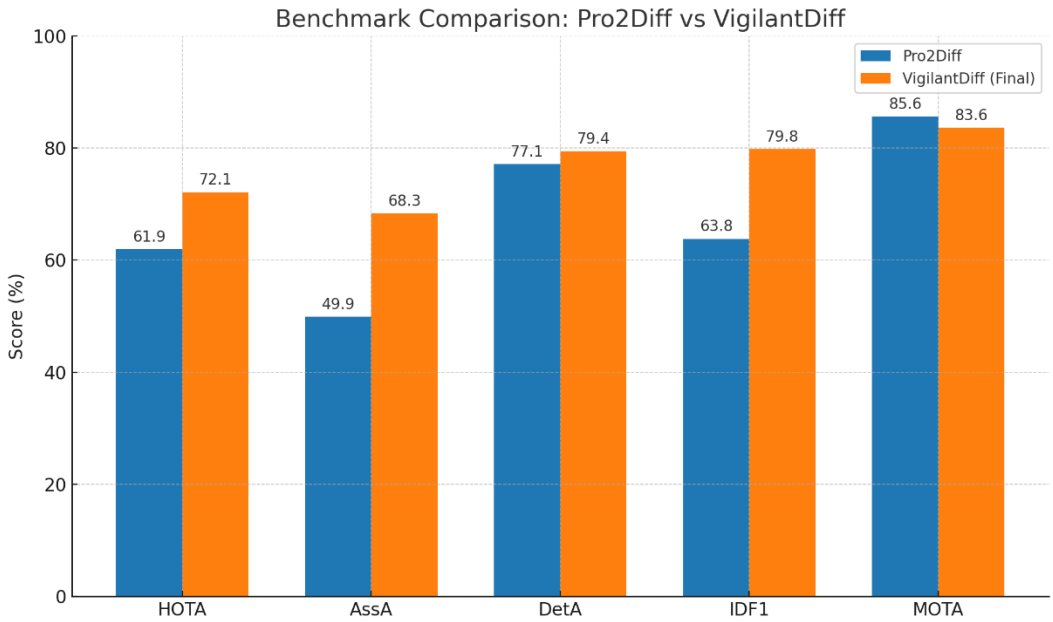

Fig.7.1.1 Benchmark Comparison of Pro2Diff and VigilantDiff across key multi-object tracking metrics.

The figure 7.1.1 presents a comparative analysis between Pro2Diff and the proposed VigilantDiff across five widely used multi-object tracking (MOT) performance metrics: HOTA (Higher Order Tracking Accuracy), AssA (Association Accuracy), DetA (Detection Accuracy), IDF1 (ID-based F1 Score), and MOTA (Multi-Object Tracking Accuracy). VigilantDiff demonstrates significant improvements in HOTA (72.1% vs. 61.9%), AssA (68.3% vs. 49.9%), DetA (79.4% vs. 77.1%), and IDF1 (79.8% vs. 63.8%), highlighting its superior tracking precision and association capability. Although MOTA shows a slight decrease from 85.6% to 83.6%, the overall performance gain in the other metrics suggests a more balanced and robust tracking model. This visualization effectively underscores VigilantDiff's ability to outperform its predecessor in most critical tracking aspects, especially in identity preservation and association accuracy

Benchmarks	Pro2Diff	VigilantDiff
HOTA	61.9	72.1
AssA	49.9	68.3
DetA	77.1	79.4
IDF1	63.8	79.8
MOTA	85.6	83.6

