Media Jurnal Informatika
Vol. 18, No. 1, June 2026
p-issn : 2088-2114, e-issn : 2477-2542

AI-Assisted Web-Based Steganography for Assessment Document Embedding Using Binarized Neural Networks

Muhammad Nasir [a,1,*], Edwar Julistina Ramdon [b,2]

[a] Software Engineering Technology, Vocational College, IPB University, Jl. Kumbang No. 14, Bogor 16128, Indonesia
[b] Informatics Engineering, Vocational Program, Universitas Sangga Buana, Jl. PH.H. Mustofa No. 68, Bandung 40124, Indonesia
[1] m_nasir@apps.ipb.ac.id*; [2] edwar.ramdon@usbypkp.ac.id
* corresponding author

ARTICLE INFO

Article history
Received 2026-06-08
Revised 2026-06-23
Accepted 2026-06-24

Keywords
Artificial Intelligence
Binarized Neural Network
Image Steganography
Information Security
Web Application

ABSTRACT

The administration of assessment documents in The National Narcotics Board requires a mechanism that can conceal confidential information while preserving the visual quality of the carrier image. This study aims to develop an AI-assisted web-based steganography system for embedding assessment documents using a Binarized Neural Network (BNN)-based embedding region selection model. The proposed method extends conventional Least Significant Bit (LSB) steganography by incorporating BNN-based patch classification before data insertion. Assessment data submitted through a web form were automatically converted into PDF files and embedded into residency cover images using an adaptive LSB technique guided by the BNN model. Due to confidentiality restrictions, this study used nine valid residency images, which were segmented into 32×32-pixel patches, producing 900 patches categorized into suitable and unsuitable embedding regions. The BNN model achieved an accuracy of 91.7%, precision of 91.2%, recall of 92.2%, and F1-score of 91.7%. Image quality evaluation showed an average MSE of 2.722, PSNR of 43.79 dB, and SSIM of 0.981, indicating high visual similarity between cover and stego images. Functional testing using black-box testing was conducted on 12 system scenarios, including login validation, role-based access, PDF generation, image upload, embedding, extraction, usage history, and user management access. All 12 scenarios were successfully passed, resulting in a functional success rate of 100%. Implementation observation also indicated that direct conventional LSB embedding tended to produce larger stego-image file sizes than the proposed BNN-assisted adaptive LSB approach. The findings suggest that BNN-assisted region selection can support imperceptible document embedding in web-based steganography applications. However, the limited number of real images, the absence of formal steganalysis, and the lack of full quantitative baseline comparison remain limitations that should be addressed in future work.

1. Introduction

The rapid development of information technology has significantly changed the management of digital information in various sectors, including healthcare, rehabilitation, and social services. The National Narcotics Board routinely manages assessment documents containing sensitive information, such as patient identities, rehabilitation histories, psychological evaluations, treatment plans, and progress reports. The confidentiality of these documents is essential because unauthorized disclosure may violate privacy regulations and negatively affect the rehabilitation process. Therefore, effective security mechanisms are required to ensure the confidentiality, integrity, and security of assessment documents stored and exchanged in digital environments [1], [2].

Various techniques have been proposed to protect digital documents, with cryptography being one of the most widely used approaches. Cryptographic methods secure information by converting plaintext into ciphertext that can only be accessed by authorized parties [3]. However, although cryptography can protect document contents, it does not hide the existence of the information itself. Encrypted files remain visible and may attract attackers' attention, increasing the risk of interception or unauthorized access [4]. Therefore, additional security mechanisms are needed to complement encryption and provide stronger protection for sensitive information.

Steganography offers an alternative approach by concealing secret data within digital media, such as images, audio files, and videos [5]. Unlike cryptography, which focuses on protecting information content, steganography aims to hide the existence of the information. Image-based steganography is particularly relevant because digital images are widely stored, exchanged, and processed in modern information systems. Among various image steganography techniques, the Least Significant Bit (LSB) method remains popular due to its simple implementation, low computational complexity, and high embedding capacity [6], [7], [8].

