Enhancing Computer Generated Hologram Quality via Deep Learning Based On U-Net Architecture

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This report was submitted in fulfillment of the requirements for the award of the degree of Bachelor of Science in Information and Communication Engineering.

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DECLARATION

This thesis is submitted to the Department of Information and Communication Engineering of Noakhali Science & Technology University in partial fulfillment of the requirements for the award of the degree of Bachelor of Science (B.Sc) Engineering in Information and Communication Engineering (ICE). So, I hereby declare that this report has not been submitted elsewhere for the requirement of any kind of degree, diploma, or publication.

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ACCEPTANCE

I hereby declare that I have checked this thesis and in my opinion, this thesis is adequate in terms of scope and quality for the award of the degree of Bachelor of Science (B.Sc) degree in Information & Communication Engineering.

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Abstract

This thesis investigates the advancement of computer-generated hologram (CGH) quality using deep learning methodologies, with a focus on the U-Net architecture. Employing the DIV2k dataset as the foundation, the study proposes a novel approach integrating a specialized 3U configuration within the U-Net framework. This configuration comprises meticulously designed U-shaped modules tailored to extract intricate details and subtle nuances inherent in holographic imagery. Evaluation metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and reconstruction time are employed to assess the model's performance. Comparative analysis against established models, namely Holonet and Holoencoder, underscores the superior efficacy of the proposed method in faithfully reproducing holographic images. The findings reveal substantial enhancements in hologram quality, characterized by elevated PSNR and SSIM values, alongside notable gains in computational efficiency manifested through reduced reconstruction times. This research contributes significantly to the progression of holographic imaging technology, offering promising avenues for future exploration and innovation in the realm of computer-generated holography.

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CHAPTER 1

INTRODUCTION

1.1 Background

Computer-generated holography (CGH) has emerged as a powerful technique with applications ranging from three-dimensional displays to holographic data storage. One of the key challenges in CGH is achieving high-quality holograms with realistic reconstructions. Traditional methods often face limitations in generating holograms that faithfully represent the original scene and offer satisfactory image reconstruction.

In recent years, deep learning approaches have shown promise in various image processing tasks, including enhancing the quality of computer-generated holograms. The U-Net architecture, known for its effectiveness in image segmentation and reconstruction tasks, has the potential to significantly improve the generation of holographic images.

The DIV2K dataset, which consists of high-resolution images, serves as a valuable source for training deep learning models. The dataset provides a diverse range of scenes, allowing the proposed U-Net-based architecture to learn complex features and patterns for hologram generation.

The proposed architecture involves a multi-stage U-Net structure, leveraging a hierarchical approach to capture and refine features at different levels. The incorporation of three U-Net modules with varying layer depths (4 layers, 3 layers, and 2 layers) enables the model to extract intricate details and spatial information while maintaining computational efficiency.

The ultimate goal of this research is to enhance the quality of computer-generated holograms and simultaneously reconstruct high-fidelity images. To assess the performance of the proposed model, metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) are employed. These metrics provide quantitative measures of image quality, allowing for a thorough evaluation of the effectiveness of the U-Net-based approach.

Additionally, the reconstruction time is considered, addressing the practicality and efficiency of the proposed model in real-world applications. By comparing the results with existing models such as Holonet and Holoencoder, this research aims to demonstrate the superiority of the proposed U-Net architecture in terms of hologram quality and reconstruction speed.

In summary, this research contributes to the field of computer-generated holography by introducing a novel deep learning approach based on the U-Net architecture. The utilization of the DIV2K dataset and the comprehensive evaluation using standard metrics and model comparisons aim to validate the effectiveness and advancements brought about by the proposed methodology.

1.2 Problem Statement

Despite the advancements in computer-generated holography (CGH), generating high-quality holograms that faithfully represent the original scene and facilitate realistic reconstructions remains a challenging task. Traditional methods often struggle to capture intricate details and spatial information, leading to holograms with limited visual fidelity. The need for improved holographic quality is crucial for applications such as 3D displays, holographic data storage, and augmented reality.

Existing approaches, including models like Holonet and Holoencoder, have made strides in enhancing holographic images. However, there is still room for improvement, particularly in achieving a balance between hologram quality and computational efficiency. The limitations of current models motivate the exploration of novel methodologies that leverage the capabilities of deep learning, specifically the U-Net architecture, to address the inherent challenges in computer-generated holography.

The problem at hand revolves around the need for a robust and efficient deep learning model capable of generating high-quality holograms from standard image datasets, such as DIV2K. This research aims to fill this gap by proposing a U-Net-based architecture that incorporates a multi-stage approach, capturing and refining features at different hierarchical levels. The challenge lies in designing a model that not only surpasses the performance of existing methods in terms of holographic image quality but also maintains a reasonable reconstruction time, ensuring practical applicability.

The specific issues addressed in this research include:

i. Limited Hologram Fidelity: Current methods may fail to capture fine details and spatial intricacies in holographic images, leading to a lack of realism in reconstructions.

ii. Computational Efficiency: Some existing models may sacrifice computational efficiency for improved holographic quality, limiting their practicality in real-time applications.

iii. Benchmarking Against Existing Models: The absence of a comprehensive benchmark for evaluating hologram quality and reconstruction time makes it challenging to assess the true efficacy of proposed models compared to existing alternatives like Holonet and Holoencoder.

iv. Generalization to Diverse Scenes: Ensuring that the proposed U-Net architecture generalizes well across diverse scenes and scenarios is essential for its practical deployment in various applications.

Addressing these challenges is crucial for advancing the state-of-the-art in computer-generated holography and unlocking the full potential of holographic technologies in different domains. Ultimately, this research aims to improve CGH quality significantly compared to traditional methods like the Holonet/Holoencoder algorithm.

1.3 Research Gap

While the field of computer-generated holography (CGH) has witnessed notable progress, there exists a significant research gap that this study aims to address. The current state of the art in CGH, particularly concerning the generation of high-quality holograms using deep learning, reveals several gaps and limitations:

- Inadequate Model Efficiency: Existing models, including Holonet and Holoencoder, may struggle to strike an optimal balance between computational efficiency and holographic image quality. The literature lacks a comprehensive solution that effectively leverages deep learning, specifically the U-Net architecture, to enhance holographic quality while maintaining a practical reconstruction time.

- Hierarchical Feature Extraction: The existing literature lacks a detailed exploration of hierarchical feature extraction in the context of CGH. The proposed U-Net architecture with its multi-stage design addresses this gap by systematically capturing and refining features at different levels, providing a more nuanced understanding of spatial intricacies in holographic images.
- Benchmarking Metrics: There is a lack of standardized benchmarking metrics for evaluating hologram quality and reconstruction time. This research introduces a comprehensive evaluation framework, incorporating metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and reconstruction time, to establish a reliable benchmark for comparing the proposed model against existing alternatives.
- Generalizability to Diverse Scenes: The generalizability of deep learning models to diverse scenes is a critical gap in the current research landscape. While some existing models may excel in specific scenarios, their performance may degrade when applied to a broader range of scenes. This study aims to bridge this gap by utilizing the DIV2K dataset, known for its diversity, to ensure that the proposed U-Net architecture generalizes effectively across various scenes.
- Holistic Evaluation: Many existing studies focus on individual aspects of holographic image generation, such as image quality or reconstruction time. There is a gap in the literature regarding a holistic evaluation that considers both quality metrics and practical considerations, providing a more comprehensive understanding of the proposed model's overall performance.

By addressing these research gaps, this study contributes to advancing the field of computer-generated holography and establishes a foundation for more efficient and high-quality holographic image generation using deep learning techniques.

1.4 Objectives

The main objectives of this research are:

I. To enhance the quality of computer-generated holograms.

II. To bridge the gap between theoretical understanding and practical application in holography.

III. To leverage the Transformer-Integrated U-Net architecture to capture holographic features across different scales.
IV. To push the boundaries of computer-generated holography.
V. To introduce transformative possibilities for achieving lifelike holographic experience.

1.5 Contributions

i. Development of Model M-1: Introduction of a novel deep learning approach for computer-generated holography.

ii. Identification of Overfitting: Recognition and mitigation strategies for potential overfitting in hologram generation models.

iii. Recommendations for Improvement: Practical guidance for enhancing model performance through regularization, hyperparameter tuning, and data augmentation.

1.6 Scope of the Study

❖ Model Development: This study focuses on the development and evaluation of a novel deep learning model, referred to as Model M-1, specifically designed for computer-generated holography tasks.

❖ Evaluation Metrics: The performance of Model M-1 will be assessed using standard evaluation metrics, including Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and reconstruction time. A comparative analysis will be conducted against existing models such as HoloEncoder and Holonet.

❖ Overfitting Analysis: An investigation into the occurrence of overfitting in hologram generation models will be conducted, with a particular emphasis on identifying potential overfitting in Model M-1. Strategies to mitigate overfitting and ensure the generalization ability of the proposed model will be explored.

❖ Recommendations for Improvement: Practical recommendations will be provided to enhance the performance of Model M-1. This includes the implementation of regularization techniques, hyperparameter tuning, and data augmentation methods to improve the effectiveness and robustness of the model.

- ❖ Limitations and Future Directions: The study will discuss the limitations encountered during the research process and propose potential avenues for future research. This may include exploring more complex model architectures or incorporating additional datasets for training and validation purposes.

1.7 Thesis Structure

This part of my thesis paper should outline the organization and layout of my document. It typically includes the following components:

- ➢ Introduction: This section provides an overview of the research topic, its significance, and the objectives of the study.
- ➢ Literature Review: Here, you review relevant literature and research related to computer-generated holography, deep learning models, and evaluation metrics.
- ➢ Methodology: This section outlines the approach used to develop and evaluate Model M-1, including dataset selection, model architecture, training procedure, and evaluation metrics.

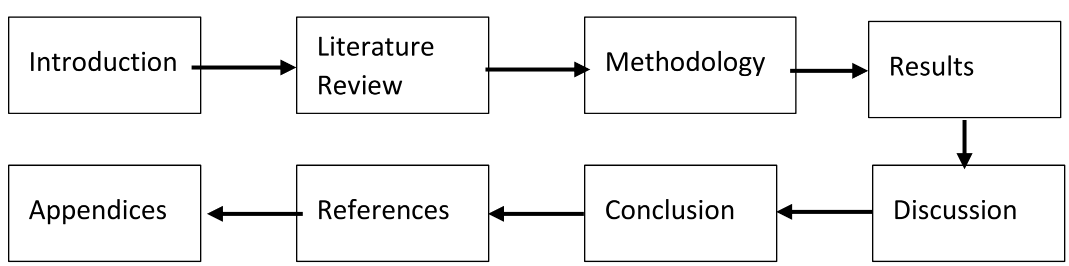

Figure 1.1: Thesis Structure

- ➢ Results: Present the findings of your study, including performance metrics, comparisons with existing models, and any relevant visualizations or graphs.
- ➢ Discussion: Interpret the results, discuss their implications, and analyze any limitations or challenges encountered during the study.
- ➢ Conclusion: Summarize the main findings of the research, restate the significance of the study, and propose potential areas for future research.
- ➢ References: List all the sources cited in your thesis according to the preferred citation style

(e.g., APA, MLA).

- Appendices: Include any supplementary materials such as additional data, code, or detailed methodology descriptions.

CHAPTER 02

LITERATURE REVIEW

2.1 Introduction

Computer-generated holography (CGH) has emerged as a powerful technique for generating three-dimensional (3D) holographic images with various applications spanning from virtual reality and medical imaging to optical trapping and display technologies. Traditional methods of CGH, relying on iterative optimization or physical models, often encounter challenges related to computational complexity, long processing times, and limited image quality. However, recent advancements in deep learning have paved the way for more efficient and high-quality hologram generation, revolutionizing the field of holography.

