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DIGITAL IMAGE QUALITY OPTIMIZATION USING DEEP NEURAL NETWORK

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Abstract: One of the main challenges in digital image processing is limited resolution, which makes it difficult to preserve visual details when images are enlarged. Conventional methods such as *Bilinear Interpolation* are commonly used for image upscaling; however, these approaches often produce blurred images, lose fine textures, and fail to reconstruct complex visual structures. This study aims to enhance digital image resolution by employing a deep learni based approach using a *Low-Light Convolutional Neural Network* (LLCNN) built upon a *Deep Neural Network* (DNN) architecture. The dataset used in this study is the DIV2K dataset, which consists of 1,000 high-resolution images. These images were downsampled using scaling factors of ×2, ×3, and ×4 to generate paired *Low Resolution–High Resolution* (LR–HR) data for training and evaluation. The proposed LLCNN is designed to extract important features such as edges, textures, and local patterns through multiple convolutional layers, followed by non-linear mapping to reconstruct high-resolution images more accurately. Quantitative performance evaluation was conducted using the *Peak Signal-to-Noise Ratio* (PSNR) and the *Structural Similarity Index* (SSIM). Model performance was evaluated quantitatively using the Peak Signal-to-Noise Ratio (PSNR) metric. Experimental results showed that the proposed method improved image quality compared to the bilinear method. These results indicate that the deep learning based approach effectively improves image sharpness and structural fidelity, thereby demonstrating its potential for digital image resolution enhancement.

Keywords: deep neural network; image resolution; low-light convolutional neural network; machine learning

Abstrak: Permasalahan utama dalam pengolahan citra digital adalah keterbatasan resolusi yang menyebabkan detail visual sulit dipertahankan ketika citra diperbesar. Metode konvensional seperti *Bilinear Interpolation* masih banyak digunakan, namun sering menghasilkan citra buram, kehilangan tekstur halus, serta tidak mampu merekonstruksi struktur visual yang kompleks. Penelitian ini bertujuan untuk meningkatkan kualitas resolusi citra digital dengan memanfaatkan pendekatan *deep learning* berbasis *Low-Light Convolutional Neural Network* (LLCNN) yang dibangun di atas arsitektur *Deep Neural Network* (DNN). Data yang digunakan dalam penelitian ini berasal dari dataset DIV2K, yang terdiri dari 1000 citra beresolusi tinggi. Citra tersebut diturunkan menjadi resolusi rendah menggunakan faktor *downsampling* ×2, ×3, dan ×4 untuk membentuk pasangan data *Low Resolution–High Resolution* (LR–HR) sebagai data pelatihan dan pengujian. LLCNN dirancang untuk mengekstraksi fitur-fitur penting seperti tepi, tekstur, dan pola lokal melalui beberapa lapisan konvolusi, kemudian melakukan pemetaan non-linear guna merekonstruksi citra resolusi tinggi secara lebih presisi. Evaluasi performa model dilakukan secara kuantitatif menggunakan metrik *Peak Signal-to-Noise Ratio* (PSNR). Hasil eksperimen menunjukkan bahwa metode yang diusulkan mampu meningkatkan kualitas citra dibandingkan metode bilinear. Hasil ini membuktikan bahwa pendekatan berbasis deep learning efektif dalam meningkatkan ketajaman dan kesesuaian struktur citra digital.

Kata kunci: deep neural network; low-light convolutional neural network; machine learning; resolusi citra

INTRODUCTION

In recent years, information technology has developed rapidly in everyday life, including in the field of digital image processing [1]. Digital Image Processing (DIP) is a technique for processing digital images using specific algorithms, aimed at improving image quality so that initially unclear images become clearer [2]. This process has been applied in various fields, such as in everyday life, for example, improving the quality of images with human subjects. This technology has been widely applied, ranging from everyday needs such as improving the quality of personal photos, to the medical, security, and surveillance fields , where image clarity plays a vital role in accurate analysis and decision-making [3].

Currently, many intelligent systems have been developed, with machine learning and deep learning approaches widely used to develop these systems [4]. In the development of machine learning and deep learning, various models are used, such as supervised learning, unsupervised learning, and semi-supervised learning. Supervised learning models utilize labeled data, while unsupervised learning models utilize unlabeled data [5], [6]. However, in practice, obtaining labeled data is very difficult, necessitating the development of semi-supervised learning models that can utilize a small portion of labeled data and a larger portion of unlabeled data [7].