Despite these advantages, conventional LSB-based steganography has several limitations. The embedding process is commonly performed uniformly across image pixels without considering image characteristics, which may cause visual distortion and increase vulnerability to statistical steganalysis attacks [8]. When a large amount of data is embedded, image quality may decrease, and hidden information may become easier to detect [9]. Therefore, a more intelligent embedding strategy is required to identify suitable image regions that can accommodate hidden data while preserving visual quality.

Recent advances in Artificial Intelligence (AI) and deep learning have created new opportunities to improve steganographic systems. Machine learning and deep learning models can analyze image characteristics and support adaptive embedding region selection based on texture complexity, entropy, and edge distribution [10], [14], [15]. By selecting embedding locations adaptively, AI-assisted steganography can reduce visual distortion and improve resistance against steganalysis techniques [11]. Consequently, the integration of AI into steganographic systems has become an important research area in information security.

One lightweight deep learning architecture that has attracted considerable attention is the Binarized Neural Network (BNN). Unlike conventional neural networks that use floating-point weights and activations, BNN employs binary values, enabling faster computation and lower memory consumption while maintaining competitive classification performance [12], [13]. These characteristics make BNN suitable for practical applications that require efficient processing and deployment. In steganographic applications, BNN can be used to classify image regions according to their suitability for data embedding, thereby supporting adaptive embedding strategies that minimize perceptual distortion.

Several studies have investigated the integration of artificial intelligence into steganography. Deep learning-based approaches have been shown to improve embedding imperceptibility and robustness by using image features to guide the hiding process [14], [15]. Prayoga, Putri, and Hidayat introduced Aletheia, a steganography system based on Binarized Neural Networks for digital image media. Their study demonstrated that BNN can improve steganographic performance while maintaining acceptable image quality, evaluated using Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), embedding capacity, and extraction success rate [16]. However, most existing studies focus on general image-hiding scenarios and do not specifically address the protection of assessment documents at the National Narcotics Board.

In addition, previous studies generally treat steganographic algorithm development and information system implementation as separate research topics. Limited attention has been given to integrating artificial intelligence, document management, and steganographic security into a single operational platform that can be applied in real-world assessment document management. The use of BNN to secure automatically generated assessment documents in a web-based system also remains relatively unexplored.

To address these limitations, this study proposes an AI-assisted web-based steganography system using Binarized Neural Networks for secure embedding of assessment documents in images used by The National Narcotics Board. The system was developed using PHP and MySQL and enables operators to input assessment data through a web-based interface. The entered data are automatically converted into PDF documents and subsequently embedded into selected images. A Binarized Neural Network is used to identify suitable embedding regions, while an adaptive LSB mechanism performs the data hiding process based on the generated embedding map.

Conventional LSB steganography provides a simple and efficient mechanism for embedding information into digital images. However, its main limitation is that data insertion is commonly performed without considering the local characteristics of image regions. As a result, embedding may occur in visually sensitive or homogeneous areas, increasing the possibility of perceptual distortion. Therefore, this study develops the conventional LSB approach into a BNN-assisted adaptive LSB method, where the BNN model is used to select suitable embedding regions before bit insertion is performed. In this method, LSB remains the bit-level embedding technique, while BNN functions as an adaptive region selection mechanism.

Recent studies show that deep learning has increasingly been applied to image steganography and steganalysis, particularly for adaptive embedding, feature learning, imperceptibility improvement, and robustness evaluation [14], [15], [26]. These studies indicate that modern steganographic systems should not only preserve visual quality but also consider detectability, payload capacity, and robustness against common image processing operations.

