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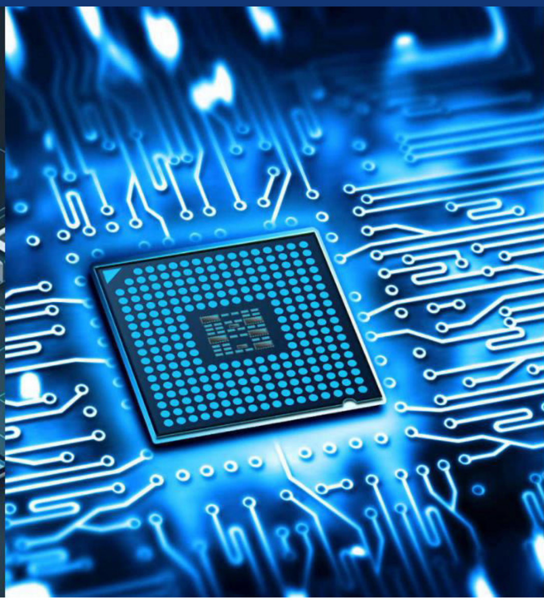


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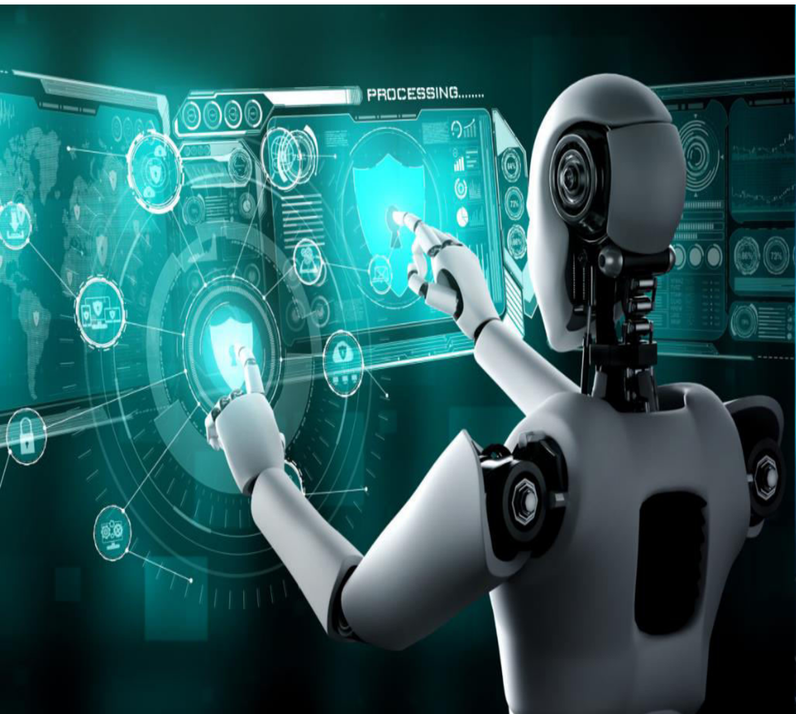

