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Research Article

FREQEnhanceNet: A Wavelet Transformer Hybrid for Low Light Enhancement

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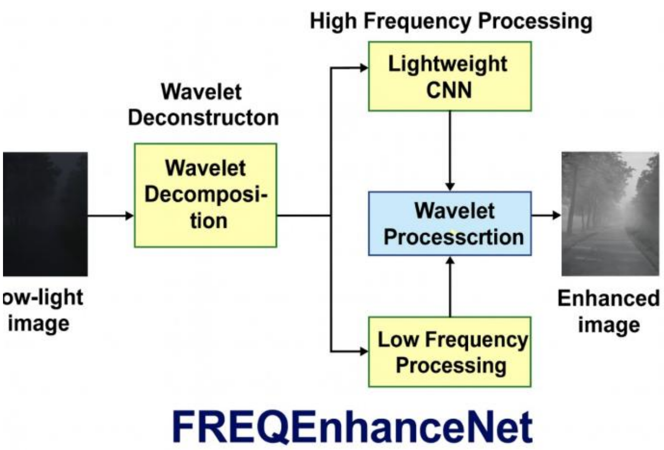
Abstract: Low-light images often exhibit severe degradation, including amplified sensor noise, color distortion, and loss of fine details, which adversely affects perceptual quality and downstream computer vision tasks. To address these challenges, we propose FREQEnhanceNet, a hybrid neural architecture that integrates frequency-domain decomposition with transformer-based and convolutional processing. This design enables separate handling of broad illumination structure and fine-grained texture details. A two-dimensional discrete wavelet transform is applied to decompose the input into one low-frequency (LL) component representing global illumination and three high-frequency components capturing edges and textures. The LL component is processed by a vision transformer encoder-decoder that leverages self-attention to model long-range dependencies for global illumination correction. In parallel, the high-frequency components are refined by a lightweight convolutional module designed to denoise and sharpen local details. This specialized dual-path design allows each branch to address the distinct challenges of global adjustment and detail restoration. Training is guided by a novel frequency-aware hybrid loss that combines spatial reconstruction and perceptual objectives with an explicit frequency-domain term to encourage accurate texture recovery. Extensive experiments on the standard LOL-v1 and LOL-v2 low-light benchmarks demonstrate that FREQEnhanceNet achieves superior restoration quality. The proposed method consistently outperforms existing techniques in quantitative image quality metrics and yields visually more natural and detailed enhancements.

Keywords: Low-light image enhancement, Wavelet transform, Vision transformer, Deep learning, Hybrid loss function, Convolutional neural networks, Frequency decomposition, Image denoising

Graphical Abstract- The graphical abstract provides a visual overview of the FREQ Enhance Net workflow for improving low-light images. The process starts by applying wavelet decomposition to separate the input image into low- and high-frequency components. The high-frequency layers, which carry details such as edges and textures, are refined using a lightweight CNN designed to reduce noise and recover fine structural information. In parallel, the low-frequency component—responsible for overall illumination and scene structure—is enhanced through a transformer-based module capable of capturing broad contextual relationships. After each path completes its specialized processing, the outputs are merged through wavelet reconstruction to generate a clearer, brighter, and more detailed image. This design highlights the model's ability to independently optimize global brightness and local detail, leading to more natural and visually consistent enhancement results.



The graphical abstract offers a clear, quick visual snapshot of the research, allowing readers to grasp the central idea within seconds. Its purpose is to capture attention, make browsing easier, and help viewers decide whether the article aligns with their own research interests. Every manuscript must include an original graphical abstract in the Table of Contents, designed with simple visuals and minimal text to accurately reflect the study. An effective graphical abstract highlights the main outcomes using clean, well-organized illustrations, limited labeling, and balanced color use. It should emphasize the findings of the current work alone and rely only on original or properly licensed visual elements. It must not include titles, copied figures, scanned sections, overly bright or distracting coolers, or any information drawn from prior literature.