The contributions of this study are aligned with the identified research gap. First, this study develops a web-based steganography application that integrates assessment form processing, automatic PDF generation, and image-based document embedding into a single workflow. Second, it extends conventional LSB steganography by incorporating a BNN-based embedding region selection mechanism, allowing the system to identify suitable image patches before data insertion. Third, it applies the proposed BNN-assisted adaptive LSB method to assessment document embedding in a sensitive institutional context, where confidentiality and anonymization are important considerations. Fourth, it evaluates the proposed method using BNN classification metrics and image quality metrics, including MSE, PSNR, and SSIM, to assess both embedding-region classification and visual quality preservation. Fifth, it evaluates the functional feasibility of the developed web application using black-box testing on authentication, role-based access, PDF generation, image upload, embedding, extraction, usage history, and user management access. These contributions address the gap in previous studies that generally discuss steganographic algorithms and information system implementation as separate topics.

2. Method

This study applied a Research and Development (R&D) approach to design, develop, and evaluate an AI-assisted web-based steganography system for embedding assessment documents into residency cover images. The R&D approach was used because this study did not only analyze an existing phenomenon but also produced a functional prototype, implemented the proposed method, and evaluated the system performance.

The R&D process in this study consisted of six main stages: requirement analysis, system design, implementation, testing, evaluation, and refinement. Requirement analysis was conducted to identify the assessment document workflow, user roles, document generation needs, and embedding/extraction requirements. System design included database design, interface design, user access design, PDF generation workflow, and the integration of BNN-assisted adaptive LSB steganography. Implementation was conducted by developing the web application, PDF generation module, image upload module, BNN-based patch classification, adaptive LSB embedding, and extraction module. Testing was conducted using black-box testing to evaluate the functional operation of the web application. Evaluation was conducted using BNN classification metrics and image quality metrics, including MSE, PSNR, and SSIM. Refinement was performed based on the testing and evaluation results to ensure that the system workflow operated according to the expected requirements.

The proposed system integrates a Binarized Neural Network (BNN) to determine suitable embedding regions and an adaptive Least Significant Bit (LSB) technique to embed assessment documents into digital images. The BNN model functions as a region selection mechanism, while LSB remains the bit-level embedding technique. Thus, the proposed method extends conventional LSB steganography by adding BNN-based patch classification before data insertion. The overall research and system development framework is illustrated in Figure 1.

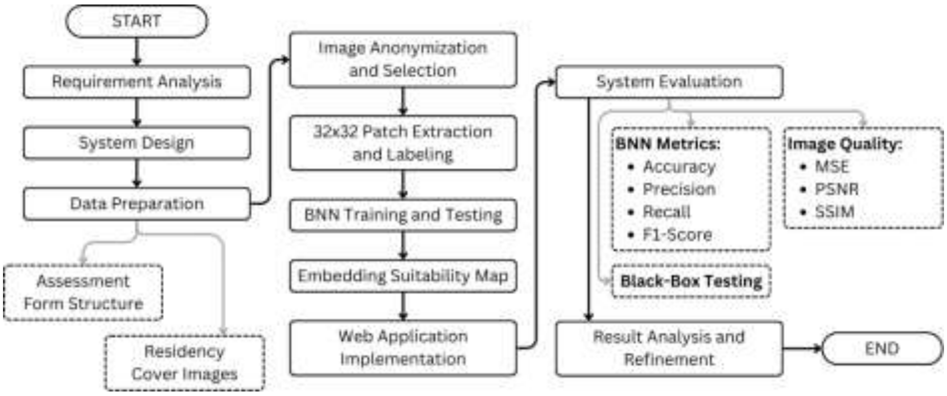


Fig. 1. Research and development framework of the proposed AI-assisted web-based steganography system

The framework consists of several connected stages. The process begins with assessment document analysis and residency cover image preparation. Valid images are selected and anonymized before being divided into 32×32-pixel patches. The patches are labeled as suitable and unsuitable embedding regions and then used to train and evaluate the BNN model. After the BNN model generates an embedding suitability map, the web application processes assessment form input, generates a PDF document, embeds the PDF bitstream into selected image regions using adaptive LSB, and produces a stego image. The extraction module retrieves the hidden document from the stego image. Finally, the system is evaluated using classification metrics, image quality metrics, and black-box testing.

