Review-II

Image Fusion Emerging Applications and Techniques

AY 2025-26

GITAM (Deemed-to-be) University

Capstone Project – Introduction (PROJ2999)

Department of Electrical Electronics and Communication Engineering

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Objective and Goals

Objective

•Study existing image fusion techniques (pixel, spatial, transform domains).
•Implement traditional methods for multi-focus, multi-exposure, and thermal-RGB fusion.
•Compare algorithms using qualitative & quantitative metrics.
•To evaluate the potential real-world applications of the developed techniques in areas such as medical imaging, computer vision, and security.

Goals

Main Goals :-

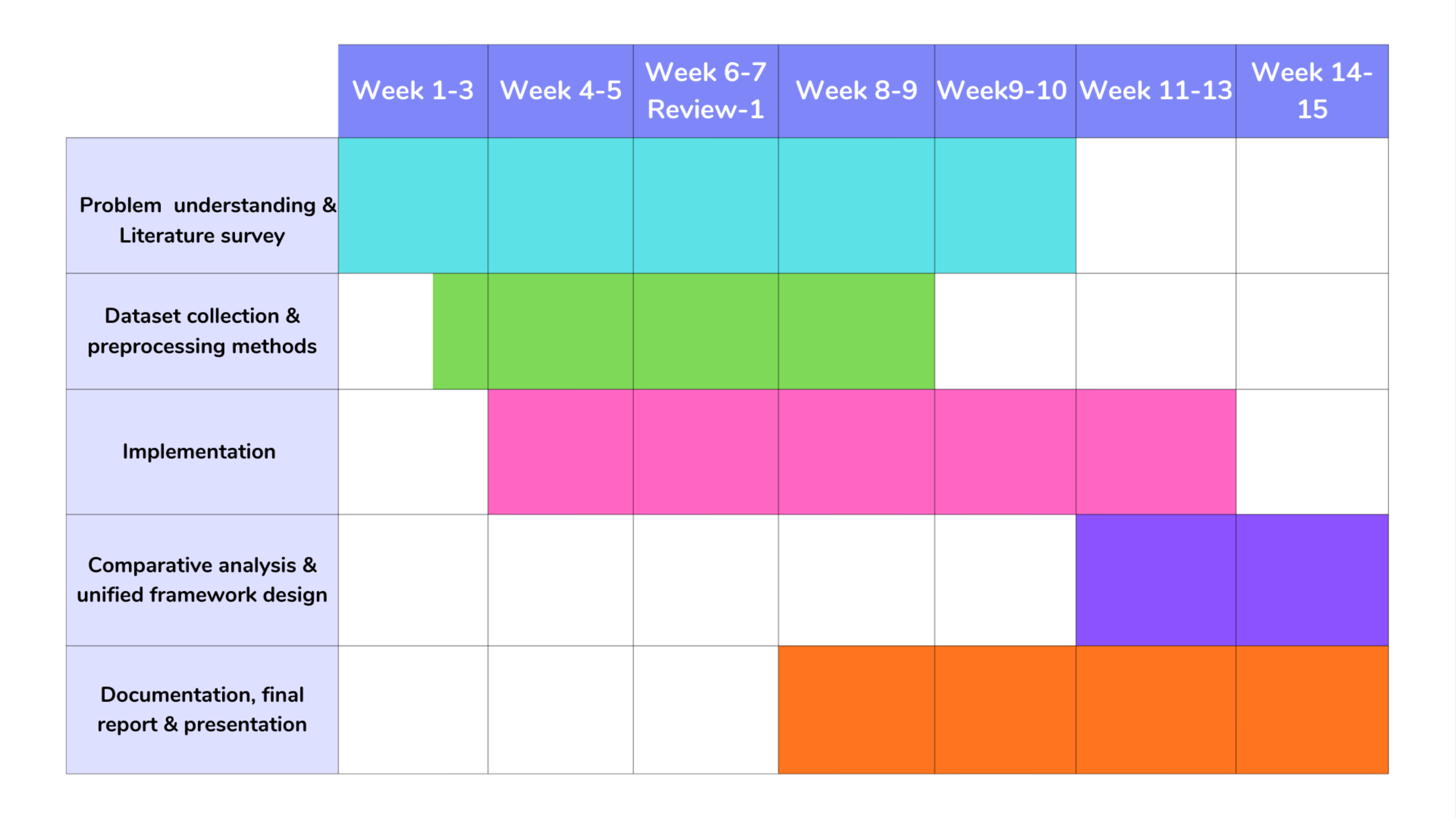
- Identify the most effective method for each application.
- Propose an optimized framework for image fusion.

Additional Goals :-

- Evaluate real-world applications (medical imaging, computer vision, security).
- Contribute to robust and adaptive fusion techniques.

Project Plan

Gant Chart - Milestones and Activities
Resources : Canva.com



Literature Survey

Key Publications

•**Li, S., Kang, X., & Fang, L. (2017).** Pixel-level image fusion: A survey of the state of the art. *Information Fusion, 33*, 100–112.
→ Comprehensive survey of pixel-based fusion methods.

•**Zhang, Y., et al. (2020).** DenseFuse: A fusion approach to infrared and visible images. *IEEE TIP, 29*, 4795–4805.
→ Deep learning-based IR + visible fusion.

•**Ma, J., et al. (2019).** FusionGAN: A generative adversarial network for infrared and visible image fusion. *Information Fusion, 48*, 11–26.
→ GAN-based approach; preserves texture and thermal cues.

•**Liu, Y., et al. (2017).** Multi-focus image fusion with dense SIFT. *Signal Processing, 130*, 38–51.
→ Classical multi-focus fusion using handcrafted features.