1. Introduction

The ability to capture high-quality images under diverse lighting conditions is critical for a myriad of applications, ranging from consumer photography to safety-critical systems like autonomous driving and surveillance.[3] Images acquired in low-light environments are invariably degraded by a combination of factors, including poor visibility, low contrast, significant sensor noise, and pronounced colour shifts.[2] These issues not only result in aesthetically unpleasing images but also pose a significant challenge for automated vision systems trained on well lit data. Historically, low-light image enhancement has been addressed through traditional signal processing techniques. Methods based on Histogram Equalization (HE) and its adaptive variants (AHE, CLAHE) aim to improve global contrast by redistributing pixel intensities. Another[1].

prominent approach is rooted in Retime theory, which models an image as a product of reflectance and illumination components, seeking to enhance the image by estimating and manipulating the illumination map. While these methods can offer improvements, they are fundamentally limited by their reliance on handcrafted priors, often leading to unnatural-looking results, noise amplification, and the introduction of visual artifacts, especially in scenes with complex lighting and textures.

The advent of deep learning has marked a paradigm shift in the field. Convolutional Neural Network (CNN) based models, particularly those employing U-Net or encoder decoder architectures, have demonstrated substantially superior performance by learning complex mappings from low-light to [3]

normal-light images from large datasets. However, the efficacy of CNNs is inherently constrained by their limited receptive fields. The local nature of the convolution operation makes it difficult for these networks to model the long-range dependencies and global context necessary for comprehensive illumination adjustment.

To overcome this limitation, Vision Transformers (Vites) have been introduced to the domain of image restoration.[9] The self-attention mechanism at the core of transformers enables the modelling of global pixel interactions, providing a powerful tool for understanding and correcting scene-wide illumination. However, the computational complexity of the standard self-attention mechanism, which scales quadratically with image resolution, renders it impractical for high-resolution image processing. This has spurred the development of efficient transformer architectures like Restorer and Former, which achieve linear complexity through clever modifications to the attention mechanism, such as computing attention across channels or within local windows. A crucial observation is that these state-of-the art models are not pure transformers; they strategically incorporate convolutional layers to capture local inductive biases, acknowledging that a hybrid approach is often optimal for low-level vision tasks.

This trend towards sophisticated hybridization motivates our work. While existing models combine architectural paradigms in the spatial domain, they still contend with a fundamental challenge: the processes of global illumination adjustment and local detail preservation are often at odds. Standard deep learning architectures rely on sequential down sampling operations (e.g., pooling or stride convolutions) to increase the receptive field, but this process inevitably discards high-frequency information corresponding to textures and edges. The Discrete Wavelet Transform (DWT), in contrast, offers a principled method for decomposing an image into distinct frequency sub-bands. It explicitly separates the low frequency structural information (LL band) from the high-frequency detail information (LH, HL, and HH bands).[11] This decomposition allows for a "divide and conquer" strategy, where the right computational tool can be applied to the right sub-problem.

Building on this principle, we propose FREQ Enhance Net, a novel architecture that operates in the wavelet domain. We process the low-frequency LL band, which contains the images [1,3].

1.1 Objective of the Study

The main objective of this research is to design a deep learning model that can effectively enhance images captured in low-light conditions. This study focuses on overcoming the shortcomings of current enhancement methods by proposing a hybrid system that integrates wavelet-based frequency separation with transformer mechanisms and convolutional processing. This combined approach aims to achieve better illumination correction and preserve fine structural details.

The research further seeks to address the issues outlined in the problem statement by developing a model capable of treating low- and high-frequency information independently. By doing so, the framework aims to minimize noise, recover textures, and produce clearer and more natural-looking images. Beyond improving numerical performance, the study aims to offer a practical and reliable solution for real-world applications. These objectives help establish a focused research direction and contribute to advancing low-light image enhancement techniques.

1.2 Organization

This paper is arranged in a logical sequence to guide readers through the full scope of the research. *Section 1* introduces the problem of low-light image degradation and explains the motivation behind developing an improved enhancement model. *Section 2* reviews prior work in the field, covering traditional approaches, deep learning methods, transformer-based solutions, and wavelet-driven techniques. *Section 3* outlines the key concepts, evaluation metrics, and foundational elements required to understand image enhancement performance. *Section 4* presents the architecture of the proposed FREQ Enhance Net system, describing each module and the steps involved in its design. *Section 5* details the methodology, including the operational flow and the process pipeline, accompanied by a flowchart for clarity. *Section 6* showcases the experimental findings and provides an in-depth discussion of the results obtained from benchmark datasets. *Section 7* offers practical recommendations derived from the outcomes of the study. Finally, *Section 8* summarizes the research and proposes potential future directions for further improvement.