2.1 Type and Approach of Research

The R&D approach was selected because this study focuses on producing, implementing, and evaluating a software prototype that combines artificial intelligence, document management, and steganographic embedding in one operational workflow [17]. In this study, the R&D approach was implemented through six stages: requirement analysis, system design, implementation, testing, evaluation, and refinement.

The requirement analysis stage identified user needs, assessment document workflow, user roles, PDF generation requirements, image upload requirements, and embedding/extraction processes. The system design stage produced the database structure, interface design, access-control design, PDF generation workflow, and steganographic process design. The implementation stage involved the development of the web application using PHP and MySQL, the PDF generation module using TCPDF, and the BNN-assisted adaptive LSB module using Python, OpenCV, and NumPy. The testing stage was conducted using black-box testing to verify whether each system function operated according to the expected requirements. The evaluation stage assessed the BNN model using classification metrics and assessed stego-image quality using MSE, PSNR, and SSIM. The refinement stage was conducted based on the testing and evaluation results to improve system consistency and functional performance.

The AI component was implemented using a Binarized Neural Network to classify image patches into suitable and unsuitable embedding regions. The classification result was then used as an embedding suitability map for the adaptive LSB algorithm. BNN was selected because it offers a lightweight architecture with lower computational requirements compared with conventional deep neural networks [12], [13]. Therefore, the proposed method does not replace LSB but improves conventional LSB by adding BNN-based embedding region selection.

2.2 Object and Scope of Research

The object of this research is the design, implementation, and evaluation of an AI-assisted web-based steganography system for embedding assessment documents into residency cover images. The system was studied as a complete workflow consisting of assessment data input, automatic PDF generation, cover image selection, BNN-based embedding region classification, adaptive LSB embedding, stego-image generation, document extraction, usage history, and role-based access control.

The research object is not limited to the interface of the web application, but includes the interaction between the web-based information system, the document generation module, the BNN model, and the adaptive LSB embedding process. The web application acts as the operational platform, while the BNN-assisted adaptive LSB method acts as the document embedding mechanism. The use of AI in this context supports the classification of image regions, while the steganographic process follows an adaptive image embedding strategy based on the selected regions [10], [16].

The scope of this study includes: (1) assessment documents generated through the web application, (2) residency cover images used as steganographic carrier media, (3) BNN-based patch classification into suitable and unsuitable embedding regions, (4) adaptive LSB embedding and extraction processes, (5) role-based access for administrator and staff users, and (6) evaluation using classification metrics, image quality metrics, and black-box testing. The administrator role has full access to dashboard, assessment form input, assessment viewing, usage history, and user master management. The staff role is limited to dashboard access, assessment form input, and assessment form viewing.

This study does not focus on cryptographic encryption, network security mechanisms, or formal steganalysis. Instead, it emphasizes document embedding, visual quality preservation, BNN-assisted region selection, and functional feasibility of the developed web-based prototype [10], [16].

2.3 Data Collection Techniques

Data collection was conducted using observation, documentation, and literature review. These techniques were applied systematically to support both system development and experimental evaluation. Observation was conducted to understand the assessment documentation workflow, user interaction needs, and the required functions of the proposed web-based steganography system. The observation results were used to define system requirements, including login authentication, role-based access, assessment form input, PDF generation, image upload, embedding, extraction, usage history, and user management.

Documentation was used to collect assessment form structures, residency cover images, and supporting operational information required for system design and evaluation. The images and assessment documents used in this study were obtained from restricted institutional documentation and were used only for research and system evaluation purposes. Access to the original data was limited to the researchers involved in this study. To protect privacy and confidentiality, identifiable information in the images was anonymized before being included in the manuscript. The original identifiable images and assessment documents were not publicly distributed and were stored in a restricted local research environment.