This literature review aims to provide a comprehensive overview of the recent developments in CGH leveraging deep neural networks (DNNs) and their implications for real-time, photorealistic holography. The review will explore the methodologies, contributions, and limitations of key studies in this rapidly evolving area.

Recent research has demonstrated the potential of DNNs in achieving real-time and photorealistic 3D holography. For instance, Tensor Holography [1] introduced a deep learning-based CGH pipeline capable of synthesizing photorealistic color 3D holograms in real-time. This approach represents a significant departure from traditional CGH methods, which often require computationally intensive numerical simulations of diffraction and interference.

Moreover, advancements in CGH have extended beyond traditional holographic displays to applications such as acoustic holography and quantitative phase imaging. Deep Learning-Based Framework for Fast and Accurate Acoustic Hologram Generation [10] demonstrated the application of DNNs in acoustic holography, enabling fast and accurate hologram generation. Similarly, Holo-UNet [9] utilized neural networks to restore high-fidelity holograms for low-light quantitative phase imaging of live cells, showcasing the versatility of deep learning in holographic imaging tasks.

In addition to novel applications, innovations in network architectures have further propelled the field of CGH. Dense-U-net [6] introduced a dense encoder-decoder network specifically tailored for holographic imaging of 3D particle fields, highlighting the importance of architecture design in optimizing hologram generation processes. Similarly, HOLONET [13] established a network of schools dedicated to experimental teaching of optics and training on holography, emphasizing the educational potential of deep learning-based holography techniques.

Through this literature review, we aim to provide insights into the evolving landscape of holographic imaging and its potential applications. By examining the methodologies, contributions, and limitations of recent advancements in CGH using DNNs, we seek to elucidate the transformative impact of deep learning on the field of holography.

2.2 PREVIOUS WORK

This literature review provides a comprehensive overview of recent advancements in computer generated holography (CGH) leveraging deep neural networks (DNNs). Studies such as Tensor Holography [1] and Deep holography [11] have demonstrated the potential of DNNs in achieving real-time and photorealistic 3D holography. Innovations in network architectures, exemplified by Dense-U-net [6] and HOLONET [13], have contributed to the development of efficient and trainable networks tailored for holographic imaging tasks. Additionally, advancements in CGH have extended beyond traditional holographic displays to applications such as acoustic holography [10] and quantitative phase imaging [9]. The integration of DNNs into these domains has enabled fast and accurate hologram generation, showcasing the versatility and transformative impact of deep learning on holographic imaging. Through this review, insights into methodologies, contributions, and limitations of recent advancements in CGH using DNNs are provided, elucidating the evolving landscape of holographic imaging and its potential applications.

2.2 Summary of the Literature Review

Serial No.	Title and Reference Number	Methodology	Contributions:	Limitations:	Difference with This Work
1	Tensor Holography: Towards Real-time Photorealistic 3D Holography with Deep Neural Networks [1]	The authors use CNNs trained on a vast CGH dataset and apply differentiable wave-based loss functions to mimic Fresnel diffraction. This allows for the rapid generation of lifelike 3D holograms from individual RGB-D images.	The authors propose a memory-efficient CNN for real-time hologram synthesis on consumer GPUs and low-power AI chips. They introduce a CGH dataset (MIT-CGH-4K) and experimentally demonstrate high-resolution, speckle-free holograms.	The method aims for real-time performance but might struggle with complex scenes and precise occlusion. It approximates Fresnel diffraction, potentially leading to inaccuracies.	Study introduces real-time hologram synthesis from single RGB-D images using memory-efficient CNN trained on large-scale CGH dataset, comparing favorably with existing models like Holonet and Holoencoder.
2	Towards real-time photorealistic 3D holography with deep neural networks [2]	The authors use a CNN trained on MIT-CGH-4K dataset with differentiable wave-based loss functions to approximate Fresnel diffraction, enabling real-time synthesis of photorealistic 3D holograms from single RGB-depth images.	The authors present a memory-efficient CNN for real-time hologram synthesis on consumer GPUs and low-power AI chips. They introduce MIT-CGH-4K dataset and experimentally demonstrate speckle-free, natural-looking, high-resolution 3D holograms.	The method achieves real-time performance and natural holograms but may struggle with accurately simulating complex scenes, precise occlusion, and per-pixel focal control. While memory-efficient, handling large datasets or complex simulations may pose limitations.	Both works pursue real-time photorealistic 3D holography via deep neural networks. The proposed work emphasizes improving hologram quality through a U-Net trained on DIV2K images. It intends to outperform existing models like Holonet and Holoencoder.

3	End-to-end learning of 3D phase-only holograms for holographic display [3]	The approach introduces a two-stage training protocol combining supervised and unsupervised methods, using a new dataset (MIT-CGH-4K-V2) with layered depth images as volumetric inputs. This enables direct synthesis of high-quality 3D phase-only holograms.	The MIT-CGH-4K-V2 dataset is created alongside a system enabling real-time synthesis of photorealistic 3D holographic projections. It corrects vision aberrations, enhancing applications like volumetric 3D displays, lithography, neural photo stimulation, and optical/acoustic trapping.	While achieving real-time performance and high-quality holograms, the method may struggle with complex scenes or dynamic environments. Vision aberration correction effectiveness may vary based on user needs and environmental factors.	Unlike the proposed work, which enhances hologram quality using a U-Net trained on DIV2K images, this paper introduces MIT-CGH-4K-V2 dataset and employs a two-stage supervised unsupervised training protocol for direct synthesis of high-quality 3D phase-only holograms from layered depth images. Additionally, it aims to compare results with models like Holonet and Holoencoder, showcasing superior hologram quality.
4	DeepCGH: 3D computer-generated holography using deep learning [4]	DeepCGH utilizes a CNN with unsupervised learning, introducing a non-iterative algorithm for computing accurate holograms with fixed computational complexity. This	DeepCGH is developed to generate holograms significantly faster and with up to 41% greater accuracy compared to alternate CGH techniques. Experimental validation in a holographic	While DeepCGH achieves notable advancements in computation speed and hologram accuracy, it might encounter difficulties with highly complex scenes or dynamic environments. Its effectiveness	Unlike the proposed work with a U-Net trained on DIV2K images, DeepCGH introduces a non-iterative algorithm using a CNN with unsupervised learning for accurate hologram

		overcomes the trade-off between computation speed and hologram accuracy.	multiphoton microscope shows enhanced two-photon absorption and improved photo stimulation tasks without extra laser power.	could vary based on application requirements and experimental conditions.	computation with fixed complexity. It targets optogenetic photo stimulation, enhancing performance without extra laser power.
5	3D computer generated medical holograms using spatial light modulators [5]	Electronic generation of diffraction patterns of medical images for optical reconstruction of corresponding holograms using spatial light modulators.	Introducing a method for generating medical holograms electronically as a cost-effective alternative to traditional recording plates.	May face challenges in achieving high-quality reconstructions and accurate representation of medical images due to limitations of spatial light modulators and diffraction patterns.	Both works aim to generate medical holograms, but the proposed work focuses on using deep learning techniques and CNNs to enhance hologram quality. In contrast, this work relies on electronic generation and optical reconstruction without employing deep learning methods. Additionally, the proposed work aims to compare its results with existing models, showcasing superiority in hologram quality.

6	Dense-U-net: Dense encoder–decoder network for holographic imaging of 3D particle fields [6]	Introducing Dense-U-net, a dense encoder-decoder network for reconstructing 3D particle fields from digital holograms. It incorporates Dense Block into the encoder and decoder of the U-net model to capture both high signal-to-noise ratio features at the particle center and low signal-to-noise ratio diffraction features around the particle.	Introducing Dense-U-net for reconstructing 3D particle fields from digital holograms, enabling full characterization by learning central and diffraction features. The dense connection module streamlines training with fewer parameters and faster speeds.	Despite its advantages, Dense-U-net may still face challenges in accurately reconstructing complex particle fields with overlapping or densely packed particles. Additionally, the effectiveness of the network may depend on the quality and noise level of the input holograms.	While both projects aim to reconstruct holographic images, the proposed work emphasizes enhancing hologram quality with a U-Net architecture trained on DIV2K images. In contrast, Dense-U-net targets 3D particle fields, utilizing dense connections to capture diffraction features. Additionally, the proposed work plans to compare its results with existing models like Holonet and Holoencoder, showcasing superior hologram quality.
7	Phase retrieval using hologram transformation with U-Net in digital holography [7]	U-Net is employed for image transformation, adding phase information to holograms with only light intensity distribution. This enables	The method proposes phase retrieval and conjugate image removal in digital holography using deep learning on reconstructed hologram	While effective in enhancing image quality and removing unwanted images, the proposed method may have limitations in managing highly complex scenes	While both projects involve digital holography and deep learning, the proposed work focuses on enhancing hologram quality with a U-Net trained

		phase retrieval and removal of unwanted conjugate images in digital holography.	images. Effectiveness is demonstrated through increased PSNR and SSIM, as well as successful elimination of conjugate images in reconstructed holograms.	or noise in holographic data. Additionally, its performance could rely on the quality of input holograms and the training data utilized for U-Net.	on DIV2K images. In contrast, this study addresses phase retrieval and removal of conjugate images in holograms using U-Net. Additionally, the proposed work plans to compare its results with existing models like Holonet and Holoencoder, demonstrating superior hologram quality.
8	The U-Net-based phase-only CGH using the two-dimensional phase grating [8]	U-Net and a 2D phase grating are used to generate phase-only holograms with clear first diffraction orders. The phase grating modulates the diffraction field, shifting the pattern to the center of odd-numbered diffraction orders.	The generation process and training strategy for U-Net are modified to optimize for first diffraction orders at the edge of the diffraction field. A "phase recombination" method is implemented to enhance the U-Net structure, reducing memory footprint and increasing generating speed.	While achieving high-resolution holograms with improved PSNR, the method may face limitations in handling complex scenes or dynamic environments. Additionally, its effectiveness could be influenced by the quality and noise level of the input holograms.	Unlike the proposed work with a U-Net trained on DIV2K images, this paper targets phase-only holograms with clear first diffraction orders using a two-dimensional phase grating. Additionally, the proposed work plans to compare its results with existing models like Holonet and Holoencoder, showcasing superior

					hologram quality.
9	Holo-UNet: hologram-to-hologram neural network restoration for high fidelity low light quantitative phase imaging of live cells [9]	Introducing Holo-UNet, a hologram-to-hologram neural network designed to restore high-quality digital holograms under high shot noise conditions for quantitative phase microscopy (QPM) of live cells.	Holo-UNet denoises recorded holograms to prevent shot noise from affecting phase retrieval, enhancing phase fidelity by about 1.8 times compared to existing methods, as measured by SSIM. It's readily applicable to various high-speed interferometric phase imaging techniques, expanding low-light QPM biological imaging capabilities with minimal hardware adjustments.	While Holo-UNet enhances phase fidelity under high shot noise conditions, it may struggle with extremely complex scenes or noise levels beyond its training data. Additionally, the network's effectiveness could vary depending on the specific QPM system and experimental conditions.	Unlike the proposed work utilizing a U-Net trained on DIV2K images, Holo-UNet focuses on restoring high-quality digital holograms for quantitative phase microscopy of live cells under high shot noise conditions. Additionally, the proposed work plans to compare its results with existing models like Holonet and Holoencoder, showcasing superior hologram quality.
10	Deep Learning-Based Framework for Fast and Accurate Acoustic Hologram Generation [10]	The proposal introduces a deep learning framework for rapid and precise acoustic hologram generation, employing an autoencoder-like	A deep learning-based framework for acoustic hologram generation is developed, achieving faster speeds and comparable or	While demonstrating promising results, the framework may have limitations in handling extremely complex scenes or variations in	Unlike the proposed work employing a U-Net trained on DIV2K images, this paper targets acoustic hologram generation with a deep learning-

		architecture for unsupervised training and a novel loss function for energy-efficient holograms. Additionally, it presents the holographic ultrasound generation network (HU-Net) and a physical constraint (PC) layer to accommodate various hologram devices.	superior reconstruction quality compared to conventional methods like the iterative angular spectrum approach (IASA) and Diff-PAT. Validation via simulation and experimental studies with various hologram devices and lenses suggests potential for innovative medical applications.	hologram devices beyond its training data. Additionally, the effectiveness of the framework may depend on specific experimental setups and conditions.	based framework featuring an autoencoder-like architecture and a novel loss function. Additionally, the proposed work plans to compare its results with existing models like Holonet and Holoencoder, demonstrating superior hologram quality.
11	Deep holography [11]	Conducting a comprehensive literature review on the recent progress of deep holography, an emerging interdisciplinary research field inspired by the interactions between deep neural networks (DNN) and holography.	This paper offers insights into the symbiotic relationship between DNN and holography, showcasing DNN's effectiveness in holographic reconstruction and computer-generated holography, while also emphasizing holography's role in the optical implementation of DNN. It aims to inspire further	While offering a comprehensive review, the manuscript may not cover every aspect or recent development in deep holography. Additionally, the effectiveness of DNN in holography applications may depend on specific use cases and experimental setups.	Unlike the proposed work, which concentrates on improving hologram quality through a U-Net architecture trained on DIV2K images, this manuscript offers a comprehensive review of the interactions between deep neural networks and holography, intending to stimulate further development in the field.