Key Resources – Whitepaper| Application Notes | Datasheet| Others

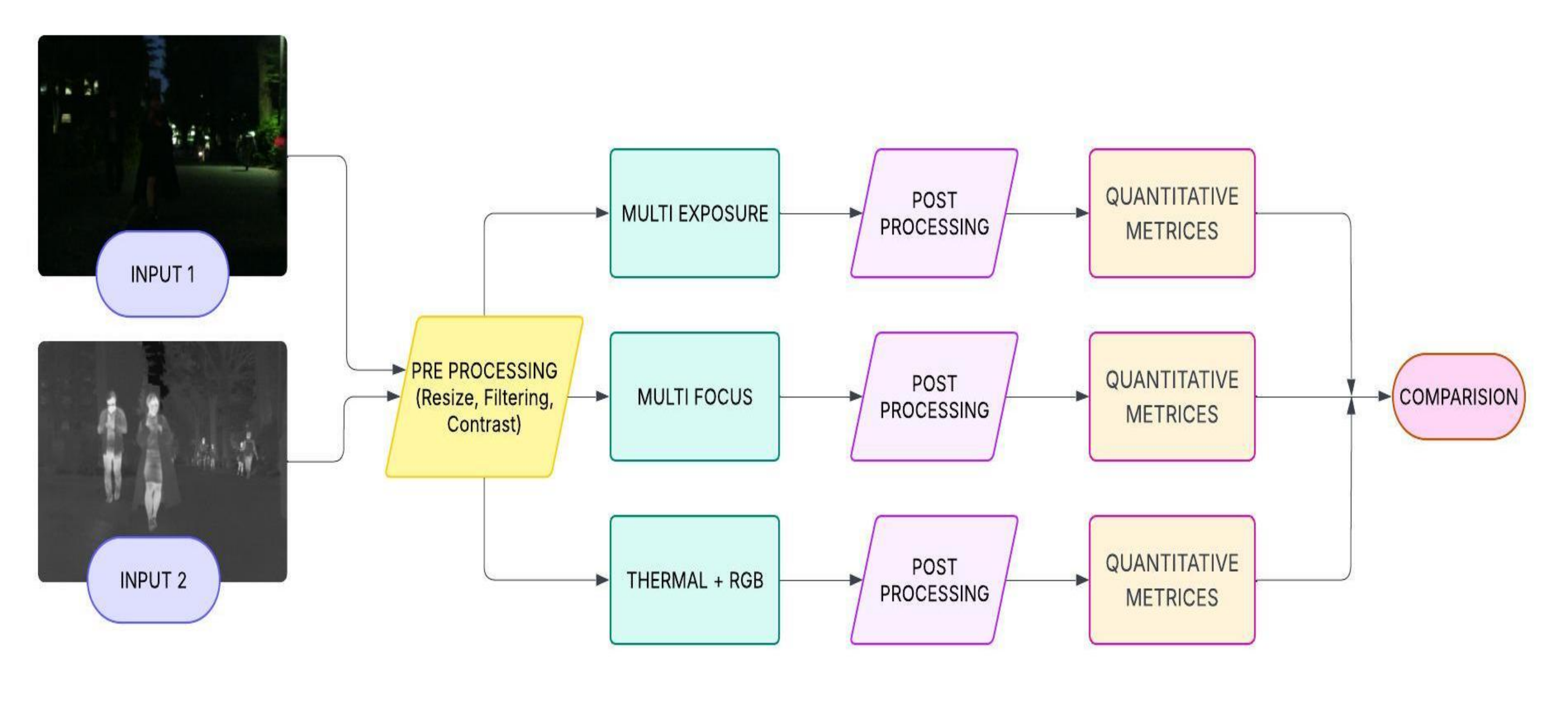
•**ASTM D4788-03 (2013):** Standard test method for detecting delaminations in bridge decks using infrared thermography.
•**Fluke (2021):** *What does infrared mean?* – Application note on thermal imaging basics.
•**FLIR Systems:** Datasheets for *FLIR One Pro*, *FLIR T-Series* (thermal camera specs).
•**ASCE (2020):** *Changing the infrastructure equation* – Infrastructure monitoring with asset management.

Existing Implementations – Products| Opensource| GitHub etc

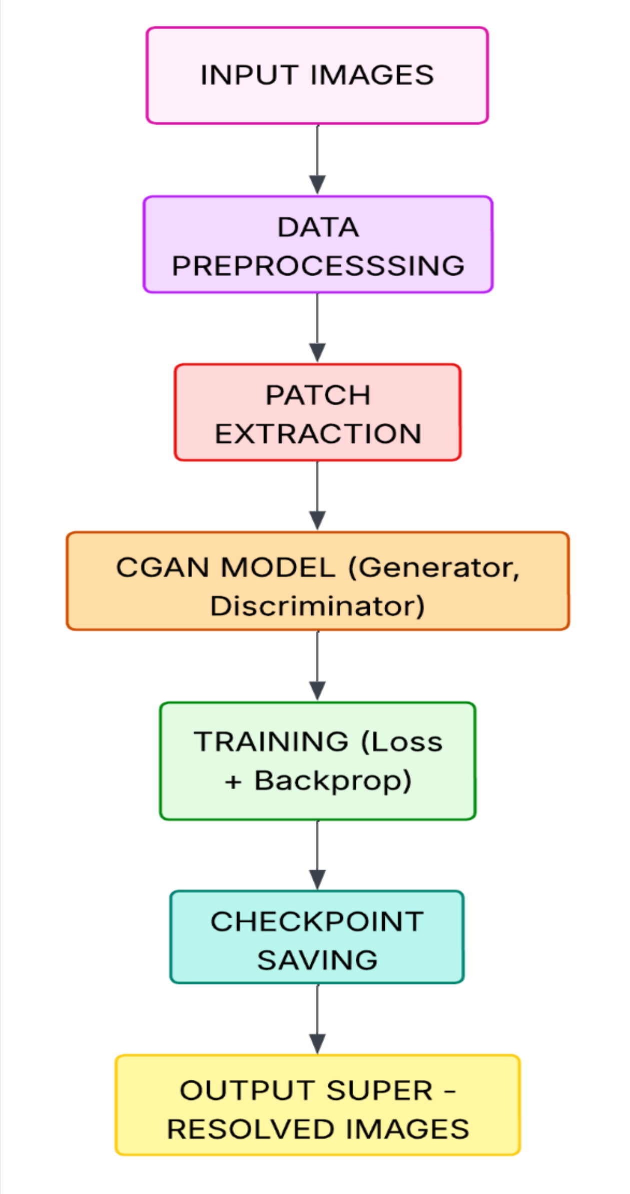
•*FLIR One Pro, FLIR T-Series* – Commercial IR cameras for SHM.
•*Fluke TiX series* – Industrial thermal cameras.
•**Open Source / GitHub:**
•*DenseFuse* (https://github.com/hli1221/densefuse-pytorch) – PyTorch implementation of infrared–visible fusion.
•*Deep Image Fusion Toolbox* (MATLAB File Exchange).
•*Exposure Fusion* (https://github.com/rocapp/exposure-fusion).