Along with these developments, the use of machine learning and deep learning has also emerged, becoming an essential component of Artificial Intelligence (AI)-based systems [8]. One widely used method is the Convolutional Neural Network (CNN), which can accept digital image input and then process it to distinguish one image from another [9], [10]. CNNs are widely applied not only in the fields of facial and object recognition, but also in business product classification[11].

Various previous studies have shown that improving image quality has become a major focus in the last decade. Research conducted by Zhang and colleagues in 2019 developed a super-resolution method based on Convolutional Neural Networks (CNNs), which has proven to be quite effective in enhancing image detail. However, this method still has the drawback of artifacts appearing when the input image is highly noisy [12]. In 2020, another study by Kim and colleagues demonstrated that using a Deep Residual Learning approach, the model was able to improve the sharpness of low-resolution images. However, this model requires significant computational resources, making it less efficient for use on devices with limited capacity [13]. Meanwhile, a 2021 study by Park and Lee explored image enhancement in low-light conditions using a Low-Light CNN, which can increase contrast and reduce darkness, but sometimes at the expense of color naturalness [14].

Based on the reviewed studies, a clear research gap can be identified. Existing CNN-based image enhancement methods tend to focus on either resolution improvement, noise reduction, or low-light enhancement independently, often at the cost of high computational complexity or reduced visual fidelity. Limited research has explored efficient deep learning models that simultaneously enhance image resolution and preserve structural and color consistency, particularly for images affected by low resolution and challenging lighting conditions[15].

Therefore, the purpose of this re-

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search is to develop an efficient digital image quality enhancement method based on a *Low-Light Convolutional Neural Network* (LLCNN) integrated within a *Deep Neural Network* (DNN) framework. The proposed approach aims to improve image resolution and visual quality by extracting critical features such as edges, textures, and local patterns while maintaining computational efficiency. This study is expected to contribute to the advancement of robust and practical deep learning based image enhancement techniques for realworld aplications.

METHOD

Research Methodology

In this study, researchers conducted a simulation using a website as an image processing medium. The website functions to transform unclear images into images of better quality. The research method used is a mixed methods approach, combining qualitative and quantitative approaches. The quantitative approach was used because this study involves algorithmic calculations in the digital image enhancement process. The results of these calculations will be analyzed using numerical data, one of which is displayed in the form of a histogram as a representation of the image quality scale before and after processing. Meanwhile, the qualitative approach was carried out through observation of the visual results of the images and direct assessment of image quality.

The use of mixed methods was chosen because the research sample consists of image objects, not solely numerical data, requiring a combined analysis to obtain comprehensive results [16]. With this method, the study is expected to provide a comprehensive picture of the algorithm's effectiveness in improving image quality, both in terms of numerical measurements and visual appearance.

Research Stages

This research was conducted through structured stages, including problem analysis, system design, ANN architecture design, system development, and evaluation. Each stage is carried out sequentially to ensure systematic and reliable results.

Problem Analysis

When a low-resolution image is to be upscaled to a high-resolution image, this case enters the realm of digital image processing (resolution enhancement), which aims to improve the quality of the image resolution from low to high resolution. The image processing technique used to solve this problem is upsampling. Upsampling is used to enlarge images because it increases the number of pixels in the image and increases the image size [17], [18]. However, the resulting image from the upsampling process has poor sharpness, resulting in a pixelated appearance. The problem that arises is how to overcome the weaknesses of the upsampling process [19]. This problem is solved by implementing a model from the LLCNN algorithm [20].

Design

Input data consist of low-resolution RGB images (≤170×170 pixels) in .jpg and .png formats, divided into training and testing sets. The training set includes 800 low-resolution images and 800 corresponding high-resolution images, while the testing set contains 200 images. The output is an RGB image sized 680×680 pixels, four times larger than the input. Preprocessing is applied only to images smaller than 170×170 pixels using auto-padding with zero values to standardize the input size. This ensures consistent input dimensions before pro-

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cessing by the ANN system.