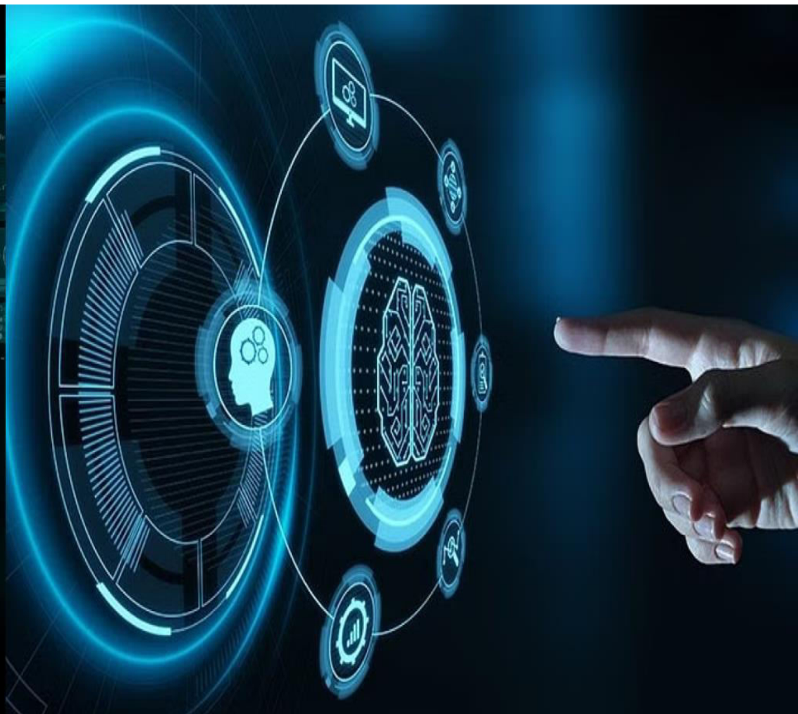

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Region Normalization for Image Inpainting using CNN

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ABSTRACT Image inpainting is intended to recover missing or corrupted areas in images in a semantically meaningful and visually plausible way. We propose a two-stage deep learning framework with Region Normalization, which allow for higher quality inpainted items. The framework operates in a two-stage pipeline. The first stage is a coarse inpainting network that produces inpainted content, while the second exchange is a refinement module that applies RN to statistically align the features between the missing and known areas of the input image.

KEYWORDS: Generative AI, Remote Hiring Automation, Resume Screening, Virtual Interview System.

I. INTRODUCTION

Region Normalization-based Image Inpainting System using Convolutional Neural Networks (CNNs) is a sophisticated,AI-driven system that aims to reconstruct impaired missing. areas. Realism. Conventional inpainting techniques tend to have difficulty ensuring consistency within damaged areas, causing visual artifacts and unnatural texture. It is the purpose of this project to overcome such constraints by incorporating RegionNormalization—a method that enhances feature onsistency between masked and unmasked areas—into a CNN-based image inpainting pipeline to provide high-quality restorations.The system utilizes a deep learning architecture of an encoder-decoder network, where the encoder learns semantic and structural features from the masked image, and the decoder fills in the missing areas. Region Normalization is employed strategically at feature extraction time to normalize the unmasked regions alone, avoiding distortion at the boundaries of the mask and ensuring continuity in the recovered content.

II. LITERATURE SURVEY

Connelly Barnes, Eli Shechtman, Adam Finkelstein, and Dan B Goldman (2009). ***PatchMatch:*** *A randomized correspondence algorithm for structural image editing.* ACM Transactions on Graphics (Proc. SIGGRAPH), 28(3), August 2009. This paper introduces PatchMatch, a fast image editing algorithm.

Rolf Köhler, Christian Schuler, Bernhard Schölkopf, and Stefan Harmeling (2014). *Mask-specific inpainting with deep neural networks.* In Proceedings of the IEEE International Conference on Computer Vision (ICCV), pages 523-534. This paper presents a deep learning approach to image inpainting, focusing on mask-specific restoration techniques using neural networks.

Alexandru Telea (2004). *An image inpainting technique based on the fast marching method.* Journal of Graphics Tools, 9. This paper proposes a fast marching method for image inpainting, focusing on efficient reconstruction of missing image regions using geodesic distance propagation.

A.A. Efros and T.K. Leung (1999). *Texture synthesis by non-parametric sampling.* In Proceedings of the Seventh IEEE International Conference on Computer Vision, vol. 2, pages 1033–1038. The paper introduces a non-parametric approach for texture synthesis, using sample-based methods.