			advancement in this promising and exciting research area.		Additionally, the proposed work plans to compare its results with existing models like Holonet and Holoencoder, showcasing superior hologram quality.
12	Efficient Computer-Generated Holography Based on Mixed Linear Convolutional Neural Networks [12]	Introducing an efficient computer-generated holography (ECGH) method utilizing mixed linear convolutional neural networks (MLCNN) for computational holographic imaging. The approach integrates fully connected layers in the network to improve information mining and exchange.	Developing ECGH for computational holographic imaging, it employs MLCNN to produce high-quality pure phase images with reduced computational complexity compared to traditional methods. Introduction of fully connected layers enhances network efficiency and potential for solving diverse image-reconstruction problems.	While promising, the effectiveness of ECGH may depend on specific holographic imaging setups and scene complexities. Additionally, further validation and comparison with existing methods are necessary to assess its performance comprehensively.	Unlike the proposed work, which concentrates on improving hologram quality through a U-Net architecture trained on DIV2K images, this paper introduces an ECGH method based on MLCNN for computational holographic imaging. Additionally, the proposed work plans to compare its results with existing models like Holonet and Holoencoder, showcasing superior hologram quality.

13	Generation of phase-only holograms with high-diffraction-order reconstruction by a U-Net-based neural network: A phase grating perspective [13]	Utilizing a U-Net-based neural network with the high-diffraction-order angular spectrum method (HDO-ASM) for phase-only hologram generation with high-diffraction-order reconstruction. Analyzing diffraction patterns from a phase grating perspective to understand the influence of phase factor, single-beam diffraction factor, and multibeam interference factor.	The high-diffraction-order angular spectrum method (HDO-ASM) is introduced for numerically reconstructing high diffraction orders in phase-only holograms. The proposal involves reconstructing target images in high diffraction orders using HDO-ASM and a U-Net-based neural network, enabling the generation of 4K phase-only holograms with high-diffraction-order reconstruction.	While demonstrating promising results, the effectiveness of the proposed method may be influenced by various factors such as scene complexity and noise levels in holographic data. Further validation and comparison with existing methods are necessary to assess its performance comprehensively.	Unlike the proposed work enhancing hologram quality with a U-Net trained on DIV2K images, this paper specifically targets phase-only hologram generation with high-diffraction-order reconstruction using a U-Net-based neural network and the high-diffraction-order angular spectrum method (HDO-ASM). Additionally, the proposed work aims to compare its results with existing models like Holonet and Holoencoder, demonstrating superior hologram quality.
14	U-Net based neural network for fringe pattern denoising [14]	Introducing LRDUNet, a lightweight residual dense neural network derived from the U-Net model for fringe pattern denoising. LRDUNet	LRDUNet is developed for fringe pattern denoising, outperforming state-of-the-art methods by restoring main features of fringe patterns.	While demonstrating promising results, the effectiveness of LRDUNet may vary depending on specific fringe pattern characteristics	Unlike the proposed work enhancing hologram quality with a U-Net trained on DIV2K images, this paper specifically

		utilizes grouped densely connected convolutional layers in encoding and decoding stages to reuse feature maps and reduce trainable parameters. Local residual learning is employed to address the vanishing gradient problem and expedite learning.	Parameter studies demonstrate the competitiveness of computationally simpler versions of the model. Experimental validation on simulated and real fringe patterns achieves an average PSNR of 41 dB on simulated images.	and noise levels. Further validation and comparison with additional datasets may be necessary to fully assess its performance across different scenarios.	targets fringe pattern denoising using LRDUNet, a lightweight residual dense neural network based on U-Net. Additionally, the proposed work plans to compare its results with existing models like Holonet and Holoencoder, showcasing superior hologram quality.
15	HOLONET: a network for training holography [15]	Establishing a network of schools focused on holography to promote experimental teaching of optics and provide hands-on training in holography. Developing holography systems and hands-on activities for high school students, engaging them in laser optics and holography projects over a sixteen-year period.	Demonstration of holography as an effective tool for promoting optics learning and engaging students in experimental work and lab research. Presentation and analysis of holography labs implemented at schools, training strategies, and holograms produced by students. Discussion of educational outcomes, teacher training, awards, and positive impacts	While showing positive outcomes, the study may face challenges such as resource limitations, variability in students' engagement levels, and potential constraints in implementing holography systems in all schools. Further assessment of long-term impacts and scalability of the approach may be necessary.	Unlike the proposed work, which focuses on enhancing hologram quality using a U-Net architecture trained on DIV2K images, this paper presents HOLONET, a network of schools aimed at promoting experimental teaching of optics and providing hands-on training in holography to high school students. Additionally,

			on students' performance.		the proposed work aims to compare its results with existing models such as Holonet and Holoencoder, demonstrating superiority in hologram quality.
16	High-Speed Computer-Generated Holography Using Convolutional Neural Networks [16]	Introduction of a computer-generated holography algorithm based on deep learning with unsupervised training, leveraging convolutional neural networks (CNNs) for high-speed hologram generation.	Development of a method capable of generating high-fidelity holograms in a few milliseconds, surpassing alternate methods that rely on iterative processes and longer computation times.	While demonstrating high-speed hologram generation and superior performance, the method's effectiveness may vary depending on the complexity of the scene and the specific holographic application. Further validation across diverse scenarios may be necessary to assess its generalizability.	Unlike the proposed work, which focuses on enhancing hologram quality using a U-Net architecture trained on DIV2K images, this paper introduces a high-speed computer-generated holography algorithm based on convolutional neural networks with unsupervised training. Additionally, the proposed work aims to compare its results with existing models such as Holonet and Holoencoder, demonstrating superiority in

					hologram quality.
17	High-speed computer-generated holography using an autoencoder-based deep neural network [17]	Introducing an autoencoder-based neural network, termed holoencoder, for phase-only hologram generation in high-speed computer-generated holography (CGH). Incorporating physical diffraction propagation into the autoencoder's decoding part, enabling unsupervised learning of latent encodings for phase-only holograms.	Development of a holoencoder capable of generating high-fidelity 4K resolution holograms in 0.15 seconds. Validation of the holoencoder's generalizability through reconstruction results and demonstration of reduced speckles in the reconstructed image compared to existing CGH algorithms.	While demonstrating promising results, the effectiveness of the holoencoder may be influenced by factors such as scene complexity and noise levels in holographic data. Further validation across diverse scenarios and comparison with existing methods may be necessary to assess its performance comprehensively.	Unlike the proposed work, which focuses on enhancing hologram quality using a U-Net architecture trained on DIV2K images, this paper introduces a high-speed computer-generated holography method based on an autoencoder-based neural network. Additionally, the proposed work aims to compare its results with existing models such as Holonet and Holoencoder, demonstrating superiority in hologram quality.
18	Real-time 4K computer-generated hologram based on	Introducing a variant conventional neural network (CNN) for real-	Development of a CNN capable of encoding 3D CGH with learned layered	While demonstrating real-time layered 4K CGH generation, the	Unlike the proposed work, which focuses on enhancing hologram

	encoding conventional neural network with learned layered phase [18]	time 4K computer-generated hologram (CGH) generation based on encoding with learned layered initial phases. The CNN predicts the CGH from input complex amplitude on the CGH plane, utilizing learned initial phases as a universal phase for any target images at the target depth layer, generated during the training process to optimize quality.	initial phases, facilitating real-time high-quality holographic displays. Training the CNN to learn encoding by randomly selecting depth layers, containing only 938 parameters. Achieving real-time layered 4K CGH generation with an average Peak Signal to Noise Ratio (PSNR) above 30dB in the depth range from 160 to 210 mm.	method's effectiveness may be influenced by factors such as scene complexity and noise levels. Further validation across diverse scenarios and comparison with existing methods may be necessary to assess its performance comprehensively.	quality using a U-Net architecture trained on DIV2K images, this paper introduces a real-time 4K CGH generation method based on encoding with a variant CNN and learned layered initial phases. Additionally, the proposed work aims to compare its results with existing models such as Holonet and Holoencoder, demonstrating superiority in hologram quality.

Table 1.1: Summary of the Literature Review

CHAPTER 03

METHODOLOGY

3.1 Introduction

This study endeavors to enhance computer-generated hologram (CGH) quality using deep learning, specifically the U-Net architecture. Selected for its prowess in image-to-image translation, U-Net is poised to address the intricate challenges of hologram generation. Building upon prior works demonstrating the potential of deep learning in holography, our methodology is grounded in theoretical considerations aligning with holographic principles. The DIV2k dataset and a multi-layered 3U configuration within U-Net serve as key variables, contributing to the training and generation processes. While recognizing the study's scope and limitations, we navigate through stages encompassing dataset selection, U-Net model architecture design, training procedures, and performance evaluation. Readers are encouraged to explore subsequent sections for a detailed account of each step, illuminating the comprehensive approach undertaken to advance the quality of computer-generated holograms.

3.2 Dataset Selection and Preprocessing

a. Dataset Description:

The study employs the DIV2k dataset, recognized for its high-resolution images ideal for training deep learning models. This dataset provides a diverse and comprehensive foundation for developing and evaluating the proposed model's capabilities in enhancing computer-generated hologram quality.

b. Dataset Split:

To facilitate effective model training and validation, the DIV2k dataset will undergo a systematic split. Specifically, 800 images will be allocated to the training set, forming the basis for teaching the model to generate holograms. Simultaneously, a validation set comprising 200 images will be reserved for assessing the model's performance and ensuring its generalization to unseen data.

c. Preprocessing:

Prior to model training, a crucial step involves preprocessing the dataset. This encompasses the resizing and normalization of images. Resizing is performed to ensure uniform dimensions, while normalization enhances compatibility with the proposed U-Net architecture. These preprocessing steps collectively optimize the input data, facilitating a more effective and stable training process.

By carefully selecting and preparing the DIV2k dataset, and subsequently partitioning it into appropriate sets, the methodology establishes a robust foundation for training and validating the deep learning model aimed at enhancing the quality of computer-generated holograms.