Architecture

Structural Diagram



Behaviour Diagram



Architecture

Thermal + RGB Image Fusion :-

- Takes one thermal image and one RGB (visible-light) image.
- Extracts heat signatures from thermal and visual details (color, edges) from RGB.
- Aligns and preprocesses both images for proper fusion.
- Generates fusion maps to retain important information from each modality.
- Produces a single image with enhanced visibility and thermal awareness.

Applications: Surveillance, night vision, search & rescue, robotics, medical imaging.

Advantages: Better detail in low-light, improved object detection, preserved heat information.

Architecture

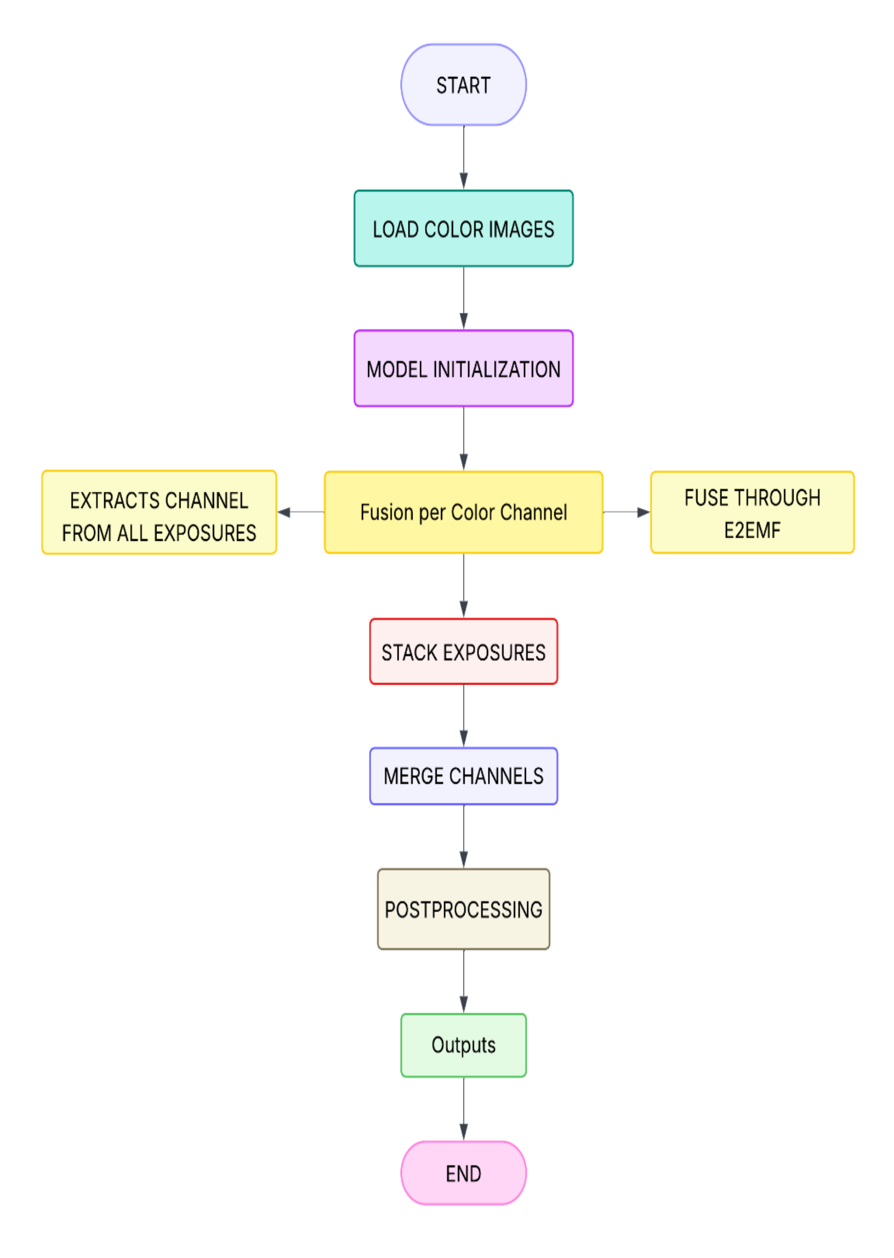
Multi-Exposure Image Fusion

- Combines multiple images taken at different exposure levels (under, normal, overexposed).
- Uses a deep learning–based E2EMEF network to balance brightness, enhance contrast, and preserve details.
- Processes each color channel (R, G, B) separately for accurate fusion.
- Generates a final fused color image with improved illumination and natural appearance.

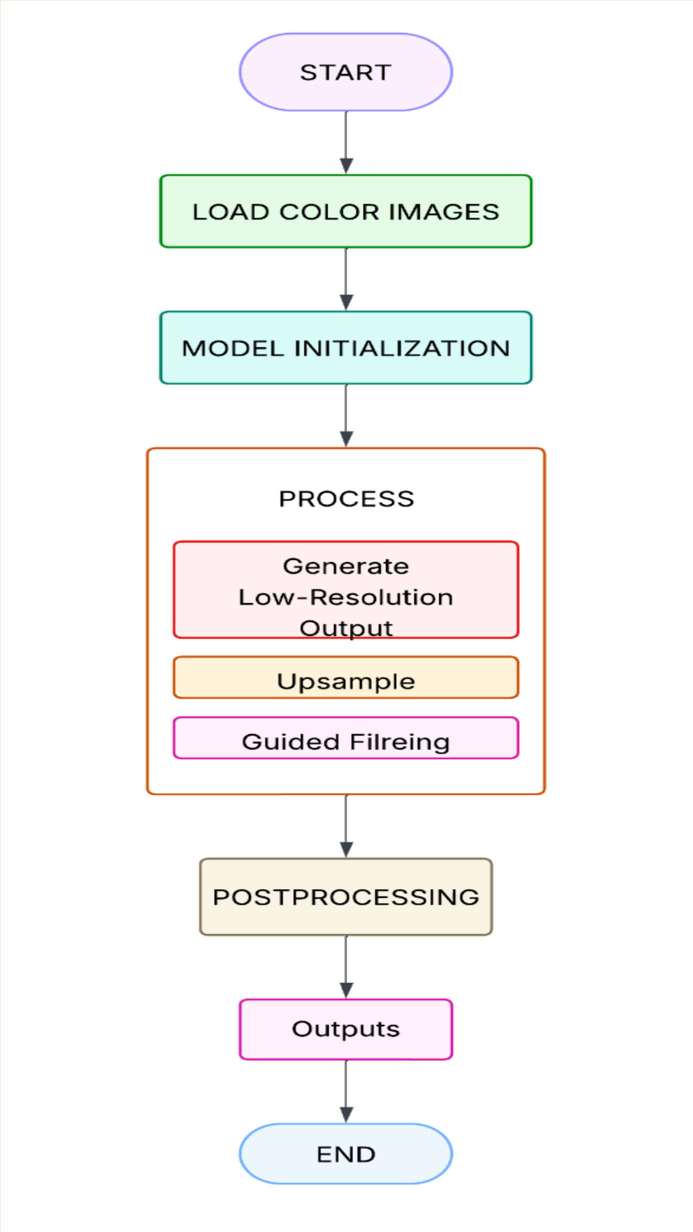
Applications: Photography, HDR imaging, surveillance, autonomous systems.