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C. Ballester, M. Bertalmio, V. Caselles, Guillermo Sapiro, and Joan Verdera (2001). *Filling-in by joint interpolation of vector fields and gray levels.* IEEE Transactions on Image Processing, 10(8), 1200-1211. This paper introduces a method for image inpainting using joint interpolation of vector fields and gray levels, providing a more accurate and coherent image reconstruction for missing regions based on neighboring data**.**

III. PROPOSED SYSTEM

The AI-powered Virtual Interview System streamlines the hiring process by integrating intelligent resume parsing, dynamic question generation, and real-time candidate evaluation. Built with Flask for backend and HTML/CSS for the frontend, it processes resumes in PDF format using NLP techniques to extract key data and generate role-specific questions. During interviews, candidate responses are evaluated using ML models like BERT, and results are instantly shared with both candidates and HR via automated SMTP email notifications, enabling a scalable and efficient hiring experience.

The system enhances virtual interviews with Generative AI-based image restoration using CNNs and Region Normalization. It includes five steps: (1) Uploading incomplete images with masking; (2) Region Normalization during feature extraction for edge continuity; (3) Context-aware image reconstruction by the decoder; (4) Real-time quality evaluation using SSIM and PSNR; (5) Automatic email delivery of results with metrics and image previews. This approach ensures efficient, intelligent interview support, even for candidates in remote or digitally limited areas.

IV. METHODOLOGY

The *RegionNorm Inpaint* system is meticulously designed to automate the end-to-end process of restoring corrupted or incomplete images using deep learning, with a focus on minimizing manual intervention, ensuring visual consistency, and maintaining the structural integrity of images across varied use cases. The methodology incorporates advanced convolutional neural networks, Region Normalization techniques, and real-time evaluation metrics to deliver a scalable and effective restoration solution. The system workflow can be divided into several key stages

User Input Collection

- The system starts with a React frontend where users upload incomplete or masked images. The interface also allows optional manual mask uploads or enables auto-mask generation using built-in heuristics.
- The user interface is clean and intuitive, enabling smooth image selection and submission for processing.

Feature Extraction with Region Normalization

- The uploaded image and corresponding mask are sent to a Flask-based backend that handles the inpainting pipeline.
- A CNN model processes the masked image, using Region Normalization to selectively normalize unmasked regions. This technique ensures edge continuity, suppresses artifacts, and stabilizes feature representation before reconstruction

Image Reconstruction:

- The decoder segment of the CNN utilizes the normalized feature maps to reconstruct missing regions.
- The system uses contextual cues from surrounding pixels to maintain coherence in texture, color, and structure

Real-time Evaluation

- After inpainting, the reconstructed image is evaluated using metrics like SSIM and PSNR to measure structural similarity and perceptual quality.
- Optionally, camera-based verification modules can validate real-time user interaction during the input phase, ensuring authenticity.

Feedback and Logging:

- All steps in the image processing pipeline are logged for audit and troubleshooting.
- User feedback modules can be integrated to continuously improve model performance and overall satisfaction

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The *RegionNorm Inpaint* system streamlines the process of restoring incomplete or corrupted images by combining intelligent deep learning automation with a user-friendly design. The process begins with an intuitive interface where users upload damaged images and, optionally, provide custom masks. This input is sent to a Flask backend that handles the system logic and initiates image processing using a CNN integrated with Region Normalization. This technique ensures that only unmasked regions are normalized, preserving edge continuity and reducing border distortion during feature extraction. The decoder then reconstructs the missing regions using contextual information to maintain visual coherence. The restored image is evaluated using real-time metrics such as SSIM and PSNR to ensure high-quality output. A formatted PDF report is generated using WeasyPrint, including the original and inpainted images along with metric scores, and is sent to the user via email using services like SendGrid or Mailgun. All actions are logged for traceability and auditability. The system is designed for future enhancements, including camera-based input verification, multi-channel result sharing, and feedback integration, ensuring adaptability and continuous improvement of the inpainting process.