Literature review was conducted to establish the theoretical and methodological basis of the study. The reviewed literature included digital steganography, LSB embedding, Binarized Neural Networks, adaptive image steganography, image quality assessment, and software development evaluation. The literature review supported the formulation of the proposed BNN-assisted adaptive LSB method and the selection of evaluation metrics, including Accuracy, Precision, Recall, F1-Score, MSE, PSNR, SSIM, and black-box testing.

The data collection framework consisted of four stages. First, system requirement data were collected through observation of the assessment document workflow. Second, document and image data were collected through restricted documentation. Third, the collected images were screened using inclusion and exclusion criteria. Fourth, the valid images were prepared for BNN training and steganographic evaluation through anonymization, patch extraction, and patch labeling.

Initially, sixteen images were available; however, seven images were excluded because of file corruption, incomplete visual information, or unreadable image formats. Therefore, nine valid images were used in the experiment. The inclusion criteria were images that could be opened, processed, and used as cover media for embedding. The exclusion criteria included corrupted files, incomplete images, and files that could not be read by the image-processing module.

Each valid image was divided into non-overlapping patches of 32×32 pixels, resulting in 900 image patches for BNN training and testing. The use of image patches is common in image classification and adaptive image processing because it increases the number of training samples and supports feature learning [18], [19]. The image patches were manually categorized into two classes: suitable embedding regions and unsuitable embedding regions. The classification was based on texture complexity, edge density, and local entropy. Regions with richer textures are considered more suitable for embedding because pixel changes are less noticeable in such areas [11], [14].

However, because the dataset was constructed from only nine real images, the results should be interpreted as prototype-level evaluation and may not fully represent broader image variations. This condition is also considered a limitation because patch-level splitting may introduce potential data leakage when patches from the same image appear in both training and testing subsets.

Table 1. Dataset Distribution

Category	Number of Patches
Suitable Regions	450
Unsuitable Regions	450
Total	900

The dataset was divided into training and testing sets using an 80:20 ratio.

Table 2. Dataset Split

Dataset	Number of Patches
Training	720
Testing	180
Total	900

2.4 Ethical Consideration and Data Protection

The residency images and assessment documents used in this study contain sensitive information and were treated as restricted institutional research data. The data were used only for system development, prototype testing, and experimental evaluation. Access to the original data was limited to the researchers involved in this study, and the data were stored in a restricted local research environment.

To protect individual privacy and confidentiality, facial regions and identifiable visual information were anonymized before the images were included in the manuscript. The generated assessment documents used in the experiment were also handled in a restricted environment and were not uploaded to public repositories. The use of real residency images was necessary to evaluate the proposed steganography system under realistic image characteristics, including variations in texture, lighting, and background. However, only anonymized versions of the images were presented in the manuscript.

The limited number of images and the sensitive nature of the data are acknowledged as methodological limitations. Future studies should involve larger datasets with clearer data governance procedures to improve research transparency, reproducibility, and generalizability.

2.5 Tools and Materials Used

The proposed system was developed using a MacBook with 8 GB RAM as the primary development and testing device. The operating system used was macOS 13.0.1. The local development environment was configured using MAMP 6.8, which provides Apache, PHP, and MySQL services. PHP version 8.2 was used as the main programming language for developing the web application. MySQL was used as the database management system through phpMyAdmin bundled with MAMP. TCPDF was utilized to generate assessment documents in PDF format.

For the artificial intelligence and image-processing components, Python was used to implement the BNN-based embedding region selection, image preprocessing, patch extraction, difference-map generation, and image quality evaluation. OpenCV was used for image reading and preprocessing, while NumPy was used for matrix operations, pixel-level difference calculation, and numerical computation. The BNN component was implemented as a lightweight Python-based model using binary-weight and binary-activation principles, following the concept of Binarized Neural Networks. This implementation was used to classify 32×32 image patches into suitable and unsuitable embedding regions. The use of pixel-level analysis and image quality metrics is relevant to digital image processing studies that evaluate the effect of image manipulation on visual quality [24]. The experimental materials consisted of assessment form data and nine valid residency cover images used for steganographic embedding and evaluation.

