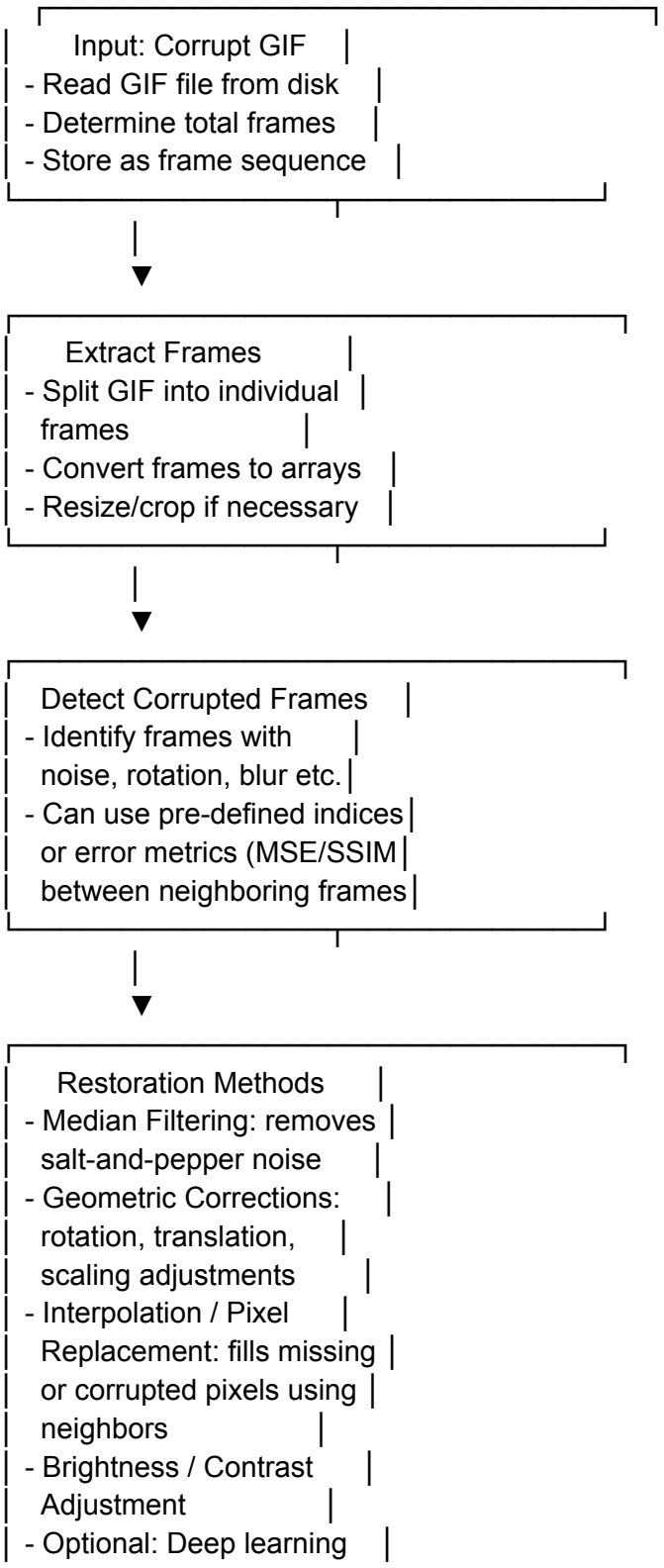
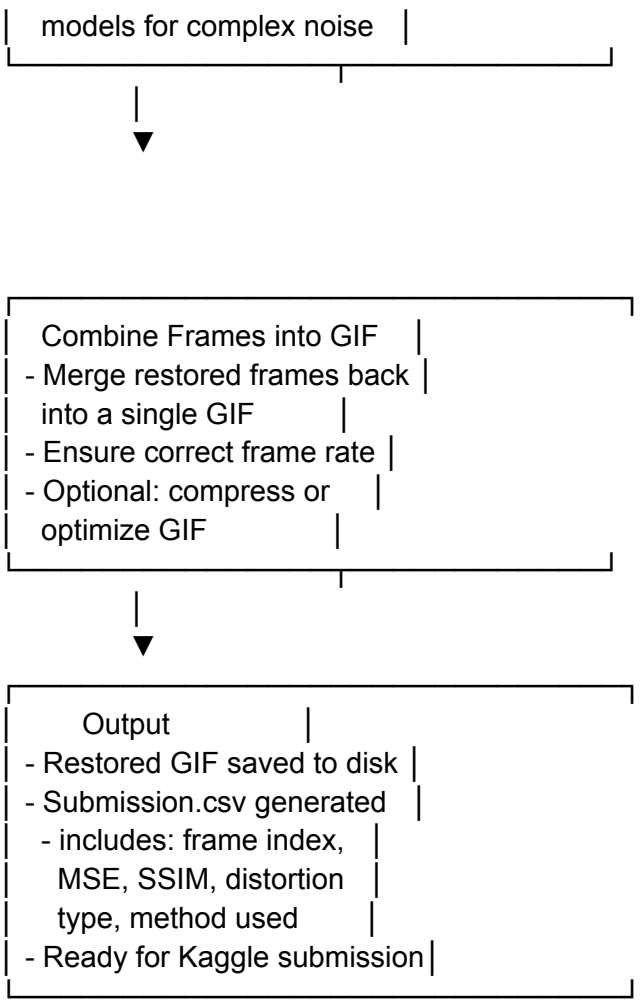
Section - C