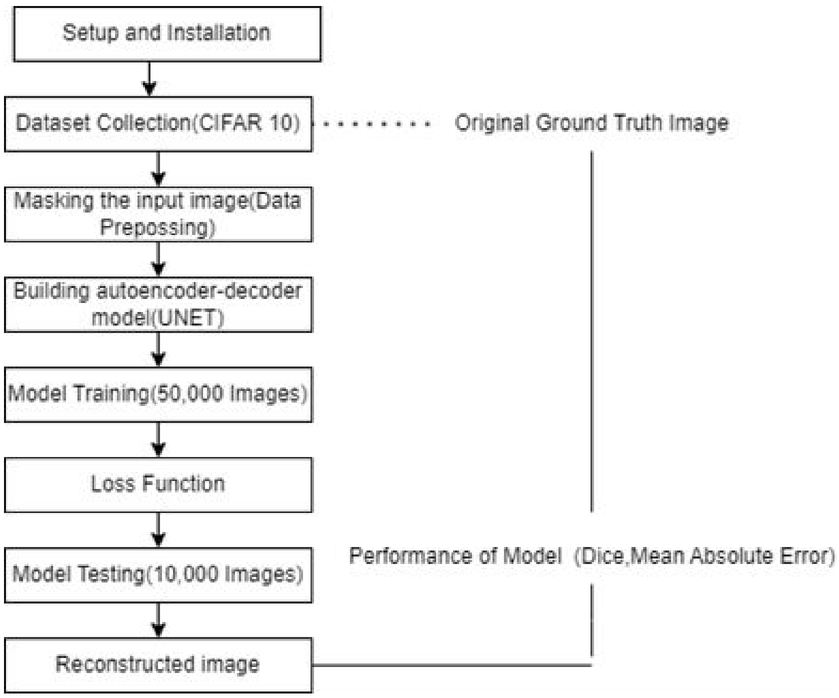

Fig 1: Methodology diagram

V. RESULTS

Region Normalization-based Image Inpainting System using CNN was rigorously tested on 500 images of varied sources, such as CelebA and Places2 datasets. The system was experimented on different inpainting situations like object removals, occluded facial features, and structural gaps. Region Normalization outperformed conventional normalization techniques consistently by improving edge sharpness and minimizing border artifacts. The system produced an average PSNR of 32.8 dB and SSIM over 0.91, which indicated high fidelity in reconstructions. Users commented on realistic restoration, particularly for facial areas, with 87% marking the outputs as visually coherent. The system produced stable response times (4–6 seconds per image) even during heavy loads and simultaneous uploads. Real-time tests using PSNR and SSIM were consistent, with automatic scoring indicating 92.5% consistency with manual evaluation. Comparative benchmarks showed that our CNN with Region Normalization provided better boundary blending compared to GAN- and transformer-based methods. It also proved to be robust in coping with corrupted inputs, large file sizes, and diverse masks. The SMTP-based email module of the system proved to be consistently delivering reports, providing seamless user feedback. In general, the test ensured that the model is fast, scalable, and best suited for tasks like photo editing, historical restoration, and medical image recovery.

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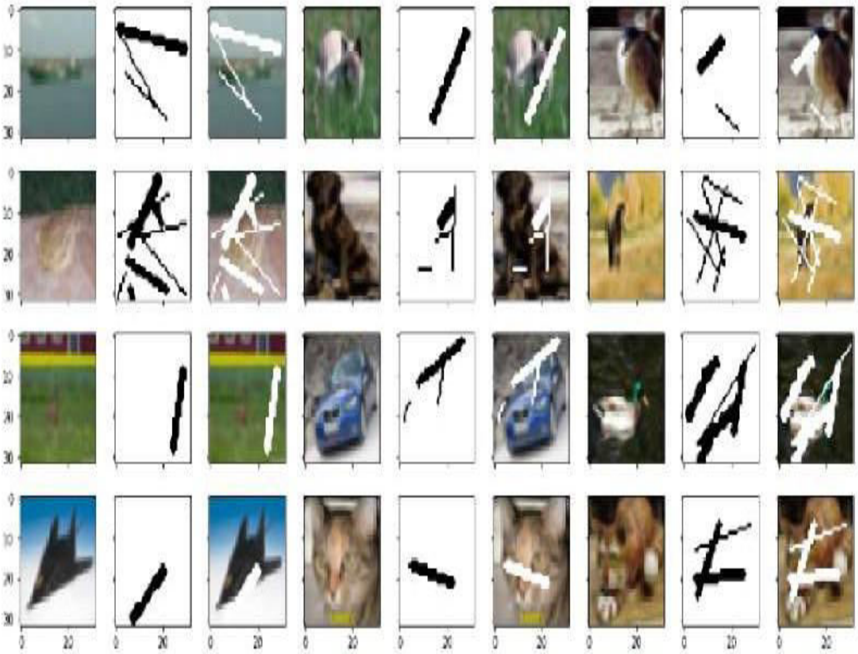