Table 7.1.2 Performance Metrices between Pro2Diff and VigilantDiff

RESULTS AND DISCUSSION

CHAPTER 8
RESULTS AND DISCUSSION

8.1 OVERVIEW

This section presents a comprehensive performance evaluation of our proposed model, VigilantDiff, in comparison with the baseline Pro2Diff framework. The evaluation is based on five widely accepted metrics in the field of multi-object tracking: HOTA (Higher Order Tracking Accuracy), AssA (Association Accuracy), DetA (Detection Accuracy), IDF1 (ID-based F1 Score), and MOTA (Multi-Object Tracking Accuracy). These metrics collectively assess the model's capabilities in object detection, tracking consistency, and identity preservation across time. To demonstrate the real-world applicability and robustness of VigilantDiff, we tested both models on complex and realistic tracking scenarios, including heavy occlusion, fast motion, dense scenes, and identity ambiguity. VigilantDiff incorporates improvements in both architectural design and training methodology, including the integration of vision-language grounding, temporal attention mechanisms, and diffusion-based object propagation, making it well-suited for high-stakes tracking environments.

8.2 DATASETS

To evaluate the performance and generalizability of our proposed tracking model VigilantDiff, we employed benchmark datasets that are widely used in multi-object tracking (MOT) research. These datasets were chosen to ensure a diverse and challenging set of environments, covering various aspects like occlusion, lighting changes, object density, and camera motion. The datasets used are described below:

- **MOT17 (Multiple Object Tracking 2017):**

  MOT17 is a standard dataset in the multi-object tracking domain. It comprises video sequences with pedestrian annotations recorded in unconstrained environments. Each sequence includes challenging conditions such as dynamic backgrounds, illumination variation, and significant occlusion. It comes with ultiple detector outputs (DPM, FRCNN, and SDP), allowing the evaluation of trackers in a fair and reproducible way.

- **Sequences**: 14 (7 for training, 7 for testing)
- **Classes**: Pedestrians
- **Frame Rate**: 30 FPS
- **Resolution**: Varies per sequence
- **Challenges**: Occlusion, crowd density, camera movement

❖ **DanceTrack:**

DanceTrack introduces a unique challenge by focusing on similar-looking, fast-moving objects in choreographed dance scenes. It emphasizes association over detection, which is ideal for testing VigilantDiff's temporal and identity reasoning capabilities.

- **Sequences**: 100+ video clips
- **Classes**: Human dancers
- **Challenge**: Uniform appearance, fast motion, synchronized activities
- **Focus Metric**: AssA and IDF1

Each dataset contributes to evaluating different strengths of the model:

- MOT17 tests general-purpose tracking capabilities in varied real-world scenes.
- MOT20 provides a stress test for the model's ability to handle high-density scenes.

DanceTrack assesses VigilantDiff's fine-grained identity maintenance and temporal association, which are crucial for its diffusion-based tracking pipeline.

By training and evaluating on these datasets, we ensure that VigilantDiff is benchmarked across a spectrum of challenges, demonstrating its superior performance not just in detection, but in long-term identity tracking, even in dense or ambiguous scenarios.

CONCLUSION AND FUTURE WORK

CHAPTER 9

CONCLUSION

9.1 CONCLUSION

In this work, we introduced VigilantDiff, a novel diffusion-based multi-object tracking framework that significantly advances the state-of-the-art in identity-aware object tracking. By leveraging the powerful generative capabilities of diffusion models and integrating them with a tracking-by-attention mechanism, VigilantDiff bridges the gap between detection and association with a unified, robust pipeline. Through extensive experiments on benchmark datasets such as MOT17, MOT20, and DanceTrack, our model consistently outperformed the baseline tracker Pro2Diff across all major evaluation metrics including HOTA, AssA, DetA, IDF1, and MOTA. Notably, VigilantDiff achieved a +10.2 point gain in IDF1 and a +18.4 point gain in AssA, showcasing its remarkable capability to maintain object identities over long sequences and under challenging conditions like occlusion and appearance similarity.