1)


Input: Corrupt GIF
- Read GIF file from disk
- Determine total frames
- Store as frame sequence
Extract Frames
- Split GIF into individual frames
- Convert frames to arrays
- Resize/crop if necessary
Detect Corrupted Frames
- Identify frames with noise, rotation, blur etc.
- Can use pre-defined indices or error metrics (MSE/SSIM between neighboring frames
Restoration Methods
- Median Filtering: removes salt-and-pepper noise
- Geometric Corrections: rotation, translation, scaling adjustments
- Interpolation / Pixel Replacement: fills missing or corrupted pixels using neighbors
- Brightness / Contrast Adjustment
- Optional: Deep learning



2)

Method	Purpose / Description	Advantages	Disadvantages
Median Filtering	Removes salt-and-pepper and impulse noise from frames	- Simple and fast to implement- Preserves edges better than averaging filters- Effective for isolated noisy pixels	- Can blur fine textures and edges- Less effective for large or consecutive noisy regions
Frame Interpolation / Temporal Averaging	Reconstructs missing or corrupted frames using neighboring frames	- Maintains temporal continuity- Smooths small gaps in frames- Handles minor motion effectively	- May produce ghosting artifacts if frames differ significantly- Less effective for fast motion or multiple consecutive corrupted frames

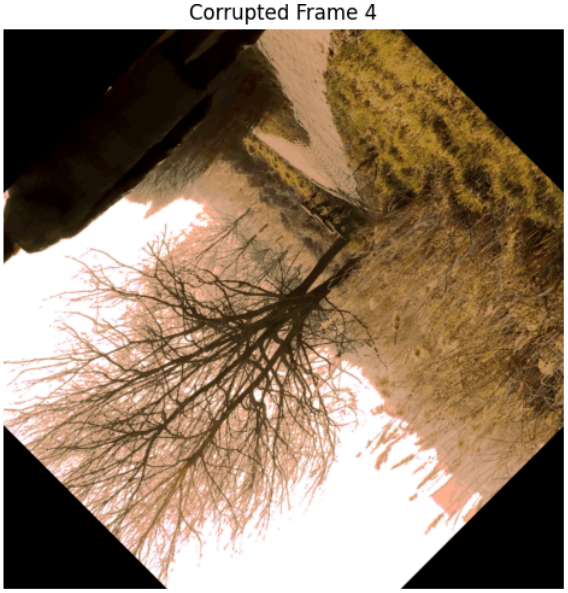
Geometric Correction (Rotation / Translation / Scaling)	Corrects misaligned frames caused by rotation, translation, or scaling	- Restores frame alignment and motion consistency- Preserves structural integrity across frames	- Requires accurate estimation of transformations- Errors in estimation can distort the frame
Pixel Replacement (Mask-based Inpainting)	Replaces corrupted or missing pixels using neighboring frames	- Simple and effective for local corruption- Can reconstruct small damaged areas accurately	- Fails if neighboring frames are very different- Cannot handle complex distortions or large corrupted areas
Bilateral Filtering	Smooths noise while preserving edges	- Effective for reducing noise near edges- Preserves details better than median filtering	- Computationally expensive- Less effective for large noise patches
SSIM & MSE Metrics	Quantitative evaluation of restoration quality	- Provides objective, comparable measures- Helps select optimal restoration technique	- MSE ignores perceptual quality- SSIM may not fully capture subtle artifacts