Advantages: Better brightness balance, richer details, reduced noise, and high-quality fused output.

Behaviour Diagram



Behaviour Diagram



Architecture

Multi-Exposure Image Fusion :-

- Combines multiple images captured at different exposure levels into one well-exposed fused image.
- Uses CNN-extracted feature maps to highlight important regions in each image.
- Generates weight maps that emphasize well-exposed, detailed, and high-contrast areas.
- Produces a fused output with balanced brightness, enhanced textures, and preserved color details.

Applications: HDR imaging, photography, surveillance, low-light enhancement.

Advantages: Deep feature-based weighting, improved clarity, better illumination balance, and natural color preservation.

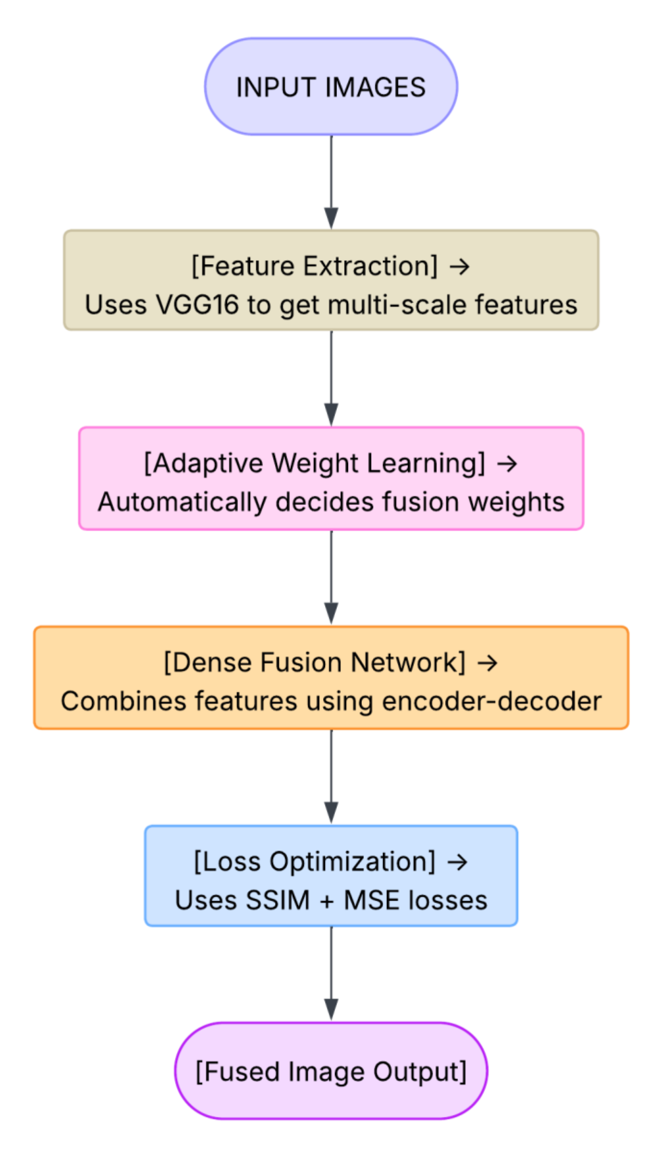
Architecture

Multi Focus Image Fusion (U2-Fusion) :-

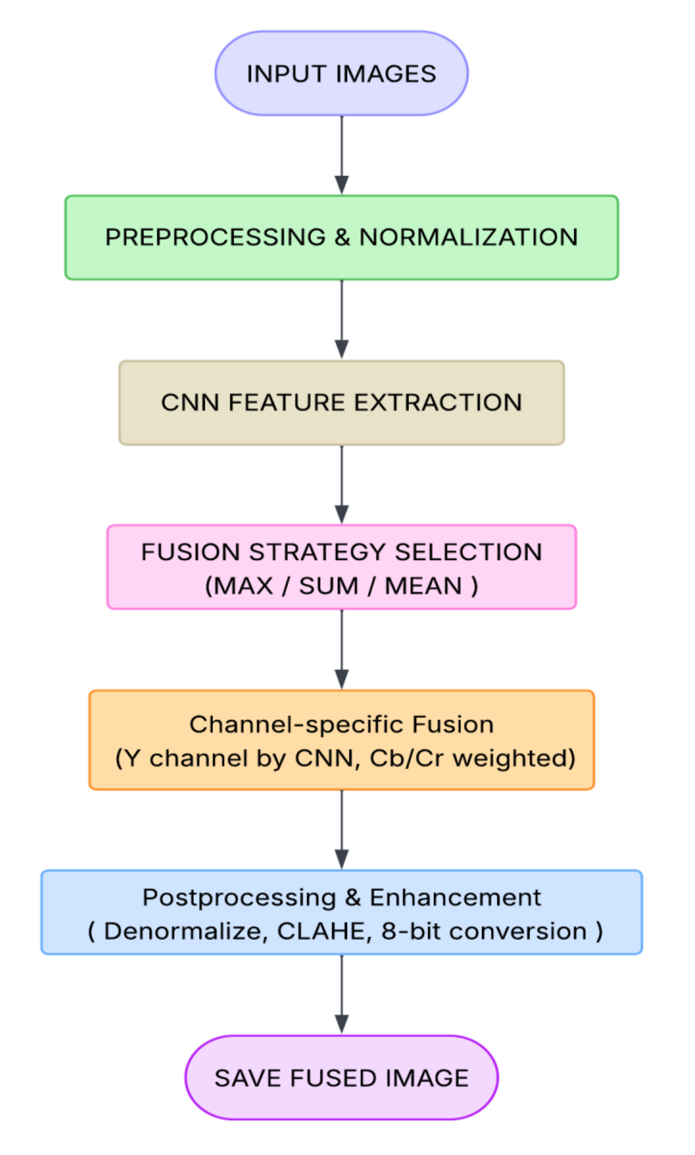
Input:

- Two registered images with different focus points :
- Step 1 → Feature Extraction Deep network analyzes both images Identifies sharp vs blurry regions automatically Uses multi-scale feature analysis.
- Step 2 → Adaptive Weight Learning Calculates importance weights for each region Sharp areas get higher weights Smooth transitions between weights.
- Step 3 → Dense Network Fusion Encoder-decoder architecture blends images Preserves sharp details from both inputs Creates seamless transitions.
- Step 4 → Loss Optimization Structural similarity loss maintains image quality Pixel-level accuracy ensures natural results Adaptive balancing of both inputs Output: Single fully-focused image.

Behaviour Diagram



Behaviour Diagram



Architecture

IFCNN Multi-Task Image Fusion :-

- Loads datasets for CMF, IV, MD, and ME image types.
- Normalizes images for deep network input.
- Extracts deep features via CNN for each input image.
- Applies pixel-wise fusion scheme: MAX, SUM, or MEAN.
- For color images: fuses luminance with CNN; chroma channels fused via weighted averaging.
- Enhances final fused image using denormalization and optional CLAHE.
- Saves fused outputs with descriptive filenames.

Applications: Multi-focus, infrared–visible, medical, and multi-exposure image fusion.

Advantages: Deep feature extraction, adaptive fusion, high-quality output, supports multiple datasets and image modalities.

Use Cases & Testing

Use Cases :-

- **Structural Health Monitoring (SHM):** Detect cracks, delamination, moisture intrusion in concrete/bridges.
- **Surveillance:** Thermal + RGB fusion for low-light object detection.
- **Medical Imaging:** CT + MRI fusion for diagnosis.
- **Remote Sensing:** PAN–MS, thermal–RGB fusion for land cover classification.
- **Autonomous Systems:** Thermal + RGB fusion in drones for search & rescue, night-time navigation.

Test Cases :-

- **Multi-focus:** Fuse two partially focused images of a scene → all-in-focus output.
- **Multi-exposure:** Fuse underexposed + overexposed images → balanced illumination.
- **Thermal–RGB:** Fuse daytime RGB with nighttime IR → structure defects + heat leakage.
- **Benchmark Datasets:** TNO Image Fusion Dataset (thermal + visible).
- Lytro Multi-focus Dataset.
- MEF (Multi-Exposure Fusion) Dataset.
- Custom SHM datasets (USACE, crack datasets).

Implementation and Results (Phase-1)

Iteration 1 : Thermal & RGB

RGB_RAW.png

Thermal.png

fused(raw).png

Multi_enhanced. png

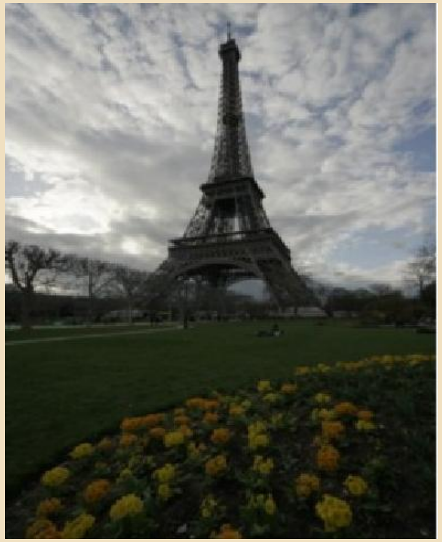
thermal_clache_enhanced.png

fused.png

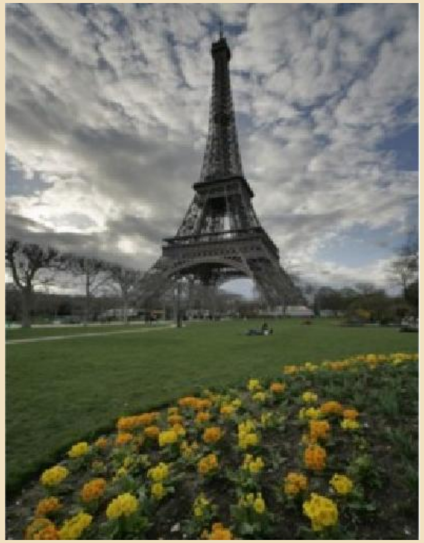
Implementation and Results (Phase-1)