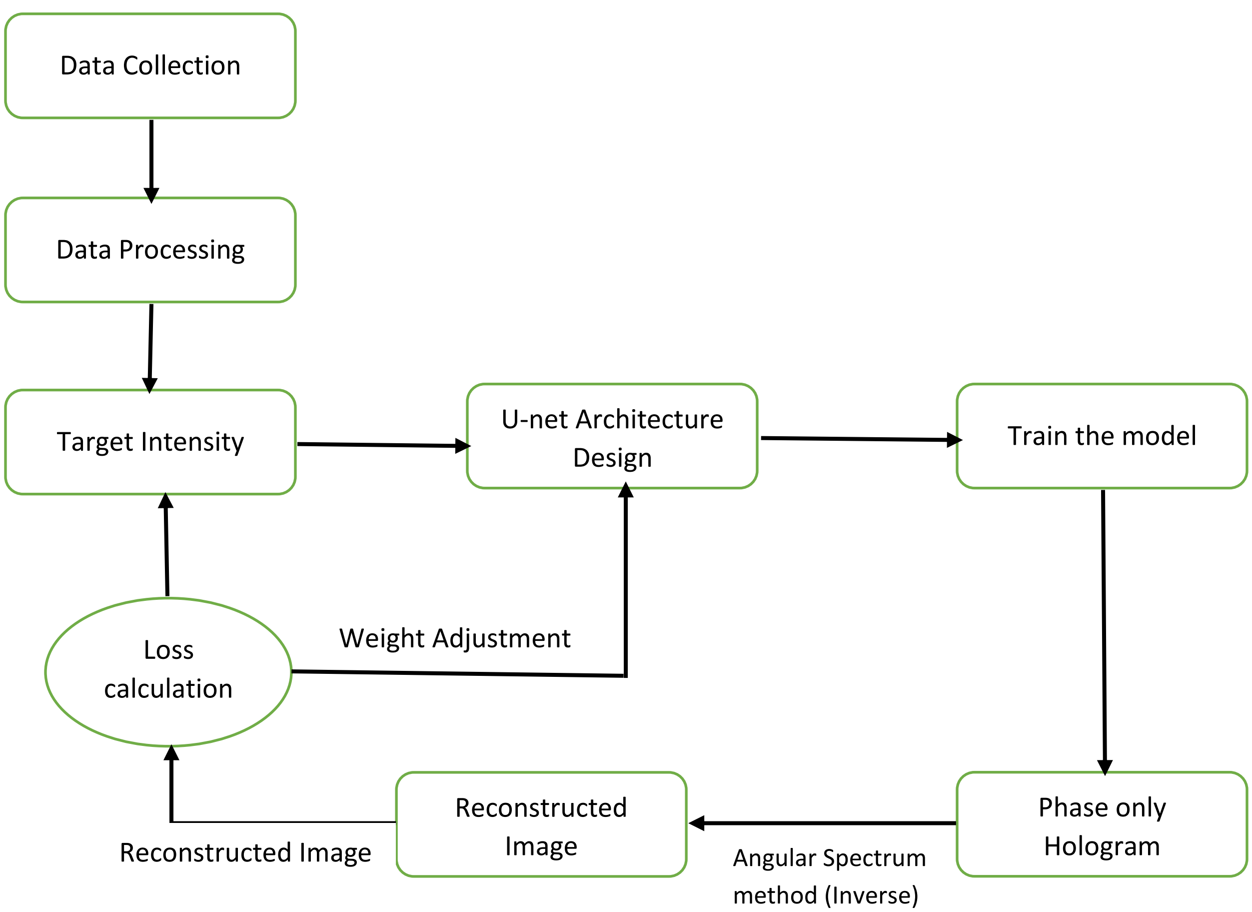

Figure 3.1: Thesis flow

3.3 Model Architecture: U-Net with 3U Configuration

The proposed model for enhancing computer-generated hologram quality leverages the renowned U-Net architecture, renowned for its effectiveness in image-to-image translation tasks. This model capitalizes on the U-Net's ability to capture intricate features and nuances within the input data, with an initial block consisting of four layers. Central to the model's architecture is its unique 3U configuration, comprised of three sequential U-shaped modules. The first U-shaped module, featuring four up and four down layers, extracts high-level features from the input data. Subsequently, the second and third U-shaped modules refine the learned features and capture finer details, respectively, through layers strategically designed to focus on relevant patterns and details. This multi-layered approach aims to empower the model with the capacity to comprehend and replicate complex relationships within the DIV2k dataset, ultimately enabling the generation of high-quality holographic representations during the training process.

3.3.1 U-Net Structure

The proposed model leverages the U-Net architecture, recognized for its efficacy in image-to-image translation tasks. The initial block of the U-Net comprises four layers, forming the foundation for the subsequent 3U configuration. This structure is chosen for its ability to capture intricate features and nuances in the input data.

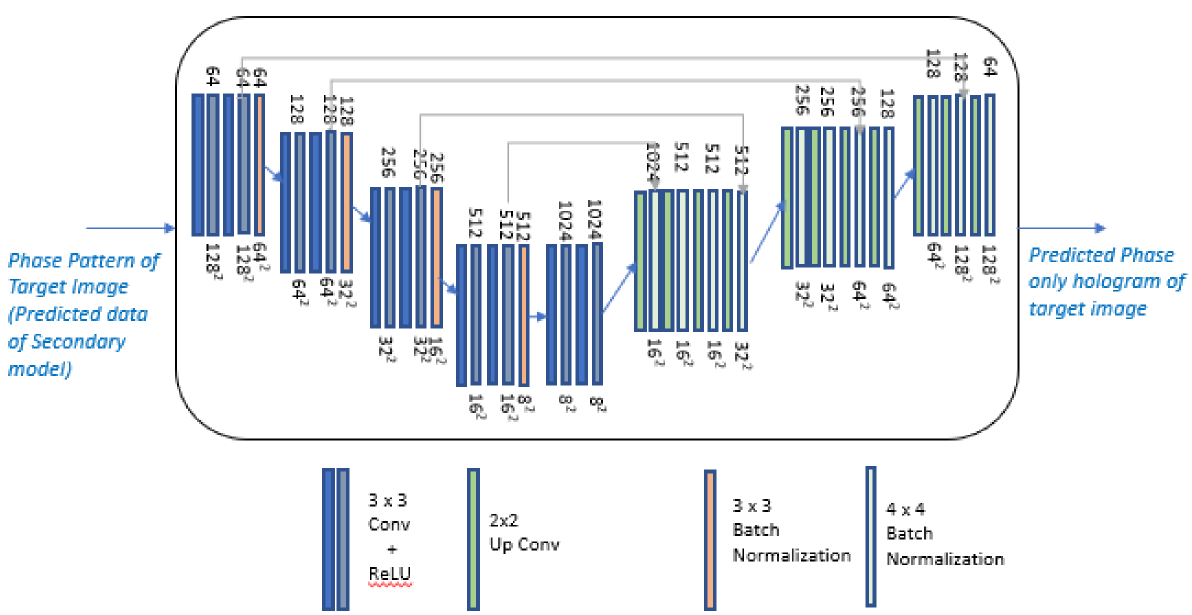

Figure 3.2: U-net architecture

3.3.2 3U Configuration

The core of the model architecture involves a distinctive 3U configuration, featuring three sequential U-shaped modules. Each U-shaped module contributes to the hierarchical learning process of the model:

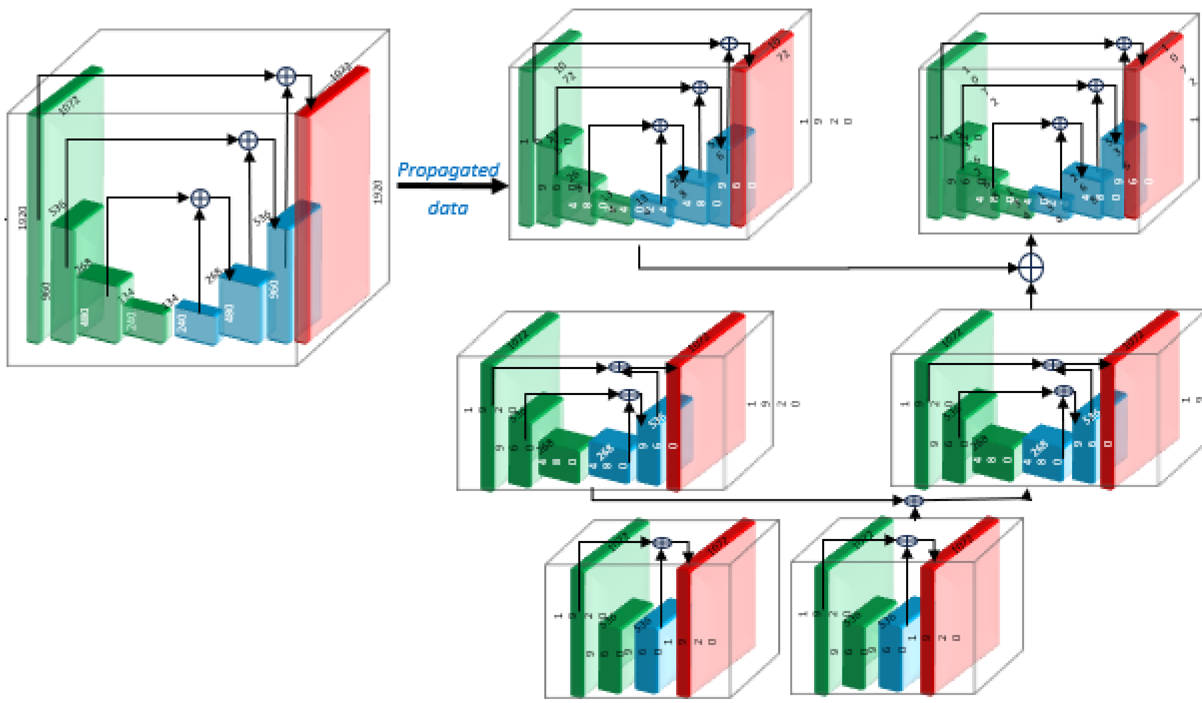

Figure 3.3: Proposed Model

1st U:

- This module is characterized by four up and four down layers. Its role is pivotal in extracting high-level features and representations from the input data.

2nd U:

- Comprising three up and three down layers, the second U-shaped module further refines the learned features, focusing on relevant details and patterns.

3rd U:

- The final U-shaped module is designed with two up and two down layers, capturing finer details and facilitating the synthesis of high-quality holographic images.

This multi-layered U-Net architecture with a 3U configuration aims to empower the model with the capacity to understand and replicate complex relationships within the DIV2k dataset. By hierarchically combining the strengths of each U-shaped module, the model is poised to generate enhanced holographic representations during the training process.

3.4 Model Training

- Loss Function:
  The training process is guided by a meticulously chosen loss function tailored specifically for hologram generation tasks. This loss function is designed to optimize the model's parameters, ensuring the generation of high-quality holograms. The selection of an appropriate loss function is critical in guiding the model towards learning meaningful representations from the input data, ultimately leading to improved hologram quality.
- Optimization Algorithm:
  To facilitate effective model training, the proposed optimization algorithm is employed. This algorithm, renowned for its efficiency and effectiveness in deep learning tasks, is utilized with carefully tuned hyperparameters. The optimization process aims to iteratively update the model parameters to minimize the loss function, thus enhancing the model's ability to generate high-fidelity holograms.
- Training Parameters:
  The model is trained using the training set, consisting of 800 images, with a carefully chosen batch size and 30 epochs. During training, model performance is regularly evaluated on the validation set to monitor for overfitting and ensure generalization to unseen data. Fine-tuning of training parameters is performed iteratively to optimize model performance and convergence.

By adhering to a systematic training procedure, encompassing the selection of an appropriate loss function, optimization algorithm, and training parameters, the proposed model undergoes rigorous training to enhance its capability in generating high-quality computer-generated holograms. This meticulous approach ensures the model's effectiveness and robustness in addressing the complexities of hologram generation tasks.