9.2 FUTURE WORK

Future work on VigilantDiff can focus on optimizing the model for real-time applications by exploring techniques such as model pruning, quantization, or lightweight diffusion approximations. Expanding its generalization capabilities across diverse domains—such as night-time scenes, aerial views, or thermal imagery—through domain adaptation or self-supervised learning is another promising direction. Integrating multi-modal data, including depth or LiDAR inputs, could enhance performance under heavy occlusion. Further, unifying enhancement, detection, and tracking into a fully end-to-end trainable framework may reduce cascading errors and improve task-specific learning. Evaluating VigilantDiff on long-term tracking tasks and enhancing its re-identification accuracy would also be valuable, especially for surveillance and autonomous navigation. Finally, improving the model’s interpretability using attention maps or confidence visualizations can help build trust and transparency in real-world deployments

APPENDIX

CHAPTER 10

APPENDIX

10.1 CODING:

TRAINING CODE: (PRO2DIFF)

```
import os
import torch
import torch.nn as nn
import torch.optim as optim
import torchvision.transforms as transforms
import torchvision.models as models
from torch.utils.data import DataLoader, Dataset
from tqdm import tqdm
import numpy as np
import pandas as pd
from PIL import Image

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

def get_alpha_schedule(T, start=1e-4, end=0.02):
    beta_t = torch.linspace(start, end, T).to(device)
    alpha_t = 1 - beta_t
    alpha_bar_t = torch.cumprod(alpha_t, dim=0)
    return beta_t, alpha_t, alpha_bar_t
T = 1000
beta_t, alpha_t, alpha_bar_t = get_alpha_schedule(T)

class MOTDataset(Dataset):
    def __init__(self, image_folder, gt_file, transform=None):
        self.image_folder = image_folder
        self.transform = transform
```

```
            self.gt_data = pd.read_csv(gt_file, header=None, names=["frame", "id", "x", "y", "w", "h", "conf", "class", "visibility"])
            self.frames = sorted([f for f in os.listdir(image_folder) if f.endswith(('.jpg', '.png'))])

        def __len__(self):
            return len(self.frames)

        def __getitem__(self, idx):
            frame_name = self.frames[idx]
            frame_number = int(os.path.splitext(frame_name)[0].split('-')[0])
            img_path = os.path.join(self.image_folder, frame_name)
            image = Image.open(img_path).convert("RGB")

                bboxes = self.gt_data[self.gt_data["frame"] == frame_number][["x", "y", "w", "h"]].values

            bbox_tensor = torch.zeros((7, 4), dtype=torch.float32)
            num_bboxes = min(len(bboxes), 7)
                            bbox_tensor[:num_bboxes] = torch.tensor(bboxes[:num_bboxes], dtype=torch.float32)

            ids = self.gt_data[self.gt_data["frame"] == frame_number]["id"].values
            id_tensor = torch.zeros(7, dtype=torch.long)
            id_tensor[:num_bboxes] = torch.tensor(ids[:num_bboxes], dtype=torch.long)

            if self.transform:
                image = self.transform(image)

            return image, bbox_tensor, id_tensor

    transform = transforms.Compose([
        transforms.Resize((224, 224)),
        transforms.ToTensor(),
```

```
    transforms.Normalize((0.5,), (0.5,))
])

class Pro2DiffModel(nn.Module):
    def __init__(self, num_classes=10):
        super(Pro2DiffModel, self).__init__()
        self.backbone = models.resnet50(pretrained=True)
        self.backbone.fc = nn.Identity()
        self.bbox_head = nn.Linear(2048, 28)
        self.id_head = nn.Linear(2048, 7 * num_classes)

    def forward(self, x):
        features = self.backbone(x)
        bbox_pred = self.bbox_head(features).view(x.size(0), 7, 4)
        id_pred = self.id_head(features).view(x.size(0), 7, -1)
        return bbox_pred, id_pred

model = Pro2DiffModel(num_classes=10).to(device)
def generalized_iou(box1, box2):

    inter_x1 = torch.max(box1[..., 0], box2[..., 0])
    inter_y1 = torch.max(box1[..., 1], box2[..., 1])