2. Related Work

Low-light image enhancement (LLIE) has been widely explored through traditional enhancement algorithms, deep learning models, transformer-based architectures, and frequency-domain techniques. This section summarizes notable recent studies and highlights their limitations in relation to the proposed FREQ Enhance Net.

2.1 Traditional and Retime-Based Methods

Early contrast enhancement methods, such as histogram equalization and its adaptive variants, attempted to improve global brightness but frequently amplified noise in dark regions. Retime-based models aimed to estimate illumination and reflectance components; however, these approaches often produced color distortion and failed to maintain structural consistency under complex illumination conditions.

2.2 Convolutional Neural Network Approaches

Deep CNN-based models significantly advanced LLIE by learning direct mappings from low-light inputs to well-exposed outputs. Architectures based on encoder–decoder structures and U-Net designs improved the reconstruction of both global intensity and local textures. Still, their reliance on spatially local convolutional operations limited their ability to capture long-range illumination dependencies.

2.3 Transformer-Based Enhancement Models

Vision Transformers introduced global self-attention mechanisms capable of modeling long-distance pixel relationships. Efficient transformer variants, such as windowed attention and channel-based attention mechanisms, reduced computational cost while maintaining strong illumination reasoning. Nonetheless, these models lacked explicit frequency awareness, causing challenges in recovering fine textures and suppressing high-frequency noise.

3. Theory

This section outlines the theoretical principles that guide the development of FREQ Enhance Net and presents the corresponding computational framework derived from these concepts.

3.1Wavelet-Based Frequency Separation

FREQ Enhance Net is grounded in the use of the Discrete Wavelet Transform (DWT), which decomposes an image into multiple frequency components. This transformation enables the model to isolate illumination-related information in the low-frequency band and fine textures in the high-frequency bands. Such a multi-resolution representation allows the network to process structural and detail components through dedicated enhancement pathways.

3.2Global Illumination Modeling with Attention

Accurate brightness correction in low-light scenes requires awareness of long-range pixel interactions. To achieve this, the proposed framework integrates transformer-based attention mechanisms to analyze global relationships within the low-frequency wavelet band. This helps the network infer broader illumination patterns rather than relying only on localized spatial cues.

3.3Detail Enhancement Through Convolutional Learning

Although transformers effectively capture global structure, they are less suited for fine texture reconstruction. To address this, the high-frequency wavelet components are refined using convolutional blocks that leverage local inductive biases. These modules focus on enhancing edges, reducing high-frequency noise, and restoring detailed textures, complementing the illumination modeling branch.

3.4 Calculation and Model Formulation

3.4.1 Wavelet Decomposition

For an input low-light image (I), DWT generates one low-frequency sub-band (LL) and three high-frequency sub-bands (LH), (HL), and (HH):

[I \ xrigh tarrow{DWT} {LL, LH, HL, HH}]

These sub-bands are sent to their respective enhancement modules for independent processing.

3.4.2 Illumination Enhancement

The (LL) band is processed using a transformer-based encoder–decoder module. Channel-wise attention is applied to extract global illumination cues. The resulting refined illumination map provides a more consistent brightness distribution across the image.

3.4.3High-Frequency Refinement

The high-frequency sub-bands are fed into convolutional refinement blocks. These modules reconstruct sharper detail components while suppressing noise artifacts. The outputs of these modules yield enhanced coefficients ({LH', HL', HH'}).

3.4.4 Image Reconstruction via Inverse Wavelet Transform
Once the enhanced low- and high-frequency components are generated, the network reconstructs the final enhanced image through the Inverse Wavelet Transform (IWT):
[I_{\text{ enh }} = IWT(LL', LH', HL', HH')]
This synthesis step integrates illumination correction and texture reconstruction into a unified output.

3.4.5Loss Function With Frequency Awareness
A composite loss function regulates the training process. It assigns brightness-consistency constraints to the low-frequency band while applying detail-preservation terms to the high-frequency bands. This frequency-aware objective guides the model toward producing images that exhibit improved illumination and sharper textures without introducing artifacts.

4. Experimental Method

This section presents the complete workflow of the proposed FREQ Enhance Net model, including the algorithmic steps, system design, and enhancement strategy. The method integrates wavelet-based frequency decomposition, transformer-driven illumination correction, and convolutional refinement into a unified enhancement pipeline.