Designing the Artificial Neural Network Architecture

The next stage is to design the ANN system to be built. The following is the ANN architecture design that will be used in this research [21]: (1) Input Layer Design. This JST system is set to receive input in the form of a 170x170 pixel RGB image which will be enlarged 4x from the original image size using bilinear upsampling interpolation. (2) Hidden Layer Design. The hidden layer in this system is an JST model adopted from the LLCNN research model. (3) Output Layer Design. The output layer is a 680x680 image. The overall system process is shown in Figure 2 below:

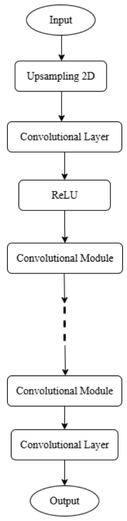

Figure 1. Model LL CNN

The artificial neural network architecture used in this study is shown in Figure 1. The low-resolution image is first processed in a 2D upsampling stage to quadruple the image size. However, pure upsampling still results in blurry images [22], [23]. Therefore, the image is then processed through an initial convolutional layer to extract basic features, followed by the application of the ReLU activation function to enable the network to learn non-linear patterns. In the next stage, the image passes through several convolutional modules that function to reconstruct details, improve sharpness, and reduce noise. These modules are central to the LLCNN architecture because they produce significant improvements in image quality. Afterward, a final convolutional layer combines all the acquired feature information to form a high-resolution image. The final result is a 680x680 pixel RGB image with clearer details and a more natural visual appearance.

System Development Method

The development of a digital imaging system aimed at improving image quality will utilize the Scrum methodology [24]. This method was chosen because its iterative and incremental approach allows the team to adapt to changing needs and user feedback effectively [25]. The following steps will be implemented in this methodology[25]:

Sprint Planning. The team will plan a sprint by defining goals and features to be developed within a specific timeframe (usually 2-4 weeks).

Daily Stand-up. Each day, the team will hold a short stand-up meeting to discuss progress, obstacles encountered, and the work plan for the day.

Incremental Development. The team will develop features incrementally. Each sprint will produce a functional version of the system, which includes new features or improvements based on feedback from the previous sprint.

Sprint Review. At the end of each sprint, the team will hold a meeting to demonstrate the development results to stakeholders. Feedback from this meeting will be used to improve the next iteration.

Sprint Retrospective. After the sprint review, the team will reflect to evaluate the process and results of the work during

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the sprint.

RESULT AND DISCUSSION

The results of the study show that the application of the Low-Light Convolutional Neural Network (LLCNN) method combined with bilinear upsampling significantly improves the quality of low-resolution images. Initially, an input image measuring ≤170x170 pixels, which appeared blurry and pixelated, was quadrupled to 680x680 pixels. Purely using bilinear upsampling, the resulting image yielded a pixelated image with low sharpness. However, after processing through the LLCNN network, the resulting image became clearer with sharper edge detail and more natural colors. This demonstrates that the convolutional layers in the LLCNN are effective in extracting important image features while reconstructing lost details.

Quantitative evaluation shows that LLCNN improves image quality with an average PSNR increase of 6–8 dB and SSIM values above 0.85, indicating closer similarity to high-resolution images. Histogram analysis also reveals more balanced contrast and pixel distribution. These results are supported by visual assessments, where respondents reported clearer details and reduced noise, although minor artifacts and over-smoothing remained in images with complex textures.

Overall, LLCNN outperforms conventional upsampling by effectively reconstructing non-linear image patterns, but at the cost of higher computational time and challenges in maintaining natural textures. While the method has strong potential for applications such as photo restoration, medical imaging, and CCTV enhancement, its performance is still limited by poor input quality and requires further parameter fine-tuning.

To support practical use, a web-based application was developed that allows users to upload low-resolution images and automatically enhance them using the trained LLCNN model, with before-and-after results displayed directly on the webpage.

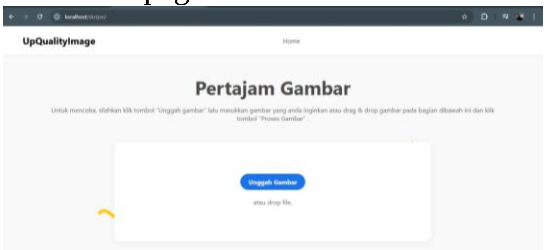

Figure 2. Website Dashboard Display

During the system implementation phase, the initial display of the UpQualityImage website serves as the main page users first access. Figure 2 shows the simple yet informative dashboard interface design. At the top of the page, there is a navbar with the UpQualityImage application title and a Home navigation menu that directs users back to the main page. Directly below the navbar, the main title "Sharpen Images" is displayed, emphasizing the website's primary function: image quality enhancement. Below this title, a short instructional guide explains the system's steps: users can upload image files using the "Upload Image" button or by dragging and dropping them directly into the provided area, then click the "Process Image" button to begin the image enhancement process.