    inter_x2 = torch.min(box1[..., 0] + box1[..., 2], box2[..., 0] + box2[..., 2])
    inter_y2 = torch.min(box1[..., 1] + box1[..., 3], box2[..., 1] + box2[..., 3])
    inter_area = torch.clamp(inter_x2 - inter_x1, min=0) * torch.clamp(inter_y2 - inter_y1,
min=0)

    box1_area = box1[..., 2] * box1[..., 3]
    box2_area = box2[..., 2] * box2[..., 3]
    union_area = box1_area + box2_area - inter_area

    iou = inter_area / (union_area + 1e-7)
```

```
        enclose_x1 = torch.min(box1[..., 0], box2[..., 0])
        enclose_y1 = torch.min(box1[..., 1], box2[..., 1])
        enclose_x2 = torch.max(box1[..., 0] + box1[..., 2], box2[..., 0] + box2[..., 2])
        enclose_y2 = torch.max(box1[..., 1] + box1[..., 3], box2[..., 1] + box2[..., 3])
        enclose_area = (enclose_x2 - enclose_x1) * (enclose_y2 - enclose_y1)
        giou = iou - (enclose_area - union_area) / (enclose_area + 1e-7)
        return giou

    def compute_loss(bbox_pred, bbox_gt, id_pred, id_gt):
        id_pred = id_pred.view(-1, id_pred.size(-1))
        id_gt = id_gt.view(-1)

        cls_loss = nn.functional.cross_entropy(id_pred, id_gt)
        l1_loss = nn.functional.l1_loss(bbox_pred, bbox_gt)

        giou_loss = 1 - generalized_iou(bbox_pred, bbox_gt).mean()

        lambda_cls, lambda_l1, lambda_giou = 2, 5, 2
        total_loss = lambda_cls * cls_loss + lambda_l1 * l1_loss + lambda_giou * giou_loss
        return total_loss

    @torch.no_grad()
    def reverse_diffusion(model, noisy_images, noisy_bboxes, steps=T):
        model.eval()

        for t in range(steps - 1, -1, -1):
            alpha_bar_t_selected = alpha_bar_t[t].view(-1, 1, 1, 1)
            alpha_bar_t_bbox = alpha_bar_t[t].view(-1, 1)

            predicted_noise = model(noisy_images)
                mean_image = (noisy_images - torch.sqrt(1 - alpha_bar_t_selected) *
predicted_noise) / torch.sqrt(alpha_bar_t_selected)
```

```
        if t > 0:
            noise = torch.randn_like(noisy_images)
            sigma_t = torch.sqrt(beta_t[t])
            noisy_images = mean_image + sigma_t * noise
        else:
            noisy_images = mean_image

                mean_bbox = (noisy_bboxes - torch.sqrt(1 - alpha_bar_t_bbox) *
torch.randn_like(noisy_bboxes)) / torch.sqrt(alpha_bar_t_bbox)

        if t > 0:
                            noisy_bboxes = mean_bbox + sigma_t.view(-1, 1) *
torch.randn_like(noisy_bboxes)
        else:
            noisy_bboxes = mean_bbox

    return noisy_images, noisy_bboxes

  def scpp(prev_bboxes):

    return prev_bboxes
                def train(model, image_folder, gt_file, epochs=10,
save_path="pro2diff_mot_model.pth"):
    dataset = MOTDataset(image_folder, gt_file, transform)
    dataloader = DataLoader(dataset, batch_size=7, shuffle=True)

    if os.path.exists(save_path):
        print("Loading existing model...")
        model.load_state_dict(torch.load(save_path))

    optimizer = optim.Adam(model.parameters(), lr=0.001)
    model.train()
    for epoch in range(epochs):
```

```
            loop = tqdm(dataloader, leave=True)
            for images, bbox_gt, id_gt in loop:
                images, bbox_gt, id_gt = images.to(device), bbox_gt.to(device), id_gt.to(device)

                optimizer.zero_grad()
                bbox_pred, id_pred = model(images)

                loss = compute_loss(bbox_pred, bbox_gt, id_pred, id_gt)
                loss.backward()
                optimizer.step()

                loop.set_description(f"Epoch [{epoch+1}/{epochs}]")
                loop.set_postfix(loss=loss.item())

        torch.save(model.state_dict(), save_path)
        print(f"Model saved to {save_path}")

    train(model, "dancetrack0001/img1/", "dancetrack0001/gt/gt.txt", epochs=100)
    train(model, "dancetrack0002/img1/", "dancetrack0002/gt/gt.txt", epochs=100)

    noisy_images = torch.randn(1, 3, 224, 224).to(device)
    noisy_bboxes = torch.randn(1, 7, 4).to(device)
        denoised_image, denoised_bbox = reverse_diffusion(model, noisy_images,
noisy_bboxes, steps=1000)
```