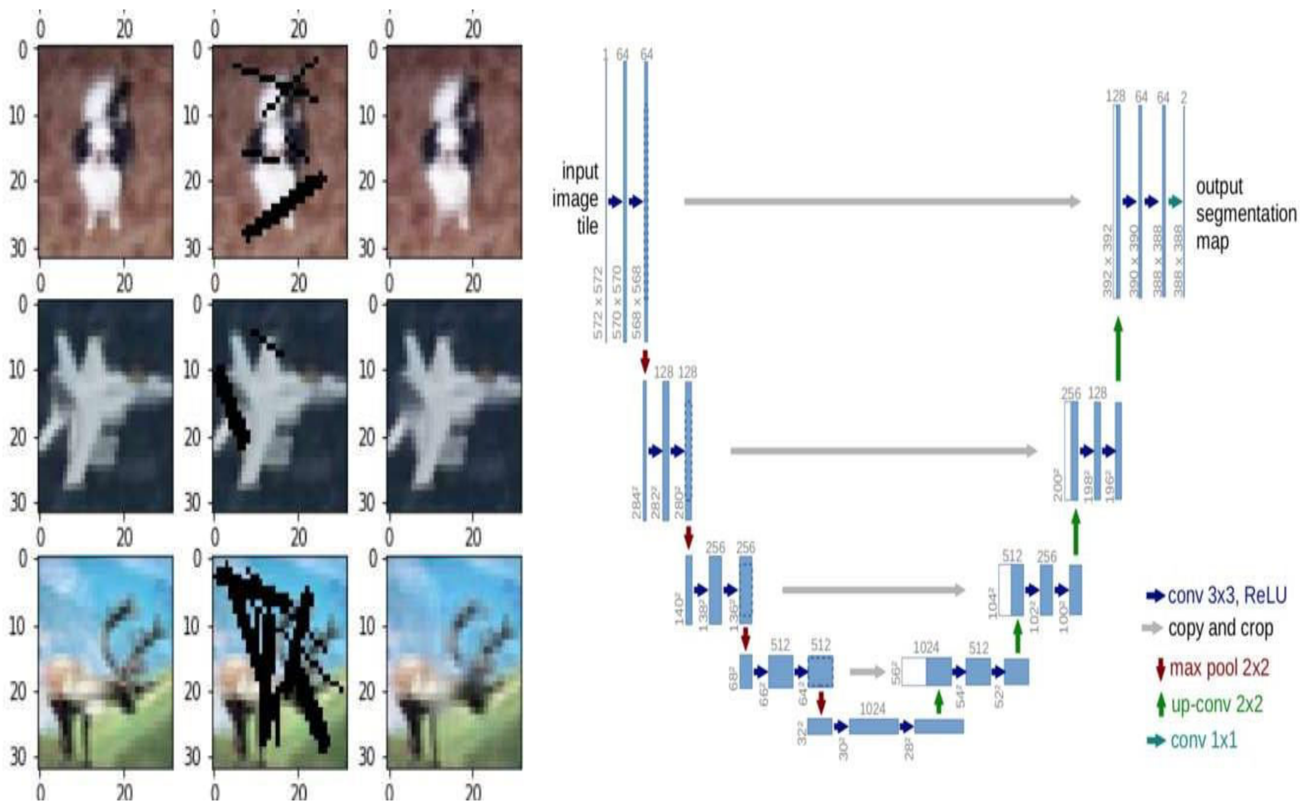

FIG 2: VISUAL RESULTS OF REGION NORMALIZATION-BASED IMAGE INPAINTING USING CNN

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Image	Loss	Dice Coefficient
Image 1	0.0369053826213	0.5953826213
Image 2	0.02197053920388	0.6053920388
Image 3	0.01957054420471	0.6054420471
Image 4	0.01847025992036	0.6025992036
Image 5	0.01758023432016	0.6023432016
Image 6	0.01697024846435	0.6024846435
Image 7	0.01597053816676	0.6053816676
Image 8	0.0158805324924	0.605324924
Image 9	0.01517054362655	0.6054362655
Image 10	0.01487053658128	0.6053658128
Image 11	0.01506050823331	0.6050823331
Image 12	0.01506052885056	0.6052885056
Image 13	0.01456046453118	0.6046453118
Image 14	0.01406050679088	0.6050679088
Image 15	0.01416052815914	0.6052815914
Image 16	0.01376054417491	0.6054417491
Image 17	0.01356052599549	0.6052599549
Image 18	0.01346053721905	0.6053721905