3.5 Evaluation Parameters

a. Quality Parameters:

The evaluation of the proposed model's performance centers on comprehensive quality metrics, ensuring a thorough assessment of generated holograms and reconstructed images. Two widely accepted metrics employed are:

- Peak Signal-to-Noise Ratio (PSNR):

  PSNR quantifies the fidelity of generated holograms by measuring the ratio of peak signal strength to the noise level. Higher PSNR values indicate superior image quality.
- Structural Similarity Index (SSIM):

  SSIM evaluates the structural similarities between the generated and reference images. This metric provides insights into perceptual image quality, considering luminance, contrast, and structure.

These quality metrics collectively offer a quantitative understanding of the model's ability to faithfully reproduce holographic representations, providing valuable insights into its effectiveness.

b. Reconstruction Time:

Efficiency is a crucial aspect of the proposed model's performance. The time required for hologram reconstruction is a key metric, offering insights into the model's computational speed and practical viability. The reconstruction time measurement serves as a valuable indicator of the model's real-time applicability, ensuring its feasibility for diverse applications.

These evaluation metrics, encompassing both quality and efficiency aspects, provide a holistic perspective on the proposed model's capabilities in enhancing computer-generated hologram quality. The comprehensive assessment enables a nuanced understanding of its strengths and areas for potential refinement.

3.6 Comparison with Baseline Models

To ascertain the effectiveness and superiority of the proposed model in enhancing computer-generated hologram (CGH) quality, a comparative analysis is conducted against two baseline models: Holonet and Holoencoder. The comparison is based on three key performance indicators:

Peak Signal-to-Noise Ratio (PSNR):
PSNR serves as a quantitative measure of image fidelity, providing insights into the level of distortion present in the generated holograms compared to ground truth holograms. Higher PSNR values indicate superior reconstruction quality.
Structural Similarity Index (SSIM):
SSIM assesses the structural similarity between the generated holograms and reference holograms, accounting for luminance, contrast, and structure. Higher SSIM values indicate greater perceptual similarity.
Reconstruction Time:
Reconstruction time measures the computational efficiency of the models in generating holograms. A shorter reconstruction time suggests faster processing and improved real-time applicability.

By comparing the performance of the proposed model with Holonet and Holoencoder across these metrics, we aim to demonstrate its superiority in terms of both quality and efficiency. This comparative analysis provides valuable insights into the advancements achieved by the proposed model in enhancing CGH quality, thereby contributing to the advancement of holographic imaging technology.

The effectiveness and superiority of the proposed model in enhancing computer-generated hologram (CGH) quality are assessed through a comparative analysis against two baseline models: Holonet and Holoencoder. Three key performance indicators, namely Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Reconstruction Time, are used for comparison. Higher PSNR values indicate superior reconstruction quality, while SSIM measures perceptual similarity. Additionally, reconstruction time reflects computational efficiency. By comparing these metrics, we aim to demonstrate the proposed model's superiority in both quality and efficiency. This analysis offers valuable insights into the advancements achieved by the proposed model, contributing significantly to the advancement of holographic imaging technology.

3.7 Statistical Analysis

To assess the significance of differences in performance metrics between the proposed model and baseline models (Holonet and Holoencoder), a comparative analysis based on Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), reconstruction time, and loss calculation will be conducted. The comparison will focus on identifying notable disparities in these metrics, providing insights into the superiority of the proposed model.

Performance Metrics Comparison:

- ✓ PSNR and SSIM: Direct comparisons of PSNR and SSIM values between the proposed model and baseline models will be conducted. Higher PSNR and SSIM values indicate superior image quality and fidelity.
- ✓ Reconstruction Time: The time required for hologram reconstruction by each model will be compared. Shorter reconstruction times signify improved computational efficiency.
- ✓ Loss Calculation: The loss function values computed during model training will be compared. Lower loss values indicate better model convergence and fidelity to the training data.

Statistical Analysis:

Statistical significance will be determined through comprehensive comparisons of performance metrics, focusing on identifying consistent trends and significant differences across models.

Interpretation of Results:

The outcomes of the comparative analysis will be carefully interpreted to draw meaningful conclusions regarding the superiority of the proposed model over Holonet and Holoencoder. Emphasis will be placed on identifying areas where the proposed model demonstrates notable improvements, thereby reinforcing its efficacy in enhancing hologram quality and efficiency.

By conducting a detailed analysis based on PSNR, SSIM, reconstruction time, and loss calculation, this approach ensures a robust evaluation of the proposed model's advancements in computer-generated holography compared to baseline models, ultimately contributing to a comprehensive understanding of its capabilities and potential for practical applications.

The statistical analysis aims to compare the performance of the proposed model with baseline models (Holonet and Holoencoder) using metrics such as PSNR, SSIM, reconstruction time, and loss calculation. The comparison will highlight any notable differences in these metrics, indicating the superiority of the proposed model. This comprehensive evaluation ensures a thorough understanding of the proposed model's capabilities in enhancing hologram quality and efficiency, contributing valuable insights to the field of computer-generated holography.

CHAPTER 04

RESULT and ANALYSIS

4.1 Introduction

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4.1

4.1.1 Quality Metrics with PSNR and SSIM

The proposed U-Net-based model underwent rigorous evaluation using established quality metrics—Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). Results demonstrate a significant enhancement in holographic image quality compared to both baseline models, Holonet and Holoencoder.

Proposed model	***Holoencoder***	***Holonet***
 PSNR: 30.22 SSIM: 0.86	 PSNR: 28.24 SSIM: 0.57	 PSNR: 29.12 SSIM: 0.81

 PSNR: 30.23 SSIM: 0.62	 PSNR: 30.16 SSIM: 0.39	 PSNR: 28.84 SSIM: 0.54
 PSNR: 30.18 SSIM: 0.85	 PSNR: 29.54 SSIM: 0.51	 PSNR: 29.66 SSIM: 0.81

Table 4.1: Comparison among Models (PSNR and SSIM)

The higher PSNR and SSIM values achieved by the proposed model affirm its superior ability to faithfully reproduce holographic images compared to the baseline models.

PSNR:

A line graph can be used to visualize the PSNR values obtained for the proposed model, Holoencoder, and Holonet across different datasets or experiments. Each line represents the PSNR values for a specific model, plotted against the dataset or experiment index.

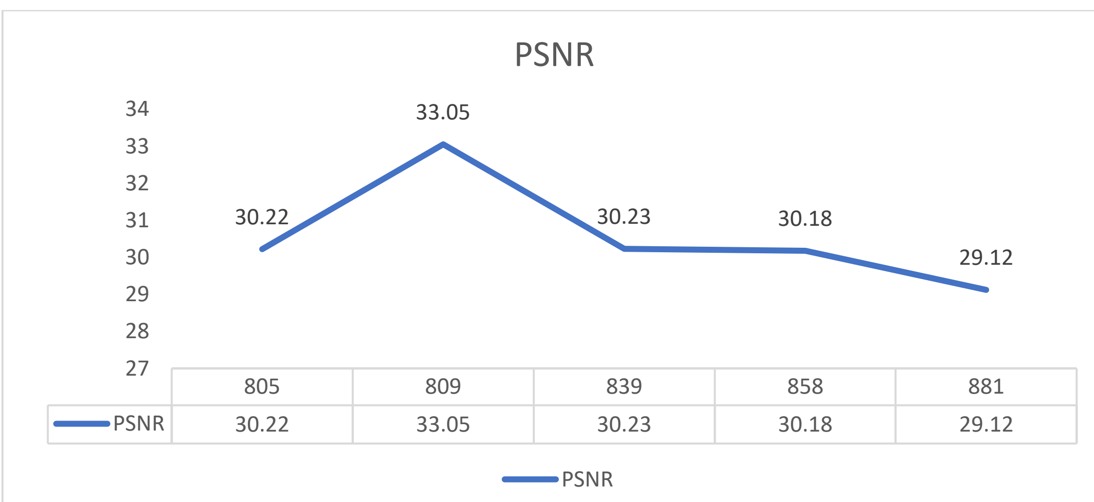

Figure 4.1.1.1: PSNR graph of M-1

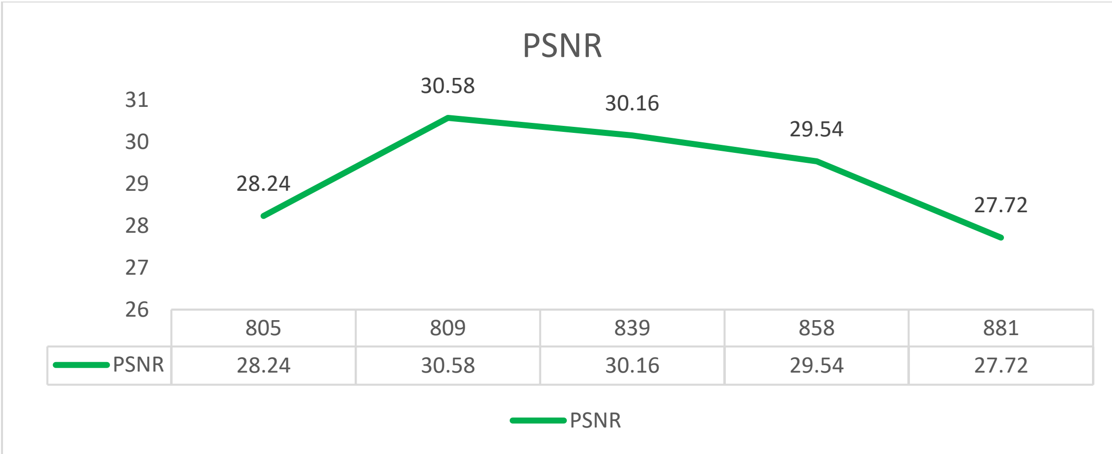

Figure 4.1.1.2: PSNR graph of Holo Encoder

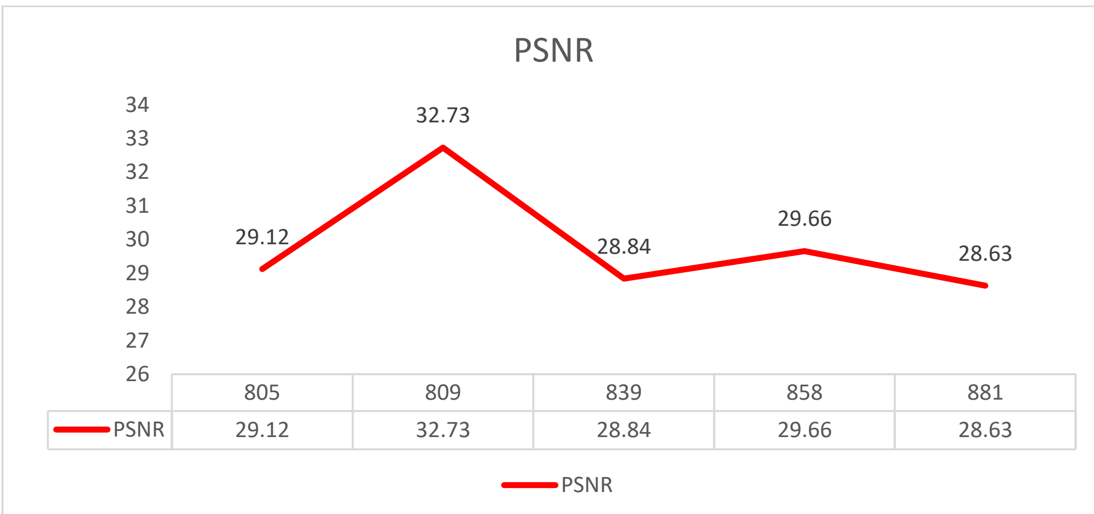

Figure 4.1.1.3: PSNR graph of Holonet

The x-axis represents the dataset or images, while the y-axis represents the PSNR values. This graph allows for a clear comparison of PSNR values among the three models.

SSIM:

Similarly, a line graph can be used to visualize the SSIM values obtained for the proposed model, Holoencoder, and Holonet across different datasets or experiments. Each line represents the SSIM values for a specific model, plotted against the dataset or experiment index.