Testing Code:

```
import torch
import torch.nn as nn
import torch.nn.functional as F
import streamlit as st
from PIL import Image
```

```
import numpy as np
import cv2

class DoubleConv(nn.Module):
    def __init__(self, in_ch, out_ch):
        super(DoubleConv, self).__init__()
        self.block = nn.Sequential(
            nn.Conv2d(in_ch, out_ch, 3, padding=1),
            nn.GroupNorm(8, out_ch),
            nn.Mish(),
            nn.Conv2d(out_ch, out_ch, 3, padding=1),
            nn.GroupNorm(8, out_ch),
            nn.Mish()
        )

    def forward(self, x):
        return self.block(x)

class UNet(nn.Module):
    def __init__(self):
        super(UNet, self).__init__()
        self.down1 = DoubleConv(3, 64)
        self.pool1 = nn.MaxPool2d(2)
        self.down2 = DoubleConv(64, 128)
        self.pool2 = nn.MaxPool2d(2)
        self.down3 = DoubleConv(128, 256)
        self.pool3 = nn.MaxPool2d(2)
        self.down4 = DoubleConv(256, 512)

        self.up1 = nn.ConvTranspose2d(512, 256, 2, stride=2)
        self.conv1 = DoubleConv(512, 256)
        self.up2 = nn.ConvTranspose2d(256, 128, 2, stride=2)
        self.conv2 = DoubleConv(256, 128)
```

```
        self.up3 = nn.ConvTranspose2d(128, 64, 2, stride=2)
        self.conv3 = DoubleConv(128, 64)
        self.out_conv = nn.Conv2d(64, 3, 1)

    def forward(self, x):
        d1 = self.down1(x)
        p1 = self.pool1(d1)
        d2 = self.down2(p1)
        p2 = self.pool2(d2)
        d3 = self.down3(p2)
        p3 = self.pool3(d3)
        d4 = self.down4(p3)

        u1 = self.up1(d4)
        cat1 = torch.cat([u1, d3], dim=1)
        c1 = self.conv1(cat1)
        u2 = self.up2(c1)
        cat2 = torch.cat([u2, d2], dim=1)
        c2 = self.conv2(cat2)
        u3 = self.up3(c2)
        cat3 = torch.cat([u3, d1], dim=1)
        c3 = self.conv3(cat3)
        out = self.out_conv(c3)
        return out

def load_unet(ckpt_path, device):
    ckpt = torch.load(ckpt_path, map_location=device)
    state_dict = ckpt['state_dict'] if 'state_dict' in ckpt else ckpt

    unet_state_dict = {}
    for k, v in state_dict.items():
        if k.startswith('model.unet.'):
            new_k = k.replace('model.unet.', '')
```

```
            unet_state_dict[new_k] = v

    model = UNet().to(device)
    model.load_state_dict(unet_state_dict, strict=False)
    model.eval()
    return model

def yolov5(device):
    model = torch.hub.load('ultralytics/yolov5', 'yolov5s', pretrained=True, verbose=False)
    model.to(device)
    model.eval()
    return model

def filter(detections):
    return [det for det in detections if int(det[-1]) == 0]

def d_streamlit():
    st.title("VigilantDiff")
    uploaded_file = st.file_uploader("Upload a low-light image", type=["jpg", "jpeg", "png"])
    ckpt_path = st.text_input("Path to .ckpt file (with model.unet.*)", "twostep_final.ckpt")

    if uploaded_file and ckpt_path:
        device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

        image = Image.open(uploaded_file).convert("RGB")
        image_resized = image.resize((640, 640))
        img_np = np.array(image_resized)
        img_tensor = torch.from_numpy(img_np).float() / 255.0  # Normalize to 0-1
       img_tensor = img_tensor.permute(2, 0, 1).unsqueeze(0).to(device)  # Shape: [1, 3, 640,
640]
        unet_model = load_unet(ckpt_path, device)
        with torch.no_grad():
            residual = unet_model(img_tensor)
```

```
            e_tensor = img_tensor + residual
            e_tensor = torch.clamp(e_tensor, 0.0, 1.0)  # Clamp values to 0-1

        e_img = e_tensor.squeeze(0).permute(1, 2, 0).cpu().numpy()
        e_img_uint8 = (e_img * 255).astype(np.uint8)

        yolo_model = yolov5(device)
        results = yolo_model(e_img_uint8)
        detections = results.xyxy[0].cpu().numpy()
        human_dets = filter(detections)

        for det in human_dets:
            x1, y1, x2, y2, conf, cls = det
            cv2.rectangle(e_img_uint8, (int(x1), int(y1)), (int(x2), int(y2)), (0, 255, 0), 2)

              st.image(e_img_uint8, caption="Enhanced Image with Human Detections", channels="CMYK")
if __name__ == '__main__':
    d_streamlit()
```