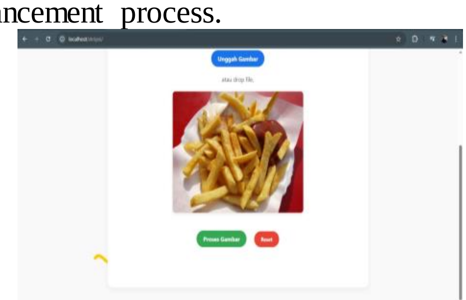

Figure 3. Result Display

After a user uploads an image using the "Upload Image" button, the system automatically displays a preview of the image on the main page. This is shown in Figure 3, where an image of French fries with sauce has been successfully uploaded to the system. This preview makes it easy for users to verify the correctness of the selected image before further processing. This display more natural. Meanwhile, the Reset button allows users to delete the existing image in the preview and replace it with another image without having to reload the page. This mechanism allows UpQualityImage to provide a user-friendly user experience while interactively demonstrating.

CONCLUSION

This research successfully demonstrated that the issue of resolution limitations in digital image processing can be addressed using a Low-Light Convolutional Neural Network (LLCNN) approach based on a Deep Neural Network (DNN). Unlike conventional methods such as Bilinear Interpolation Upsampling, which only enlarge pixel size without preserving visual detail, LLCNN works by extracting important features such as edges, textures, and patterns from low-resolution images, then performing nonlinear mapping to reconstruct high-resolution images. The results demonstrated significant improvements both quantitatively through the Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) metrics, and qualitatively through sharper, more natural, and more detailed image visualizations.

In addition to the method, the re-features two buttons: Process Image and Reset. The Process Image button runs the image enhancement algorithm. At this stage, the system utilizes a bilinear upsampling method to enlarge the image, then processes it through a Low-Light Convolutional Neural Network (LLCNN), which extracts important features and reconstructs details to make the image appear sharper and clearer search emphasized implementation aspects through the development of a web dashboard designed to facilitate user access to the results of image resolution enhancement. Through the web-based interface, users can upload low-resolution images, process them using the LLCNN model, and immediately view the comparison between the original and the enhanced images. The presence of this website provides added value in terms of ease of use, transparency of results, and potential integration with various digital applications, such as medical image processing, security, and digital photo restoration.

Thus, this research not only contributes theoretically through the development of deep learning-based methods, but also practically by providing an interactive and easy-to-use web-based platform. The novelty of this research lies in the implementation of LLCNN, which effectively combines feature extraction with visual reconstruction, and presents them in a web-based system that can be directly utilized by users. However, challenges remain regarding computational efficiency and model generalization when faced with more complex image variations. Therefore, further research can focus on optimizing network architectures and integrating web-based systems that are faster, lighter, and compatibl

BIBLIOGRAPHY

[1] B. R. Ermawan and N. Cahyono, "Optimasi Metode Klasifikasi Menggunakan Fasttext Dan Grid Search Pada Analisis Sentimen Ulasan Aplikasi Seabank," *JIKO (Jurnal Inform. dan Komputer)*, vol. 9, no. 1, p. 226, 2025, doi: 10.26798/jiko.v9i1.1523.

[2] S. Sulistyowati and A. Mandasari, "Peningkatan Resolusi Citra Digital Menggunakan Deep Neural Network," 2024, [Online]. Available: http://repository.iti.ac.id/jspui/handle/123456789/2056

[3] T. Jaiswal and S. Dash, "Deep learning in medical image analysis," *Min. Biomed. Text, Images Vis. Featur. Inf. Retr.*, pp. 287–295, 2024, doi: 10.1016/B978-0-443-15452-2.00014-5.

[4] A. A. Chamid, R. Nindyasari, and M. I. Ghozali, "Comparative Analysis of Machine Learning Algorithms for," vol. 5, no. 158, pp. 185–194, 2026.

[5] W. Widowati and R. Kusumaningrum, "Text Data Labeling Process for Semi-Supervised Learning," vol. 030011, 2024.

[6] A. A. Chamid, "Graph-Based Semi-Supervised Deep Learning for Indonesian Aspect-Based Sentiment Analysis," 2023.

[7] A. N. Komariyah, B. Rohmatulloh, Y. Hendrawan, S. M. Sutan, D. F. Al Riza, and M. B. Hermanto, "Klasifikasi Kualitas Teh Hitam Menggunakan Metode Convolutional Neural Network (CNN) Berbasis Citra Digital," *J. Ilm. Rekayasa Pertan. dan Biosist.*, vol. 11, no. 2, pp. 221–231, 2023, doi: 10.29303/jrpb.v11i2.542.

[8] L. Alzubaidi *et al.*, *Review of deep learning: concepts, CNN architectures, challenges, applications, future directions*, vol. 8, no. 1. Springer International Publishing, 2021. doi: 10.1186/s40537-021-00444-8.