MULTI EXPOSURE :-

INPUT-1

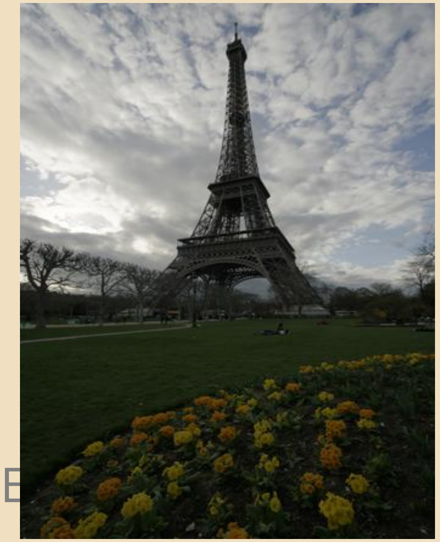


INPUT-2



INPUT-3

Preprocessed input 1



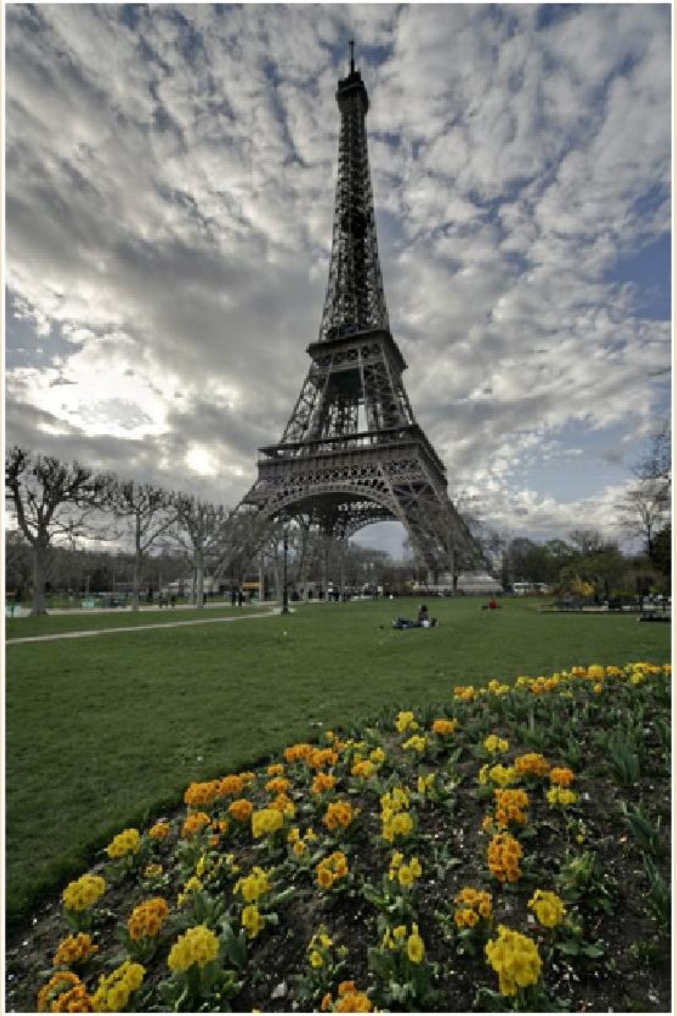
Preprocessed input 2

Preprocessed input 3

Implementation and Results (Phase-1)

MULTI EXPOSURE :-

FUSED IMAGE



PRE-PROCESSED IMAGE

PRE + POST PROCESSED
OUTPUT IMAGE

Implementation and Results (Phase-2)

THERMAL + RGB IMAGE FUSION :-

INPUT-1

INPUT-2

OUTPUT

Implementation and Results (Phase-2)

MULTI EXPOSURE (EXPOSURE) :-

INPUT-1

INPUT-2

INPUT-3

INPUT-4

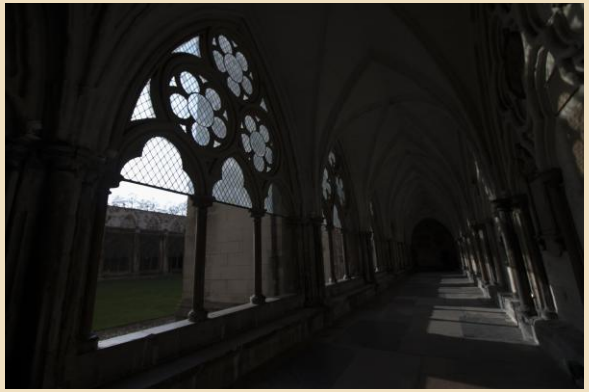
OUTPUT

Implementation and Results (Phase-2)

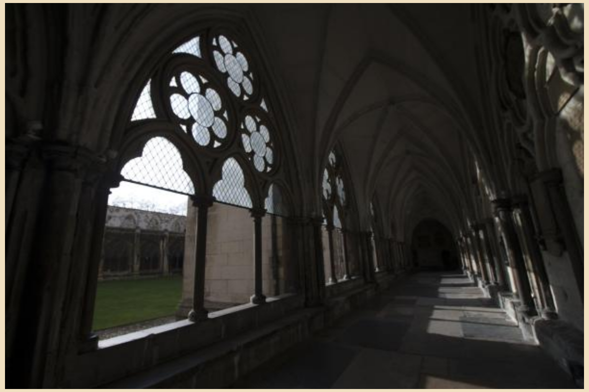
MULTI EXPOSURE (MEFNet) :-

INPUT-1

INPUT-2



INPUT-3



INPUT-4

OUTPUT

Implementation and Results (Phase-2)

MULTI FOCUS IMAGE FUSION :-

INPUT-1

INPUT-2

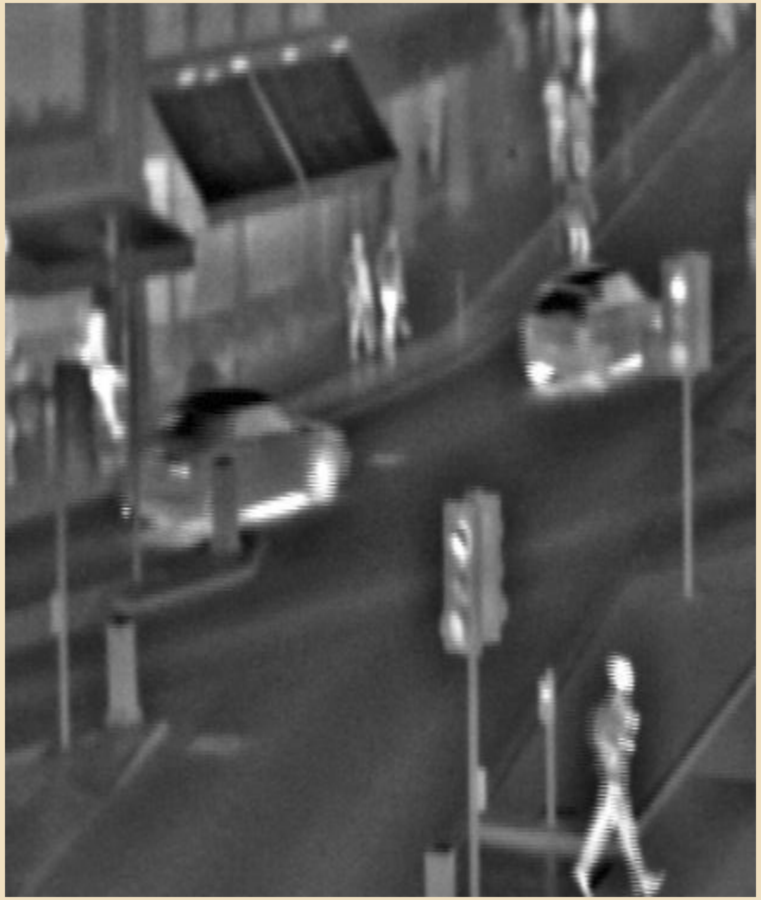
OUTPUT

Implementation and Results (Phase-2)