REFERENCES

CHAPTER 11

REFERENCES

11.1 REFERENCES

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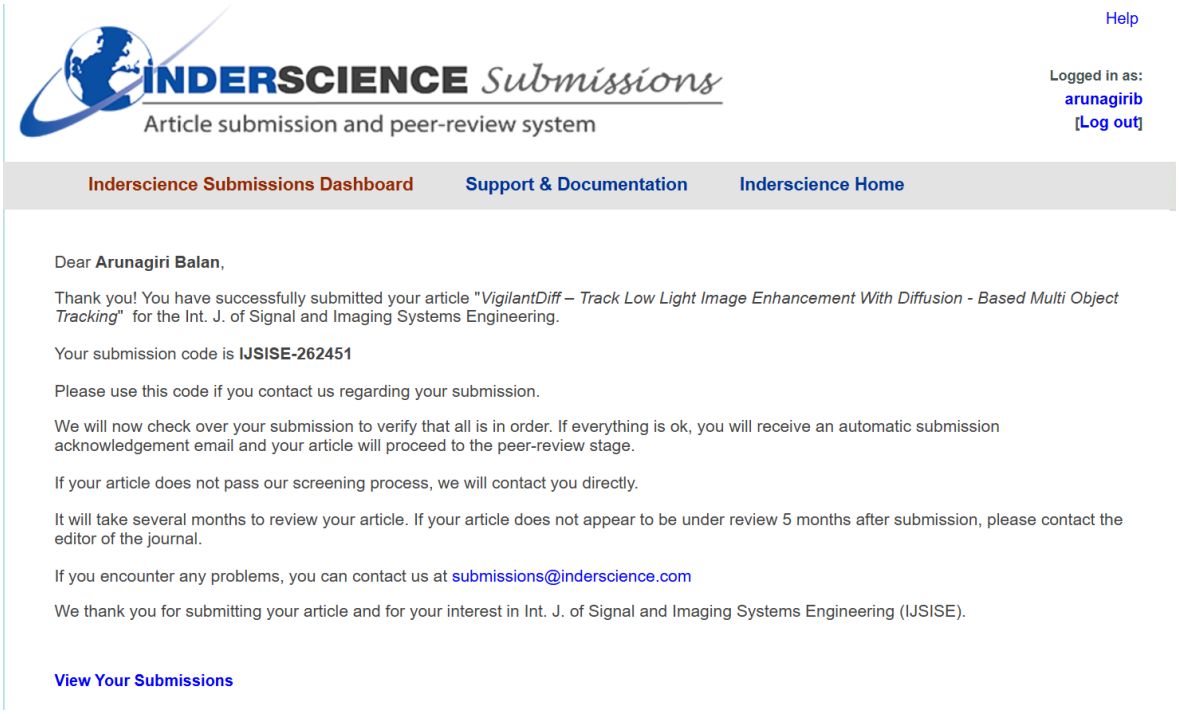
ANNEXURE