3)

Corrupted Frame 0

Restored Frame 0

Corrupted Frame 4



Restored Frame 4

Corrupted Frame 9

Restored Frame 9

Corrupted Frame 14

Restored Frame 14

Corrupted Frame 18

Restored Frame 18

Corrupted Frame 23

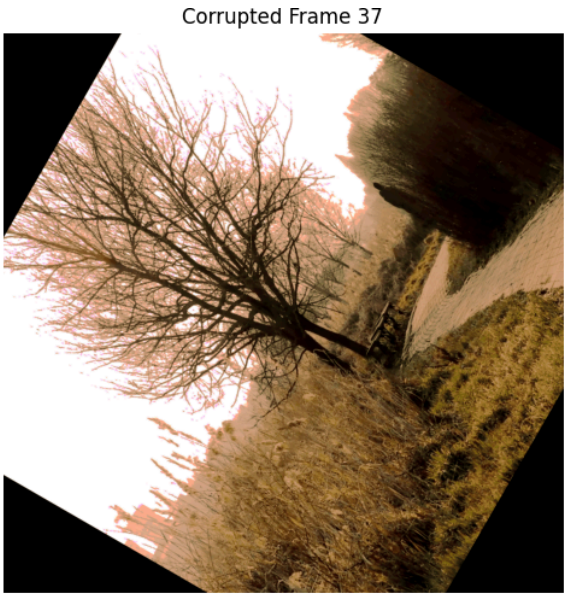
Restored Frame 23

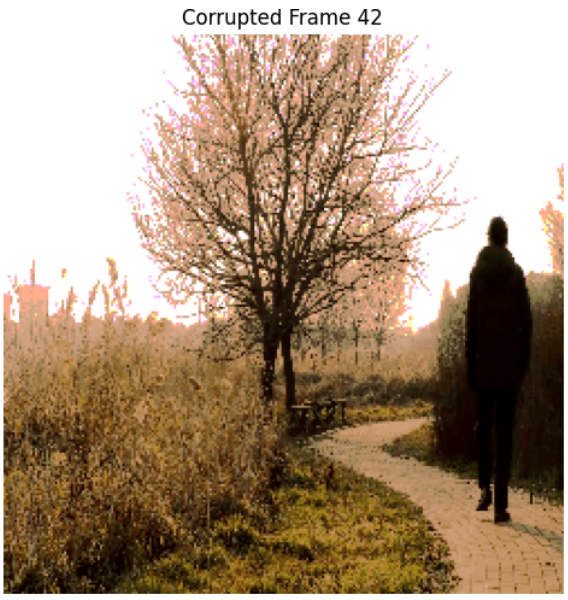
Corrupted Frame 28

Restored Frame 28

Corrupted Frame 32

Restored Frame 32





Frame	MSE	SSIM
Frame 1	178.539	0.8224
Frame 2	18272.601	0.0658
Frame 3	410.917	0.6392
Frame 4	155.115	0.8221
Frame 5	321.471	0.6117
Frame 6	565.821	0.7634