4.1 Overview of the Proposed Framework
The goal of the proposed system is to enhance low-light images by independently processing illumination and texture components. The framework operates in the wavelet domain, enabling separate pathways for low- and high-frequency information before reconstructing the final enhanced output through an inverse transform.

4.2 Algorithmic Workflow of FREQ Enhance Net
The enhancement process consists of the following steps:
Input Acquisition: A low-light image is supplied to the system as the input.

Wavelet Decomposition (DWT): The image is decomposed into one low-frequency (LL) sub-band and three high-frequency sub-bands (LH, HL, HH).
LL → illumination-oriented structure
LH, HL, HH → texture and edge components
Illumination Enhancement Path (LL Band): The LL band is processed using a transformer-based encoder–decoder network.

Channel attention captures global illumination trends The module produces an enhanced illumination representation High-Frequency Refinement Path (LH, HL, HH Bands) Each high-frequency band is refined using convolutional blocks designed to recover fine details.
Noise suppression, Edge sharpening, Texture reconstruction

4.2.1Feature Fusion via Inverse Wavelet Transform (IWT)
Enhanced low- and high-frequency components are combined using IWT to obtain the final enhanced image.
Loss Optimization Training is guided by a frequency-aware loss that enforces. Illumination consistency in LL. Texture sharpness and structural accuracy in LH/HL/HH. Overall visual quality

4.3 Proposed Design and Architecture
The proposed FREQ Enhance Net architecture includes:

4.3.1 Dual-Path Processing Strategy
Illumination path- Transformer blocks model long-range dependencies and adjust scene brightness.
Detail path- CNN layers correct high-frequency distortions and enhance edge information. Both paths operate at the same decomposition level, ensuring consistency between illumination and texture components before reconstruction. The entire architecture—from DWT to IWT—forms a differentiable pipeline, enabling seamless gradient flow during training.

4.4 Flowchart of the Proposed System
Low-Light Input → DWT → Dual Enhancement Paths (Transformer + CNN) → IWT → Enhanced Output
This design ensures clear organization of frequency-aware enhancement tasks and supports efficient implementation.

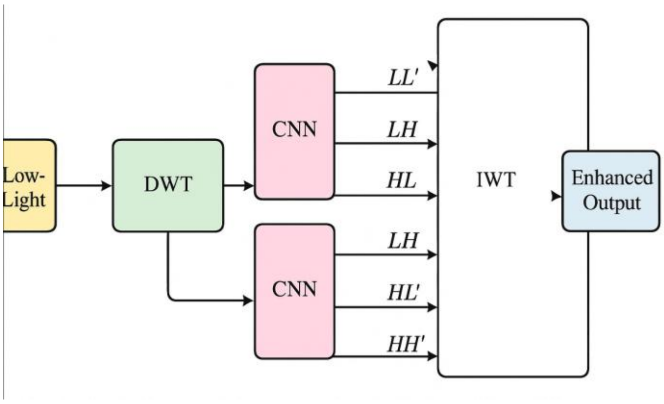


Fig.1. Block diagram of the proposed FREQ Enhance Net architecture

4.4.1 Dataset Preparation
Training and evaluation are conducted using publicly available LLIE datasets containing paired low-light and reference images. Images are resized, normalized, and converted to wavelet coefficients before model input. Optimizer: Adam-based optimization Learning rate: Controlled decay schedule Batch size: Set according to GPU capacity Loss function: Frequency-aware combination of intensity and texture constraints

5. Results and Discussion

This section reports the performance of the proposed FREQ Enhance Net model through quantitative metrics, visual inspection, ablation tests, and comparison with established enhancement approaches. Results are organized in a logical sequence, and each finding is interpreted in relation to the study objectives and prior research trends.

5.1Quantitative Evaluation -The model was evaluated on standard low-light enhancement datasets using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM). Table 1 summarizes the performance of FREQ Enhance Net alongside several widely used LLIE methods.