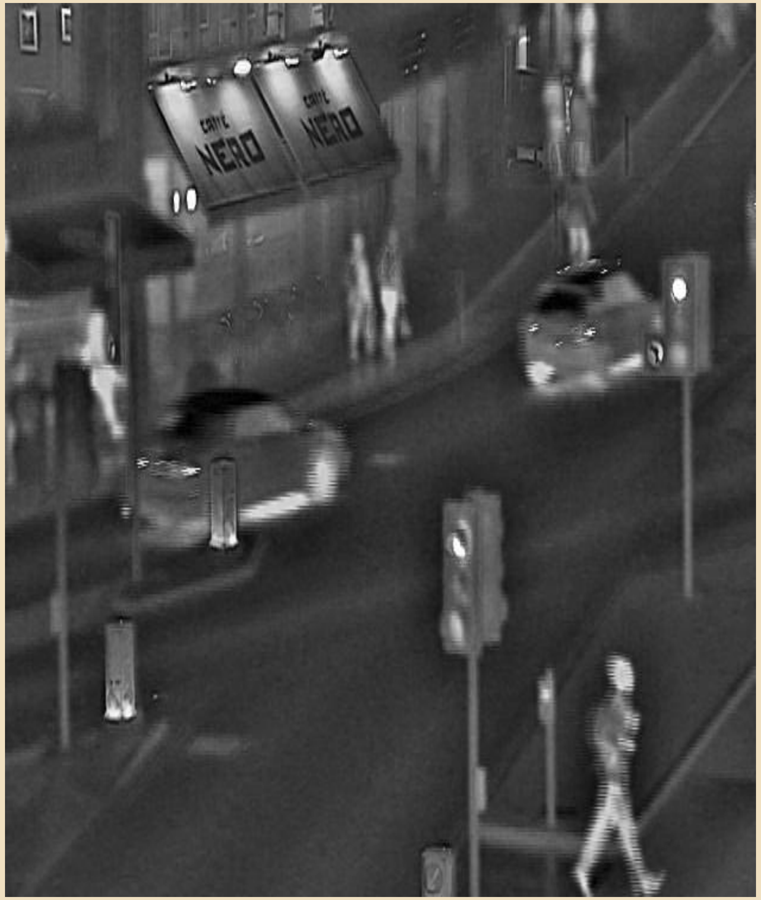
IFCNN (THERMAL + RGB) IMAGE FUSION :-

INPUT-1

INPUT-2



OUTPUT

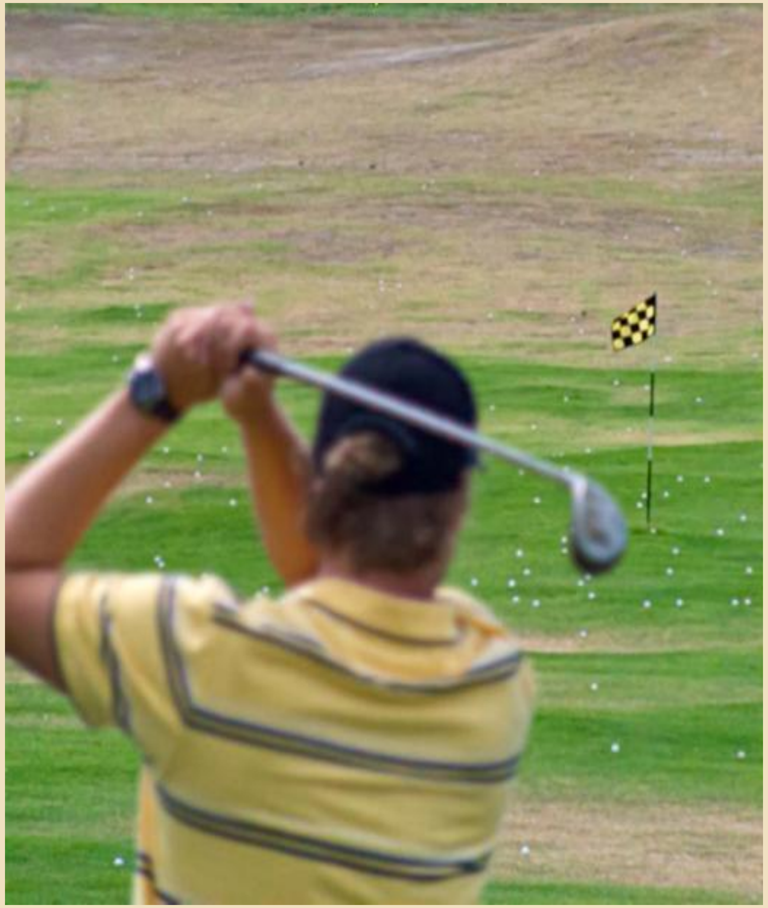


Implementation and Results (Phase-2)

IFCNN (MULTI-FOCUS) IMAGE FUSION :-

INPUT-1

INPUT-2

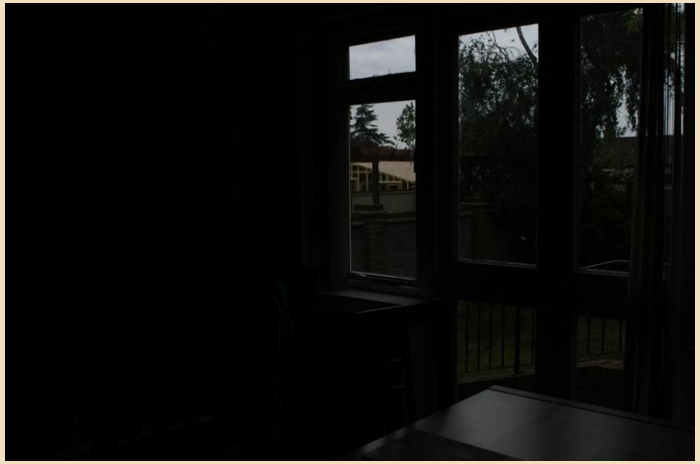


OUTPUT

Implementation and Results (Phase-2)

IFCNN (MULTI-EXPOSURE) IMAGE FUSION :-

INPUT-1



INPUT-2

OUTPUT

INPUT-3

INPUT-4

QCB – Contrast-Based Quality (Chen–Blum Metric)Used for:

1. Multi-focus and multi-exposure image fusion Indicates:
2. How well the fused image preserves local contrast, edges, and salient regions from the source images.