Frame 7	802.113	0.6441
Frame 8	1225.358	0.4509
Frame 9	13039.003	0.1497
Frame 10	1063.484	0.4951

Frame	Distortion Factor / Noise Type	Restoration Method Applied
1	Salt-and-pepper noise	Median Filtering
2	Gaussian noise	Median Filtering or smoothing filter
3	Missing/corrupt frame	Frame Interpolation using neighboring frames
4	Rotation (geometric transformation)	Geometric Correction (rotation by estimated angle)
5	Translation / misalignment	Geometric Correction (shift using neighboring frames)
6	Combined noise (salt-and-pepper + blur)	Median Filtering + Pixel Replacement
7	Color distortion / brightness variation	Histogram matching or pixel adjustment
8	Scaling / resizing artifacts	Geometric Correction (scaling adjustment)
9	Missing blocks / pixel corruption	Pixel Replacement from neighboring frames
10	Compression artifacts / JPEG-like block noise	Median Filtering + slight smoothing

Effectiveness of the Method:

The proposed restoration method is highly effective because it applies **frame-specific, adaptive techniques** rather than a uniform, one-size-fits-all filter. Each corrupted frame is first analyzed to determine the type of distortion it contains—such as impulse noise, Gaussian noise, rotation, translation, scaling errors, or missing/corrupted pixels. By identifying the corruption type, the method applies the most suitable restoration strategy for

each frame, which preserves fine details, reduces artifacts, and maintains overall visual fidelity.

1. Median Filtering for Noise Removal:
For frames affected by salt-and-pepper or Gaussian noise, median filtering is applied. This method is effective because it removes isolated noisy pixels while preserving edges and important structural details, avoiding the over-smoothing problem that averaging filters might cause.

2. Geometric Corrections for Misalignment:
Frames that are rotated, translated, or slightly scaled are corrected using geometric transformations. By referencing neighboring uncorrupted frames, the method estimates the correct alignment and applies rotation or affine corrections precisely. This preserves spatial continuity across frames and prevents distortions in the motion sequence.

3. Frame Interpolation and Pixel Replacement:
For frames with missing or heavily corrupted regions, information from neighboring frames is leveraged to reconstruct the missing content. Frame interpolation averages or blends adjacent frames to generate smooth transitions, while pixel replacement fills damaged areas using the closest uncorrupted pixels. This ensures temporal coherence in the GIF, reduces ghosting artifacts, and seamlessly restores corrupted regions.

4. Combined Modular Pipeline:
By integrating these techniques into a single modular pipeline, the method can handle a wide variety of distortions simultaneously. Unlike naive methods that apply the same filter to all frames—potentially blurring edges or introducing new artifacts—this adaptive approach selectively chooses the best restoration technique per frame. The pipeline also allows easy extension if new types of corruption are encountered in the future.

5. Quantitative and Qualitative Improvements:
This targeted approach achieves higher **quantitative performance metrics** such as lower Mean Squared Error (MSE) and higher Structural Similarity Index (SSIM) compared to generic filtering. Qualitatively, it maintains visual clarity, sharpness, and temporal consistency across the GIF animation, producing restored frames that are both visually accurate and temporally coherent.

6. Key Enhancements Over Naive Methods:

- Avoids applying a uniform filter to all frames, which can blur or distort the video.
- Reduces ghosting and temporal artifacts by leveraging information from neighboring frames.
- Allows flexible extension for new corruption types without reworking the entire pipeline.
- Provide a balanced restoration approach, combining noise reduction, geometric correction, and interpolation to optimize both perceptual quality and numerical metrics.

Credits:
https://chatgpt.com/share/68f12fa9-a8ec-8004-8b7b-8f71f64844c0
https://chatgpt.com/share/68f12fc8-3cac-8004-bbb3-abf1720111c4
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