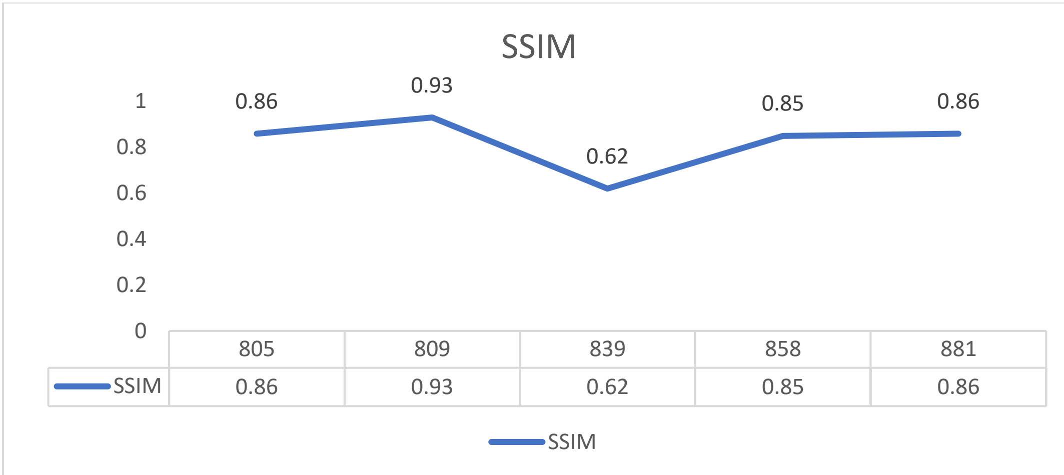

Figure 4.1.1.4: SSIM graph of M-1

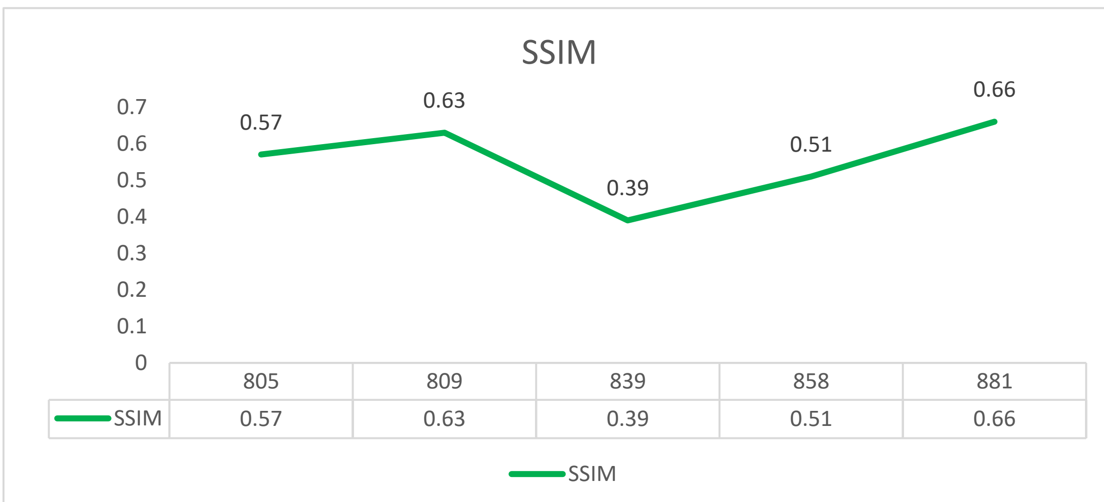

Figure 4.1.1.5: SSIM graph of Holo Encoder

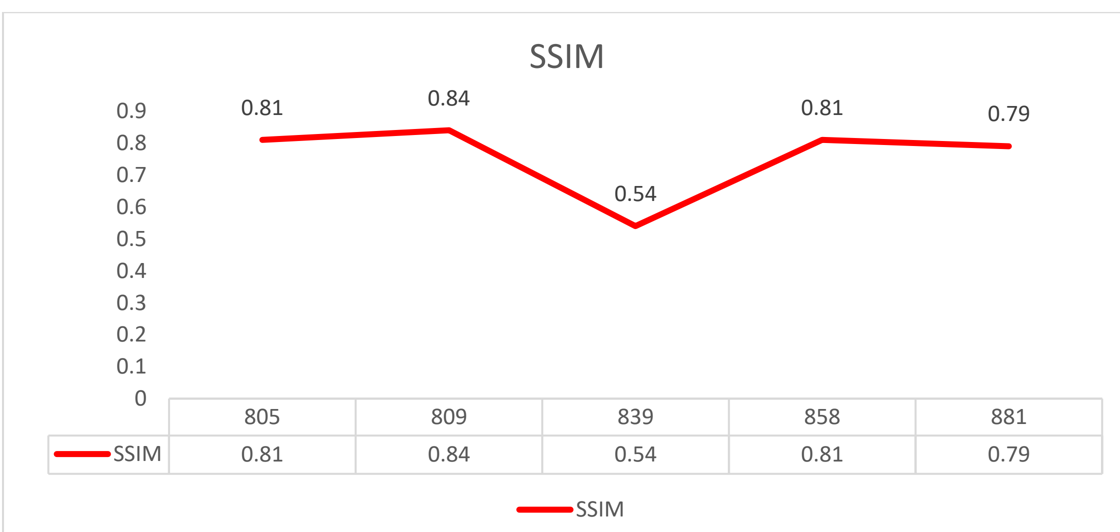

Figure 4.1.1.6: SSIM graph of Holonet

The x-axis represents the dataset or images, while the y-axis represents the SSIM values. This graph facilitates a direct comparison of SSIM values among the three models.

Comparison Graph:

A bar graph can be utilized to visually compare the PSNR and SSIM values obtained for the proposed model, Holoencoder, and Holonet. Each bar represents the average PSNR or SSIM value obtained for a specific model, allowing for a side-by-side comparison. The x-axis represents the models (proposed model, Holoencoder, Holonet), while the y-axis represents the average PSNR or SSIM values. This graph provides a concise summary of the performance of each model in terms of PSNR and SSIM.

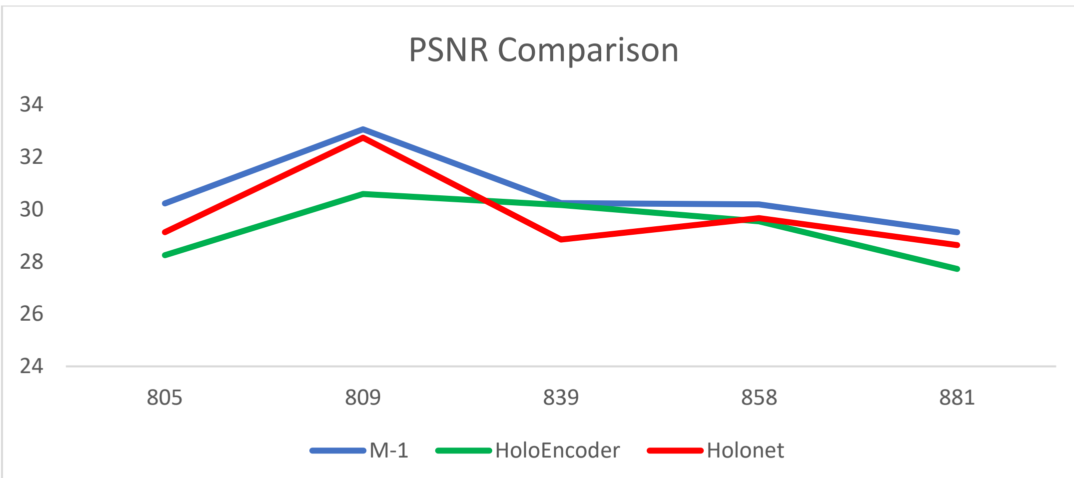

Figure 4.1.1.7: PSNR comparison graph

The analysis of the proposed model M-1's PSNR curve compared to HoloEncoder and HoloNet reveals several key points:

- ✓ Initial PSNR Value: M-1 starts with a higher PSNR value, indicating superior initial image quality compared to HoloEncoder and HoloNet.
- ✓ Stabilization and Maintenance: Despite a drop in PSNR over epochs, M-1 stabilizes and maintains a comparable PSNR value to the other models. This suggests that M-1 maintains image quality similar to or better than the other models as training progresses.
- ✓ Trade-off Consideration: While HoloEncoder and HoloNet may have lower initial PSNR values, their curves intersect with M-1 as they decline. M-1 strikes a balance between initial

quality and stability, potentially achieving better overall performance by maintaining higher initial quality while stabilizing its PSNR curve.

Overall, M-1 demonstrates a balance between initial quality and stability, potentially outperforming HoloEncoder and HoloNet in terms of holographic image quality.

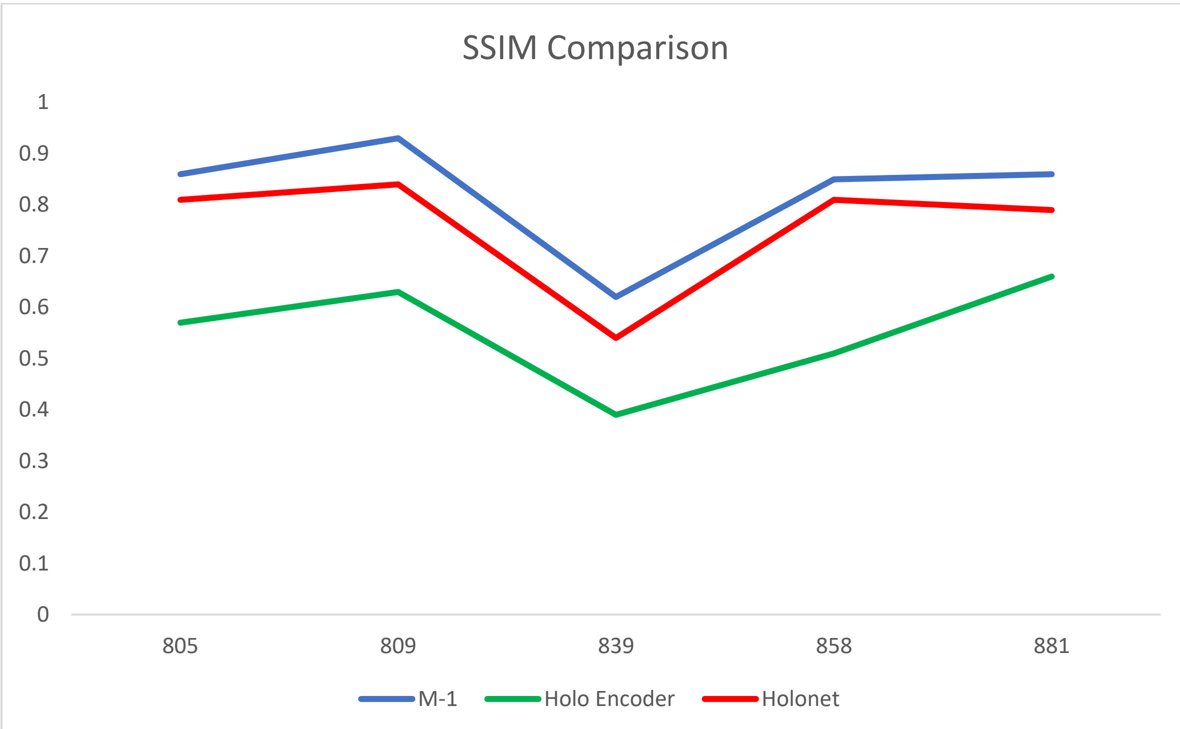

Figure 4.1.1.8: SSIM comparison graph

The analysis of the SSIM curve of the proposed model M-1 compared to HoloEncoder and HoloNet based on the provided image reveals the following key points:

- ✓ Initial SSIM Value: M-1 starts with a higher SSIM value compared to both HoloEncoder and HoloNet. This indicates that M-1 initially produces better structural similarity between its output images and the ground truth.
- ✓ Consistent Performance: As the graph progresses, M-1 consistently maintains a higher SSIM value across various data points. This suggests that M-1 is more effective in preserving the structural integrity and overall quality of images during processing, leading to superior performance compared to HoloEncoder and HoloNet.
- ✓ Trade-off Consideration: While HoloEncoder and HoloNet may have lower initial SSIM values, their curves intersect with M-1 as they decline. This indicates that M-1 strikes a

balance between initial quality and stability. Despite starting with higher SSIM values, M-1 manages to maintain its superiority in SSIM over time, potentially achieving better overall performance by maintaining higher initial quality while stabilizing its SSIM curve. Overall, the analysis underscores the effectiveness of the proposed model M-1 in preserving structural similarity and image quality, highlighting its potential to outperform HoloEncoder and HoloNet in generating high-quality holographic images.