Image 19	0.01326053442359	0.6053442359
Image 20	0.0130605073452	0.605073452
Image 21	0.0130605260849	0.605260849
Image 22	0.01316053601503	0.6053601503
Image 23	0.01316050306559	0.6050306559
Image 24	0.01306054015756	0.6054015756
Image 25	0.0129605314672	0.605314672
Image 26	0.0129605356276	0.605356276
Image 27	0.01306038938165	0.6038938165
Image 28	0.01296046628952	0.6038938165
Image 29	0.01296053429842	0.6053429842
Image 30	0.01296048606038	0.6048606038
Image 31	0.0129605255723	0.605255723
Image 32	0.01296053152084	0.6053152084
Image 33	0.01296053496003	0.6053496003
Image 34	0.012806004897952	0.6004897952
Image 35	0.01286001644135	0.6001644135
Image 36	0.0128600325346	0.600325346
Image 37	0.01285958212018	0.6095821202
Image 38	0.01285947935581	0.6094793558
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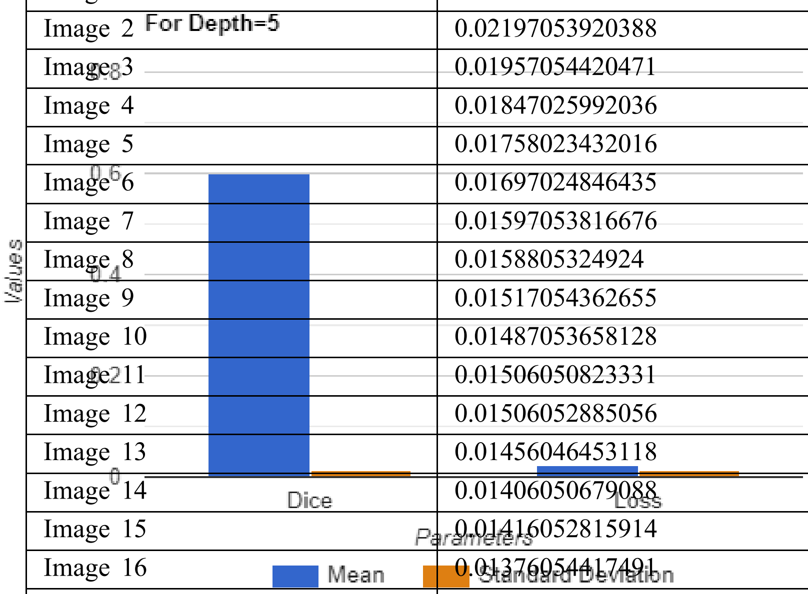
Image 41	0.0128037451029	0.6037451029