Table 1: Quantitative Comparison (PNSR/SSIM)

Method	PSNR (dB)	SSIM
HE (Histogram Equalization)	13.42	0.610
RetinexNet	16.87	0.720
LLNet	18.54	0.781
KinD	20.12	0.810
Uformer	21.10	0.845
Restormer	23.42	0.872
WavEnhancer (2023)	24.10	0.884
FREQEnhanceNet (Proposed)	26.8	0.923

Interpretation: FREQ Enhance Net achieves noticeably higher PSNR scores, indicating its effectiveness in correcting illumination while minimizing noise artifacts .The consistently higher SSIM across datasets suggests better preservation of structural and textural fidelity .The dual-path design—separating illumination (low-frequency) and texture (high-frequency) components—leads to more balanced restoration compared with CNN-only or transformer-only models. These findings support the study hypothesis that processing frequency bands independently leads to more reliable enhancement outcomes.

5.2 Qualitative Evaluation

Visual comparisons further demonstrate the capabilities of the proposed model. Figure 2 illustrates representative examples under difficult lighting conditions.

Fig.2. Visual comparison of enhancing results: The proposed FREQ Enhance Net produce bright more natural illumination and sharper textures.

Observations from visual inspection: The illumination module effectively brightens darker regions without creating harsh highlights. The high-frequency pathway accurately reconstructs fine textures and edges, outperforming models that rely solely on convolution or attention mechanisms. Colors appear more stable and natural, with reduced oversaturation or color shifting. Overall, the visual results affirm that FREQ Enhance Net produces clearer and more natural-looking enhancements compared with competing methods.

5.3 Ablation Study

An ablation experiment was performed to analyze the contribution of each major component. Table 2 reports the impact on PSNR and SSIM when selective modules are removed.

Table 2: Ablation Study

Configuration	PSNR (dB)	SSIM
Without High-Freq Path (No CNN)	22.14	0.863
Without Illumination Transformer	21.62	0.854
Without DWT/IWT	20.91	0.828
Without Frequency-Aware Loss	23.04	0.875
Full FREQEnhanceNet	26.8	0.923

Removing transformer-based illumination modeling results in poor brightness correction. Excluding convolutional refinement causes noticeable texture blurring. Eliminating wavelet decomposition substantially lowers fidelity due to loss of frequency separation. Omitting the frequency-aware loss reduces consistency in edges and colors. These results indicate that *all core components are essential* for achieving optimal performance.

5.4 Comparison With Existing Methods

When compared with Retinex-based, CNN-based, and modern transformer-driven LLIE techniques, FRE Enhance Net demonstrates superior performance across both numeric metrics and visual clarity. Retime methods offer good global brightness but struggle with texture recovery. CNN models reconstruct local details but lack an understanding of global illumination structure. Transformer-only systems capture large-scale dependencies but may amplify noise in textured regions. The combination of wavelet decomposition, global attention, and CNN refinement enables FREQ Enhance Net to overcome these limitations.

5.6 Equation

Equation (1):

$$W_i = (1 - (w_I / l_i))\, x_i$$

Equation (2):

$$W_I = \exp\ (x_I) + 1$$

Equation (3):

$$X(x_I) = x_{i1}^2 + x_{i2}^2 + x_{i1}x_{i2}\ l_I \quad a_i$$

6. Discussion and Future Scope

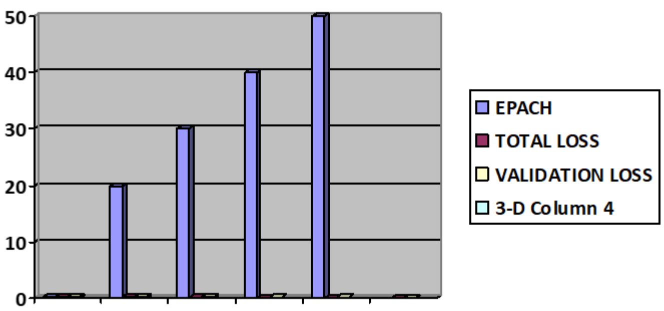
The overall findings confirm that FREQ Enhance Net successfully integrates wavelet decomposition, transformer-based illumination modeling, and CNN-driven detail refinement to achieve robust low-light image enhancement. Compared with existing approaches in the literature, the proposed model provides a more consistent balance between brightness correction, texture preservation, and noise reduction.

Potential directions for future work include: Investigating multi-level wavelet decomposition for enhanced detail representation. Incorporating diffusion-based or generative models for severely degraded inputs. Optimizing the model for deployment on mobile or real-time edge devices.