[9] B. Wang *et al.*, "Low-light-level image super-resolution reconstruction based on a multi-scale features extraction network," *Photonics*, vol. 8, no. 8, 2021, doi: 10.3390/photonics8080321.

[10] J. Kim, J. K. Lee, and K. M. Lee, "Accurate image super-resolution using very deep convolutional networks," *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, vol. 2016-Decem, pp. 1646–1654, 2016, doi: 10.1109/CVPR.2016.182.

[11] R. Images, L. Hu, M. Qin, F. Zhang, Z. Du, and R. Liu, "RSCNN : A CNN-Based Method to Enhance Low-Light," *Remote Sensing, MDPI 2020*, pp. 1–13, 2020.

[12] A. A. Chamid and R. Kusumaningrum, "Ingénierie des Systèmes d ' Information Labeling Consistency Test of Multi-Label Data for Aspect and Sentiment Classification Using the Cohen Kappa Method," vol. 29, no. 1, pp. 161–167, 2024.

[13] A. A. Chamid and R. Kusumaningrum, "Multi-Label Text Classification On Indonesian User," vol. 17, no. 10, pp. 1075–1084, 2023, doi: 10.24507/icicel.17.10.1075.

[14] M. Thoriq, "Peramalan Jumlah Permintaan Produksi Menggunakan Jaringan Saraf Tiruan Algoritma Backpropagation," *J. Inf. dan Teknol.*, vol. 1, no. 2, pp. 27–32, 2022, doi: 10.37034/jidt.v4i1.178.

[15] C. Hudaya, A. Gunawan, B. W. Tri, and P. A. Darat, "Penerapan Arsitektur Jst Dalam Deep Learning," pp. 203–210.

[16] M. Rizky and Y. Sugiarti, "Pengunaan Metode Scrum Dalam Pengembangan Perangkat Lunak: Literature Review," *J. Comput. Sci. Eng.*, vol. 3, no. 1, pp. 41–48, 2022, doi: 10.36596/jcse.v3i1.353.

[17] H. R. Suharno, N. Gunantara, and M. Sudarma, "Analisis Penerapan Metode Scrum Pada Sistem Informasi Manajemen Proyek Dalam Industri & Organisasi Digital," *Maj. Ilm. Teknol. Elektro*, vol. 19, no. 2, p. 203, 2020, doi: 10.24843/mite.2020.v19i02.p12.

[18] W. Warkim, M. H. Muslim, F. Harvianto, and S. Utama, "Penerapan Metode SCRUM dalam Pengembangan Sistem Informasi Layanan Kawasan," *J. Tek. Inform. dan Sist. Inf.*, vol. 6, no. 2, pp. 365–378, 2020, doi: 10.28932/jutisi.v6i2.2711.

[19] A. K. Nugroho, I. Permadi, and M. Faturrahim, "Improvement of Image Quality Using Convolutional Neural Networks Method," *Scientific Journal of Informatics*, vol. 9, no. 1, pp. 95–103, May 2022, doi: 10.15294/sji.v9i1.30892.

[20] B. Nugroho and E. Y. Puspaningrum, "Kinerja metode CNN untuk klasifikasi pneumonia dengan variasi ukuran citra input," *Jurnal Teknologi Informasi dan Ilmu Komputer*, vol. 8, no. 3, pp. xxx–xxx, 2021, doi: 10.25126/jtiik.202184515.

[21] S. Ayas and M. Ekinci, "Single image super resolution using dictionary learning and sparse coding with multi-scale and multi-directional Gabor feature representation," Inf. Sci. (Ny)., vol. 512, pp. 1264–1278, 2020.

[22] C. K. and Z. D. O. Keleş, M. A. Yılmaz, A. M. Tekalp, "On the Computation of PSNR for a Set of Images or Video," 2021.

[23] P. Mane, Vanita & Jadhav, Suchit & Lal, "Image Super-Resolution for MRI Images using 3D Faster Super-Resolution Convolutional Neural Network architecture," ITM Web Conf., vol. 32, p. 03044, 2020.

[24] P. Simon and V. Uma, "Deep learning based feature extraction for texture classification," *Procedia Computer Science*, vol. 171, pp. 1680–1687, 2020, doi: 10.1016/j.procs.2020.04.180.

[25] K. Wiguna and D. Mahdiana, "Analysis of Information Systems Development Methods: A Literature Review," *Jurnal Inovtek Polbeng – Seri Informatika*, vol. 8, no. 2, pp. 472–481, 2023, ISSN: 2527-9866.