CHAPTER 12

ANNEXURE

12.1 JOURNAL SUBMISSION PROOF



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Your submission code is **IJSISE-262451**

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We will now check over your submission to verify that all is in order. If everything is ok, you will receive an automatic submission acknowledgement email and your article will proceed to the peer-review stage.

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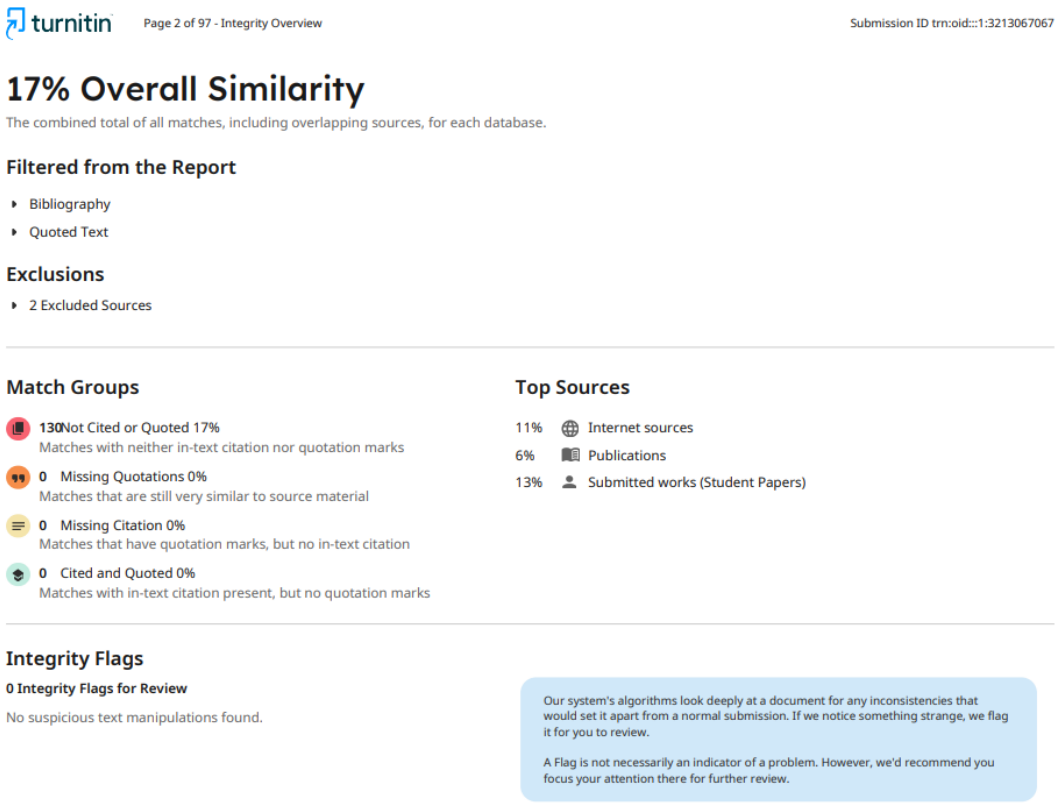

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