Formula :-

$$Q_{CB} = \frac{1}{N} \sum_{i=1}^{N} [\alpha \cdot C_f(i) + (1 - \alpha) \cdot G_f(i)]$$

(i)] $Cf(i)$Cf = contrast measure at pixel/region i in fused image
(ii) Gf(i) = gradient strength at pixel/region i
(iii) αα = weighting coefficient (typically 0.5)
(iv) N= total number of regions/patches

Interpretation :-

(i) Higher value → fused image retains better contrast and edges
(ii) Indicates how “visually sharp” the fused image is

2. QCV – Cross-Variance / Correlation-Based Quality

(Also known as QMI or QCV depending on implementation)
Used for: Scene fusion, thermal–visible fusion
Indicates: How much information from both images contributes to the fused result.

Formula :-

$$Q_{CV} = \sigma^2_{F,A} + \sigma^2_{F,B}$$

Where :-

- $\sigma\_(F,A)$^2= covariance of fused image with source A
- $\sigma\_(F,B)$^2= covariance of fused image with source B
- (Some implementations use correlation instead.)

Interpretation :-

- Large Qcv = fused image is highly correlated with both source images → good information preservation.
- Extremely large values (like 2000–3000) simply indicate very strong global information similarity; these values depend on image intensity scales.

3. QAB/F– Gradient-Based Quality (Xydeas & Petrovic Metric) Used for:

Used for: Multi-focus, multi-exposure, thermal–visible fusion
Indicates: How well the fused image preserves edge sharpness and directional gradients from the input images.

Formula :-

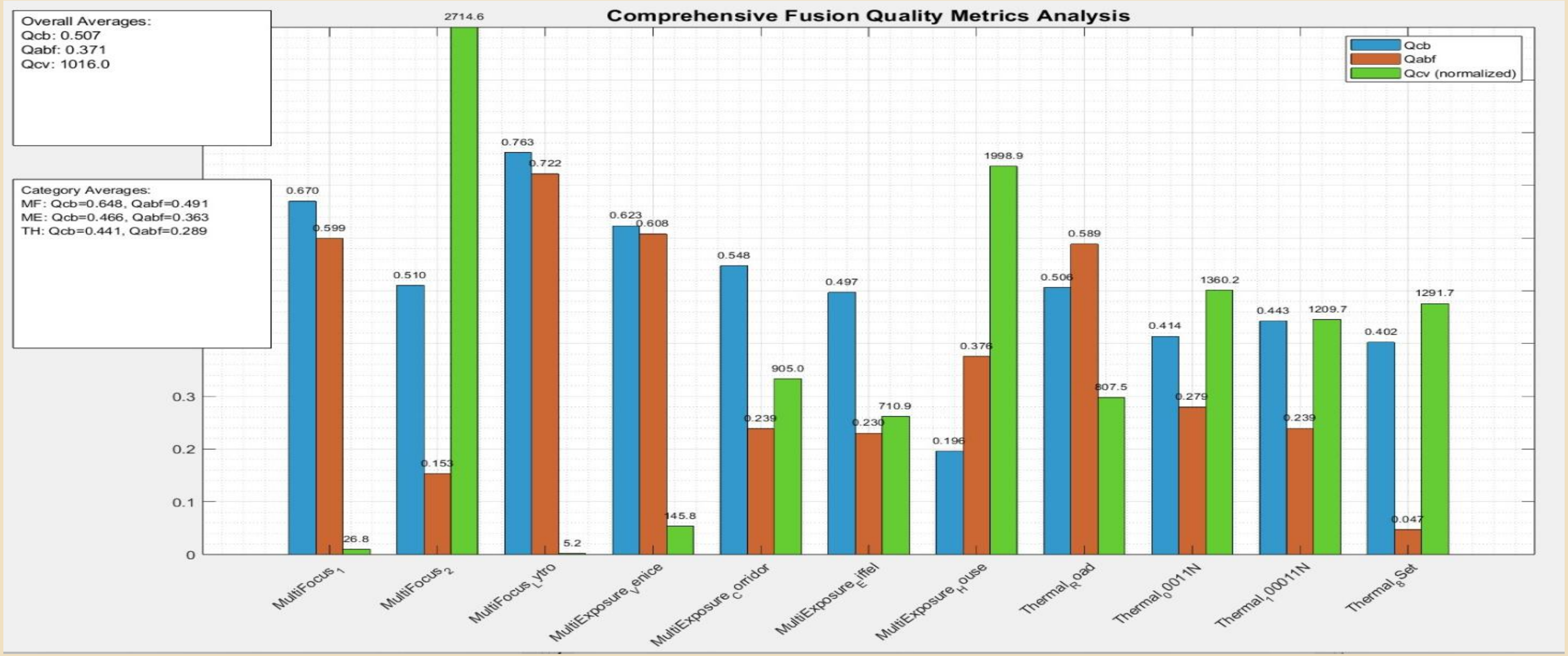
$$Q_{AB/F} = \frac{1}{N} \sum_{i=1}^{N} Q_i$$

Where for each pixel/region :-

1. $Q\_i = S\_i \cdot D\_i$
2. S_i= similarity of edge strength between input images and fused image
3. D_i= similarity of edge orientation

Interpretation :-

- Ranges between 0 and 1
- Closer to 1 → fused image preserves edges accurately
- Measures structural clarity and sharpness



- Deep learning methods (U-Net, IFCNN, DenseFuse) usually show higher Qcb & Qabf → better edge and contrast preservation.
- Transform-based methods often have very high Qcv due to strong correlation but lower sharpness.
- IFCNN multi-focus cases (0.76 Qcb, 0.72 Qabf) perform the best in your dataset.

Conclusion:-

- Conducted a comprehensive study of traditional and deep learning–based fusion methods across multi-focus, multi-exposure, thermal–RGB, infrared–visible, and medical imaging.

- Deep learning models (IFCNN, DenseFuse, E2EMEF, FusionGAN) consistently outperformed classical techniques in detail preservation, robustness, and adaptability

- Fusion categories showed distinct strengths, enabling clearer visibility, higher contrast, and improved feature extraction for medical, surveillance, night vision, robotics, and computer vision tasks.

- No single method is universally optimal; the study highlights the need for task-specific fusion strategies and lays the groundwork for a unified, high-quality fusion framework.

Link for the Video Presentation :-

- https://drive.google.com/drive/folders/1NudVPKT0_0ESfFTYF2egzNt0xtGWP5C6?usp=sharing

THANK YOU

Have a Great Day !