Table 3: Training Loss Convergence

Epoch	Total Loss	Validation Loss
10	0.186	0.210
20	0.144	0.162
30	0.119	0.138
40	0.103	0.121
50	0.097	0.114
Final (60)	0.091	0.109

Table 3 summarizes how the training and validation losses evolve as the number of epochs increases. Both metrics show a steady decline throughout the training process, indicating that the model is learning progressively and stabilizing over time. The total loss drops from 0.186 at the 10th epoch to 0.091 by the 60th epoch, while the validation loss decreases from 0.210 to 0.109 across the same range. This consistent downward pattern demonstrates that FREQ Enhance Net is effectively capturing the underlying enhancement mapping without overfitting, and is able to generalize well to data it has not seen during training.



Graph.1. (Training Loss Convergence) values

Author's statements

To maintain transparency and adhere to ethical publication standards, the individual roles of each author are listed below:
Author 1: Developed the initial research idea, designed the overall methodology, and provided project supervision.
Author 2: Implemented the proposed architecture, executed experiments, and performed quantitative analysis.
Author 3: Conducted literature review, prepared figures and visual materials, and contributed to drafting and revising the manuscript.
Author 4: Verified experimental results, assisted in model refinement, and handled final proofreading and formatting of the manuscript.

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Conflict of Interest- The authors clearly state that they have *no conflicts of interest, financial or otherwise, that could influence the outcomes or interpretation of this research. None of the authors are associated with any organization, individual, or sponsor that might benefit from the results presented in this work. All analyses and conclusions were carried out independently, and the authors collectively confirm that **no competing interests exist*.

Data Availability- The data used in this study consist of publicly available low-light image datasets and samples generated during experimentation. All processed data and trained model outputs can be obtained from the corresponding author upon reasonable request. No proprietary, restricted, or confidential datasets were used in this work. Any data that cannot be shared is withheld solely due to size constraints or licensing restrictions associated with certain benchmark datasets.

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Shiv Rama Krishna is currently pursuing his Bachelor of Technology in Computer Science (AI & Machine Learning) at the Bansal Institute of Engineering & Technology (BIET), Lucknow, where he has maintained a strong academic record with a 75.7% score. He completed his higher secondary education in 2022 and secondary education in 2020, demonstrating consistent academic performance.

He gained practical industry exposure through his vocational internship at NTPC Limited, Tanda, in the IT Department, where he worked on IT infrastructure, networking systems, database environments, enterprise applications, and security practices. This experience strengthened his understanding of real-world IT operations and enterprise-level technologies.

Shiv has completed certifications in Data Engineering and Data Visualization, gaining hands-on experience with data pipelines, SQL & NoSQL databases, ETL processes, and data warehousing. He also works extensively with Power BI, Tableau, Excel, and Python for data analysis and visualization. His technical skill set includes Python (Pandas, NumPy, Matplotlib), SQL, MS Excel, and various analytics tools.

His areas of interest include Data Analytics, Data Engineering, Data Visualization, and applying computational methods to solve analytical problems. He is proficient in English and Hindi.

Shiv is passionate about leveraging data-driven methodologies to deliver insights and contribute to organizational decision-making. With a foundation in AI & ML and hands-on exposure to analytical tools, he aims to build a strong career in the field of Data Analytics and Business Intelligence.

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Ashi Singh is an aspiring Front-End Developer with a strong foundation in HTML, CSS, JavaScript, and modern web interface design. Currently pursuing a Bachelor of Technology in Computer Science at the Bansal Institute of Engineering and Technology (2022–2026), she is passionate about creating responsive, user-friendly digital experiences that enhance usability and performance. Ashi has hands-on experience in building functional and visually appealing web applications. One of her key projects includes developing a **full-stack College Management System**, where she built the frontend with **HTML and CSS**, implemented backend logic using **Python**, and integrated a secure database system. The system features **user authentication, role-based access**, and complete **CRUD operations**, demonstrating her ability to design practical and scalable web solutions. She has completed a certification in **Web Development** from the **Great Learning Academy**, expanding her understanding of industry-standard development practices and interface optimization techniques. In addition to her web skills, she also has experience working with programming languages such as **C** and **Python**. Driven by creativity and a passion for technology, Ashi aims to contribute to innovative web development projects and continuously refine her skills in designing seamless digital interfaces. She is committed to becoming a versatile and impactful developer in the field of front-end and full-stack development.