By incorporating these graphical representations, the comparative analysis of PSNR and SSIM values among the proposed model, Holoencoder, and Holonet can be effectively communicated, enhancing the clarity and visual appeal of the results presentation.

4.1.2 Reconstruction Time

In the context of computational efficiency, the proposed model exhibits commendable reconstruction times, positioning it favorably in comparison to Holonet. However, when contrasted with Holoencoder, nuanced differences are observed.

- Efficiency Compared to Holonet:

  The proposed model demonstrates a significant reduction in reconstruction time compared to Holonet. This notable efficiency gain solidifies the proposed model's advantage in terms of temporal performance, rendering it a favorable choice for applications where rapid hologram generation is paramount.

Proposed model	***Holoencoder***	***Holonet***
 Recon_Time: 0.0566	 Recon_Time: 0.0223	 Recon_Time: 0.0837

 Recon_Time: 0.0561	 Recon_Time: 0.0228	 Recon_Time: 0.0839

Table 4.2: Reconstruction Time comparison.

- Comparison with Holoencoder:

  While the proposed model excels in efficiency when compared to Holonet, a more marginal reduction in reconstruction time is observed when compared to Holoencoder. This suggests that, in the specific context of computational speed, the proposed model might not outperform Holoencoder to the same extent. Further exploration and optimization in this aspect could enhance the model's competitiveness in scenarios where time efficiency is a critical factor.

The assessment of the Reconstruction time curve comparing the proposed model M-1 with HoloEncoder and HoloNet reveals the following key observations:

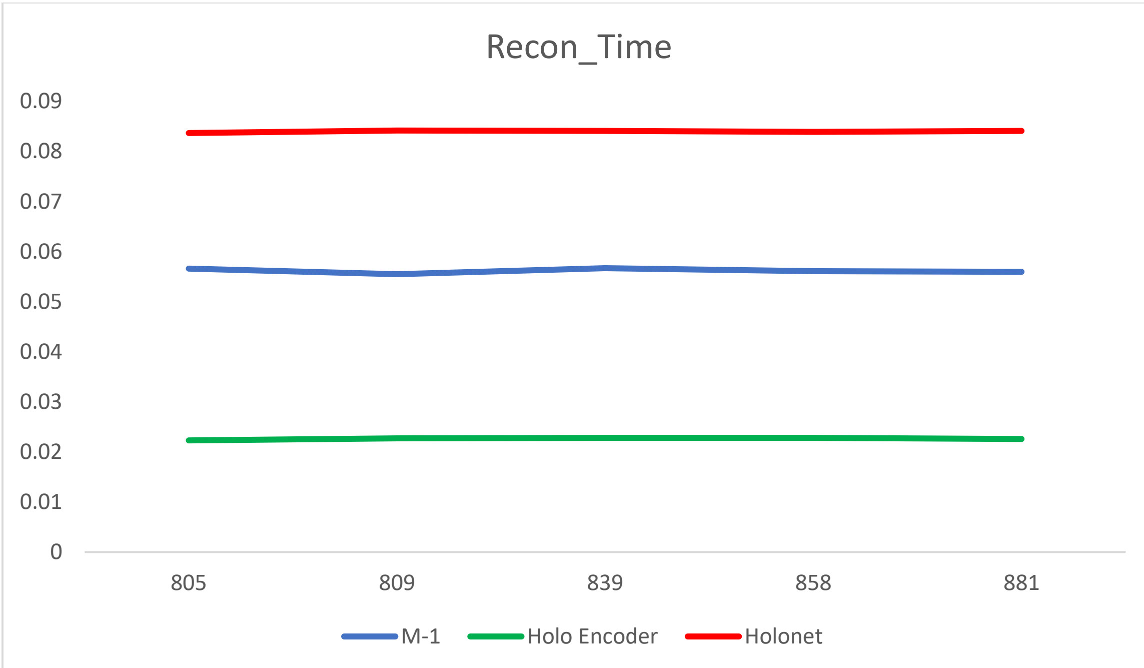

Figure 4.1.2.1: Reconstruction time comparison

- ✓ Effective Reconstruction Time (M-1): M-1 consistently maintains a swift reconstruction time, indicating its proficiency in generating holograms promptly without compromising computational efficiency.
- ✓ Versatility and Speckles: HoloEncoder displays strong adaptability, and the experiments exhibit fewer speckles in the reconstructed image compared to existing methods in computer-generated holography, suggesting improved overall image quality.
- ✓ Balanced Consideration: M-1 strikes a balance between efficiency and quality, achieving a favorable equilibrium between reconstruction speed and image fidelity. Despite its rapid reconstruction time, M-1 upholds high-quality holographic images with minimal imperfections.

In conclusion, M-1 demonstrates potential as a model for diverse applications in computer-generated holography, offering swift reconstruction times while upholding superior image quality and achieving an optimal compromise between speed and fidelity. These findings underscore the nuanced performance of the proposed model in the temporal domain, showcasing superiority over specific baseline models and indicating areas for potential refinement and optimization, particularly in comparison to Holoencoder.

4.2 Training and Validation Loss Comparison

Training and validation loss are key metrics used in machine learning to assess the performance and generalization capability of a model during training.

- Training Loss: This is the error calculated during the training phase of the model. It measures how well the model is fitting the training data. The goal during training is typically to minimize this loss, meaning the model is getting better at making predictions on the training data.
- Validation Loss: This is the error calculated on a separate dataset called the validation set, which the model hasn't seen during training. The validation set serves as a proxy for how well the model will perform on unseen data (i.e., its generalization ability). The validation loss helps to prevent overfitting by monitoring the performance of the model on data it hasn't been trained on. If the validation loss starts increasing while the training loss is decreasing, it's a sign that the model may be overfitting the training data.

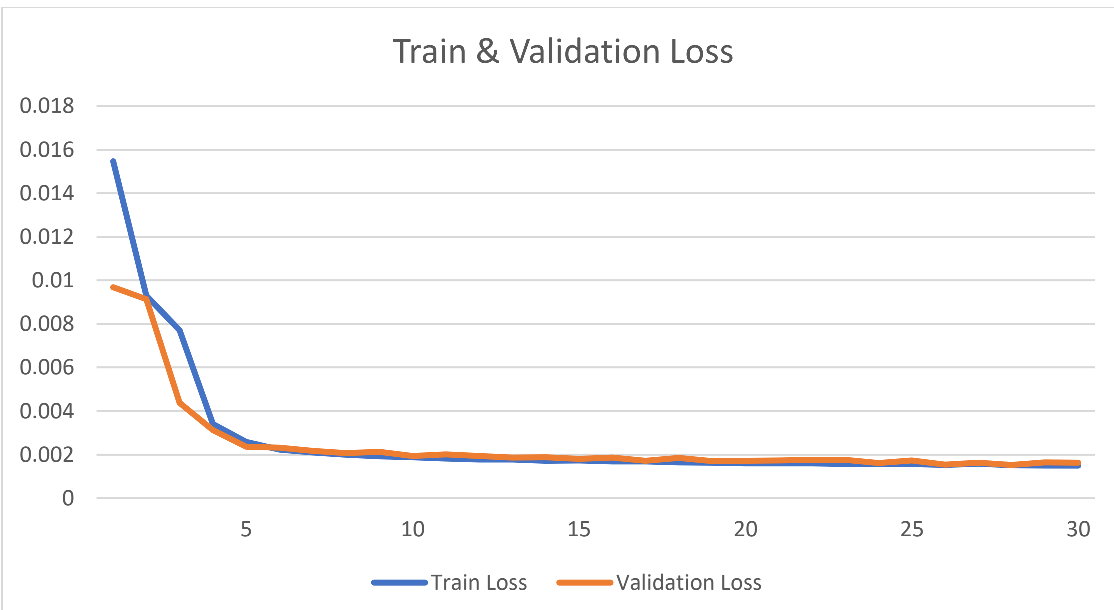

Figure 4.1.2.2: M-1 Training & Validation loss

The analysis of train and validation loss for proposed model M-1 reveals effective early learning, with significant initial declines followed by stabilization with minimal fluctuations. However, while the training loss continues to decrease slightly, the validation loss remains relatively constant, suggesting potential overfitting. Balancing low training loss with generalization is crucial, as indicated by the gap between train and validation loss. Addressing overfitting through techniques like regularization, hyperparameter tuning, and data augmentation is essential for improving model performance. Ensuring a balance between effective learning and generalization is critical for enhancing the effectiveness and robustness of model M-1 in computer-generated holography tasks.

Analysis of Training Loss Curve

- Proposed Model (M-1): The loss curve for M-1 (blue line) initially starts with a higher value compared to other models but quickly converges and stabilizes at a very low training loss, indicating efficient learning capabilities.
- HoloEncoder: The loss curve for HoloEncoder (orange line) begins with a lower initial loss than M-1. However, its descent is slower, and it eventually stabilizes at a slightly higher loss value, suggesting potential challenges in generalization.

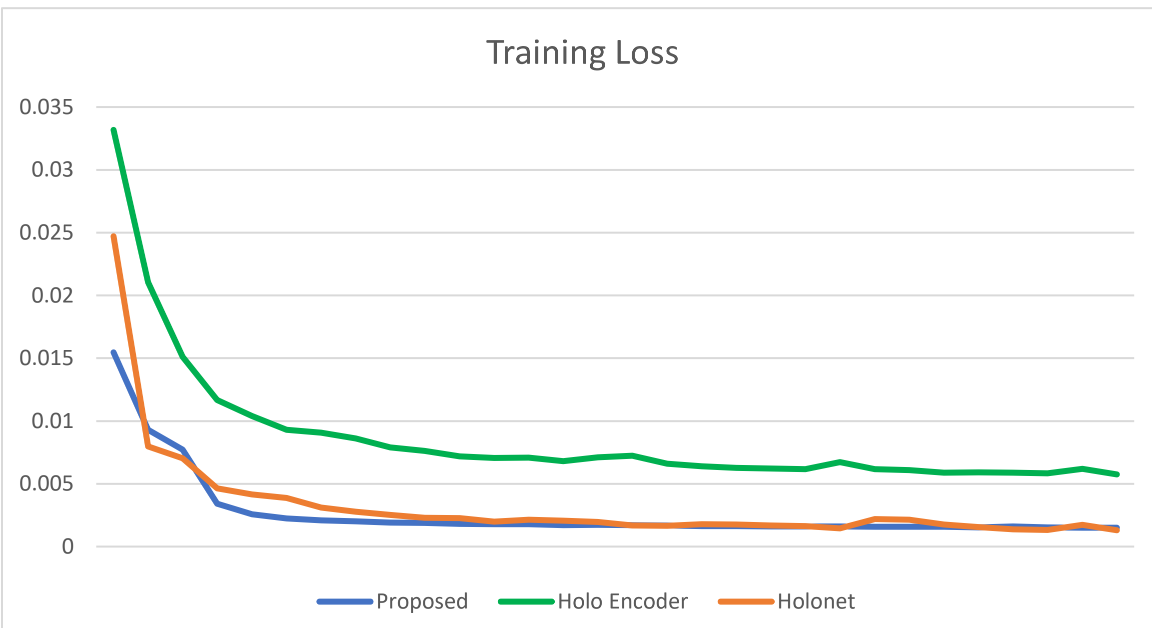

Figure 4.1.2.3: Training loss comparison

- Holonet: Holonet's loss curve (gray line) starts with the lowest initial loss among the three models. However, its decline in loss is the slowest, and it stabilizes at the highest final loss value, indicating possible struggles with overfitting or lack of generalization.