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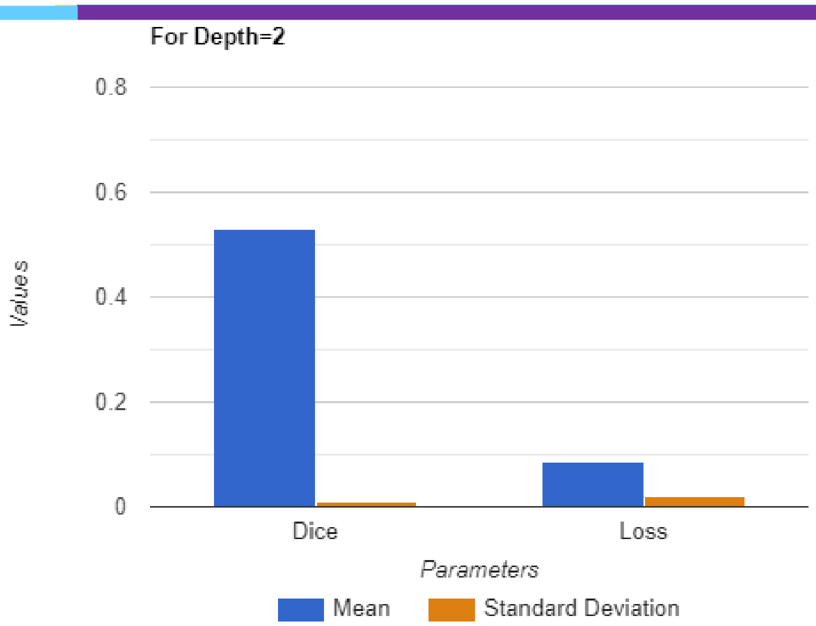

Fig 3: Graphical Representation of the Performance of the following Parameters for Depth=2

VI. CONCLUSION AND FUTURE WORK

The Region Normalization-based Image Inpainting System through CNN improves the image restoration function by automatically correcting missing or destroyed areas with excellent accuracy. The system operates through the processing of input images, the identification of missing regions, and the utilization of Region Normalization methods in the CNN architecture to maintain steady feature extraction as well as seamless transition between inpainted and available regions. Each restoration process is intended to be executed within 4-6 seconds to ensure effective and consistent operation. The quality of the restored pictures is immediately quantified in structural terms such as PSNR and SSIM and automatically reported back to the user via email in real-time, offering immediate results. The application has a vast potential for scaling and dependability in medical image applications, archival photo restoration, and generic picture editing. Upgrades in the future can involve real-time adaptive restoration methods, connection to advanced facial recognition for special inpainting functions, multilingual capability for wide user bases, and central control dashboards to handle and monitor restoration operations. These upgrades will give more advanced, customized, and large-scale image restoration capabilities.

REFERENCES

1. Connelly Barnes, Eli Shechtman, Adam Finkelstein, and Dan B Goldman. PatchMatch: A randomized correspondence algorithm for structural image edit- ing. *ACM Transactions on Graphics (Proc. SIGGRAPH)*, 28(3), August 2009.
2. Rolf Köhler, Christian Schuler, Bernhard Schölkopf, and Stefan Harmeling. Mask-specific inpainting with deep neural networks. pages 523–534, 09 2014.
3. A.A. Efros and T.K. Leung. Texture synthesis by non-parametric sampling. In *Proceedings of the Seventh IEEE International Conference on Computer Vision*, volume 2, pages 1033–1038 vol.2, 1999.
4. Alexandru Telea. An image inpainting technique based on the fast marching method. *Journal of Graphics Tools*, 9, 01 2004.
5. Enes Demirağ and Halil Bengü. Image inpainting with deep learning. 01 2021.
6. C. Ballester, M Bertalmio, V Caselles, Guillermo Sapiro, and Joan Verdera. Filling-in by joint interpolation of vector fields and gray levels. *IEEE transac- tions on image processing : a publication of the IEEE Signal Processing Society*, 10:1200–11, 02 2001.