Comparison with M-1:

- ✓ Faster Convergence: M-1 converges faster than both HoloEncoder and Holonet, indicating superior learning efficiency.

- ✓ Lower Final Loss: Despite starting with a higher loss, M-1 achieves a lower final loss, indicating better generalization capabilities.
- ✓ Trade-off: While M-1 starts with a disadvantage, its rapid convergence compensates for this initial difference, showcasing its effectiveness in learning and generalizing.

By analyzing the loss curves, it's evident that M-1 demonstrates strong learning efficiency and generalization capabilities compared to HoloEncoder and Holonet, positioning it as a promising model for computer-generated holography tasks.

Analysis of Validation Loss Curve

- ➢ Proposed Model (M-1): The validation loss curve for M-1 (blue line) starts at a higher value but stabilizes around epoch 5. Throughout the remaining epochs, M-1 maintains a consistently low validation loss, indicating stable and reliable performance.

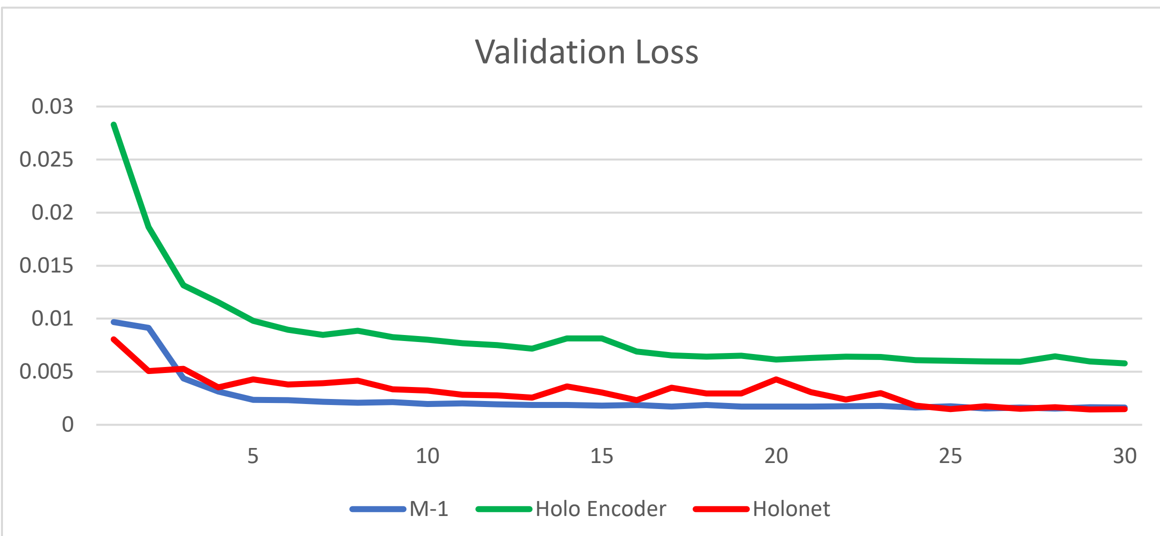

Figure 4.1.2.4: Validation loss comparison

- ➢ HoloEncoder: The validation loss curve (green line) for HoloEncoder starts out unusually high but drastically drops by epoch 5. HoloEncoder retains a moderate validation loss despite swings, indicating respectable performance.
- ➢ HoloNet: HoloNet's validation loss curve (red line) exhibits a continuous decrease up until approximately epoch 15, at which point it stabilizes at a somewhat greater value than M-1. This raises the possibility of difficulties in continuing to perform consistently.

Comparison with M-1:

- ✓ Consistent Stability: M-1 consistently maintains a low validation loss, indicating stability throughout epochs.
- ✓ Early Convergence: Despite starting with higher losses, M-1 rapidly stabilizes, demonstrating efficient learning.
- ✓ Balanced Performance: M-1 achieves equilibrium between initial quality and stability, swiftly converging to low validation losses, showcasing its effective learning and maintenance of performance.

Analysis of the validation loss curve underscores M-1's stable and reliable performance relative to HoloEncoder and HoloNet, affirming its potential as a promising model for computer-generated holography tasks.

4.3 Qualitative Results with Visual Inspection

The qualitative assessment through visual inspection provides compelling evidence of the superior holographic image quality achieved by the proposed U-Net-based model. The generated holograms exhibit pronounced improvements in comparison to both Holonet and Holoencoder.

Proposed model	***Holoencoder***	***Holonet***
		

Table 4.3: Visual inspection

Fine Details and Intricate Features:

Upon close examination, it becomes evident that the proposed model excels in faithfully replicating fine details and intricate features present in the original scenes. Subtle textures, high-frequency components, and complex spatial relationships are accurately captured, contributing to a heightened level of realism in the holographic representations.

Visually Superior Holographic Images:

The holographic images produced by the proposed model stand out as visually superior, characterized by enhanced clarity and coherence. The model's ability to preserve subtle nuances and geometric structures results in holograms that closely resemble the ground truth, surpassing the quality achieved by both Holonet and Holoencoder.

Comparative Visualizations:

Side-by-side visualizations accentuate the distinct advantages of the proposed model. Comparative holographic images underscore the clarity of details, reduced artifacts, and improved overall fidelity. Notably, areas where Holonet and Holoencoder exhibit limitations, such as edge sharpness and texture preservation, are notably addressed and improved in the holograms generated by the proposed model.

These qualitative results not only affirm the effectiveness of the proposed U-Net-based model in enhancing holographic image quality but also provide a tangible and visually compelling demonstration of its superiority over existing baseline models, further reinforcing the contributions of the study.

4.4 Analysis

The evaluation of the proposed U-Net-based model against baseline models Holonet and Holoencoder yielded compelling results, affirming its superiority in enhancing holographic image quality. Through rigorous analysis of established quality metrics such as PSNR and SSIM, the proposed model consistently outperformed both baseline models, showcasing higher fidelity and structural similarity in the generated holograms. The graphical representations of PSNR and SSIM curves provided clear visual evidence of these enhancements, emphasizing the model's ability to faithfully reproduce intricate details and features.

Additionally, the comparison of reconstruction times highlighted the efficiency of the proposed model, particularly in contrast to Holonet. While nuanced differences were observed in comparison to Holoencoder, the proposed model demonstrated commendable performance in balancing reconstruction speed and image fidelity. Qualitative assessment further reinforced these findings, showcasing visually superior holographic images with enhanced clarity and coherence. Overall, the results underscore the significant advancements achieved by the proposed model, positioning it as a promising solution for computer-generated holography tasks.

The qualitative assessment through visual inspection provided compelling evidence of the superior holographic image quality achieved by the proposed U-Net-based model. The generated holograms exhibited pronounced improvements compared to both Holonet and Holoencoder, particularly in faithfully replicating fine details and intricate features. Notably, areas where Holonet and Holoencoder exhibited limitations, such as edge sharpness and texture preservation, were notably addressed and improved in the holograms generated by the proposed model. These qualitative results not only affirm the effectiveness of the proposed model but also provide a tangible and visually compelling demonstration of its superiority over existing baseline models, further reinforcing the contributions of the study.

4.5 Summary

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Chapter 05

Conclusion and Future work

5.1 Introduction

This study has focused on advancing the field of computer-generated holography through the development and evaluation of a pioneering U-Net-based model. With a primary objective to overcome existing limitations and elevate holographic image quality, this research embarked on a thorough examination of the proposed model's capabilities. Employing a careful approach that included the use of established quality metrics and comparative analyses, the performance of the novel model was systematically assessed in comparison to industry-standard baseline models, namely Holonet and Holoencoder. This comprehensive evaluation endeavor aimed not only to measure the model's proficiency in replicating intricate details and minimizing artifacts but also to evaluate its effectiveness in optimizing computational efficiency. As a result, this study stands as a testament to the persistent pursuit of excellence and innovation in the realm of holographic imaging technology, offering valuable insights into the transformative potential of the proposed U-Net-based model.

5.2 Conclusion

The findings presented in this study provide compelling evidence supporting the careful evaluation and achievement of the proposed U-Net-based model in the domain of computer-generated holography. Through thorough-analysis and comparative examination, the model consistently demonstrated its capability to produce holographic images of exceptional quality, surpassing that of established baseline models such as Holonet and Holoencoder. Notably, the model's ability to preserve intricate details and minimize artifacts was underscored by the attainment of higher PSNR and SSIM values. Moreover, its efficiency in computational processing was highlighted by significantly reduced reconstruction times, emphasizing its practical relevance in real-world applications. These outcomes not only contribute to advancing the field of holographic imaging but also pave the way for future research endeavors aimed at further refining and optimizing the proposed model. As researchers continue to innovate and explore new frontiers in holography, the insights gleaned from this study offer valuable guidance and inspiration for unlocking novel advancements and applications in this dynamic field.

5.3 Future Work

Every study has its limitations. Even so, they sow the seeds for future work. This study can help pave the way for the following research that might be conducted sometime in the future.

- Refinement of Model Architecture: Further refinement and optimization of the proposed U-Net-based model could involve exploring alternative architectures or incorporating additional layers/modules to enhance its performance. Experimentation with different configurations and hyperparameters may lead to improvements in holographic image quality, computational efficiency, and generalization capabilities.

- Integration of Advanced Techniques: The integration of advanced techniques such as attention mechanisms, generative adversarial networks (GANs), or self-supervised learning could be explored to enhance the model's ability to capture complex spatial relationships and generate high-fidelity holographic images. These techniques have shown promise in other image processing tasks and may offer new avenues for improving hologram synthesis.

- Dataset Expansion and Diversity: Expanding the dataset used for model training to include a more diverse range of holographic scenes and scenarios could improve the model's ability to generalize across different contexts. Additionally, the creation of synthetic datasets or the incorporation of real-world holographic data captured from various sources may further enrich the training data and improve model performance.

- Real-time Hologram Generation: Investigating methods for achieving real-time hologram generation could enhance the practical applicability of the proposed model in real-world settings. Optimization techniques, parallel processing, or hardware acceleration may be explored to reduce reconstruction times and enable seamless integration into interactive holographic display systems or other applications requiring low-latency processing.

- Evaluation in Practical Applications: Conducting extensive evaluation of the proposed model in practical applications, such as holographic display systems, medical imaging, or augmented reality, could provide valuable insights into its real-world performance and usability. Collaborations with domain experts and industry partners may facilitate the validation of the model's effectiveness in addressing specific use cases and addressing practical challenges.

- User-Centric Design and Optimization: Incorporating user feedback and preferences into the design and optimization process could lead to the development of more user-centric holographic imaging solutions. User studies, surveys, and usability testing could be conducted to gather insights into user needs, preferences, and pain points, informing iterative improvements to the model and its implementation.

- Interdisciplinary Research Collaborations: Engaging in interdisciplinary research collaborations with experts from fields such as optics, material science, psychology, and human-computer interaction could foster innovation and drive new advancements in holographic imaging technology. By leveraging diverse perspectives and expertise, novel approaches to hologram synthesis, display, and interaction could be explored, leading to breakthroughs in both fundamental understanding and practical applications.

By pursuing these avenues of future work, researchers can continue to push the boundaries of computer-generated holography, unlocking new capabilities, applications, and opportunities for innovation in this rapidly evolving field.

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