2.6 Research Procedures or Stages

The research procedures followed the Research and Development (R&D) framework illustrated in Figure 1. The process began with requirement analysis to identify user roles, assessment document workflow, PDF generation needs, image upload, embedding, and extraction processes. The next stage was system design, which included database design, interface design, role-based access, and the integration of BNN-assisted adaptive LSB into the web application.

Data preparation included assessment form structure preparation and residency cover image collection. The images were anonymized, selected, and divided into non-overlapping 32×32-pixel patches. Each patch was labeled as a suitable or unsuitable embedding region based on texture complexity, edge density, and local entropy [11], [14]. The labeled patches were then used for BNN training and testing. The BNN model classified image patches into suitable and unsuitable embedding regions using binary convolution, binary activation, pooling, and fully connected layers [12], [20].

The trained BNN generated an embedding suitability map to guide the adaptive LSB embedding process. In the web application, assessment data were converted into PDF format and embedded into selected image regions using adaptive LSB guided by the BNN map [6], [8], [16]. The system was then evaluated using BNN classification metrics, image quality metrics, and black-box testing. The evaluation results were analyzed to determine system performance, limitations, and recommendations for future improvement.

2.7 Data Analysis Techniques

The BNN model was evaluated using Accuracy, Precision, Recall, and F1-Score, which are commonly used to assess classification performance in machine learning and pattern recognition studies [21], [25]. The evaluation was derived from the confusion matrix, consisting of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). In this study, TP represents suitable patches correctly classified as suitable, TN represents unsuitable patches correctly classified as unsuitable, FP represents unsuitable patches incorrectly classified as suitable, and FN represents suitable patches incorrectly classified as unsuitable.

The Accuracy value was calculated using Equation (1):

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

The Precision value was calculated using Equation (2):

$$\text{Precision} = \frac{TP}{TP + FP}$$

The Recall value was calculated using Equation (3):

$$\text{Recall} = \frac{TP}{TP + FN}$$

The F1-Score value was calculated using Equation (4):

$$F_1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

The quality of stego images was evaluated using Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index Measure (SSIM). MSE was used to measure the average pixel-level error between the cover image and the stego image. PSNR was employed to evaluate the amount of distortion introduced during the embedding process, while SSIM was used to assess the structural similarity between the original and modified images [22], [23].

The MSE value was calculated using Equation (5):

$$MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} [I(i,j) - K(i,j)]^2$$

where (I(i,j)) represents the pixel value of the cover image, (K(i,j)) represents the corresponding pixel value of the stego image, (M) represents the number of image rows, and (N) represents the number of image columns.

The PSNR value was calculated using Equation (6):

$$PSNR = 10\log_{10}\left(\frac{MAX^2}{MSE}\right)$$

where (MAX) denotes the maximum possible pixel value of the image. For 8-bit images, the value of (MAX) is 255.

The SSIM metric was used to evaluate structural similarity and perceptual quality preservation between cover and stego images. Higher PSNR and SSIM values, together with lower MSE values, indicate better image quality preservation after the embedding process. MSE, PSNR, and SSIM were used to evaluate the impact of the embedding process on image quality, as these metrics are commonly applied in digital image processing and image quality assessment studies [22], [23], [24]. The functional feasibility of the web application was evaluated using black-box testing. The black-box testing results were calculated using Equation (7):

$$\text{Success Rate} = \frac{\text{Number of Passed Scenarios}}{\text{Total Number of Test Scenarios}} \times 100\%$$

The system was considered functionally feasible when the main tested scenarios operated according to the expected results.

3. Results and Discussion

3.1 Presentation of Research Results

The proposed AI-assisted steganography system was successfully implemented as a web-based application for securing assessment documents in narcotics residency institutions. The system enables users to input assessment information, automatically generate assessment reports in PDF format, and embed the generated documents into residency images using a Binarized Neural Network (BNN)-assisted adaptive steganography mechanism.

The implemented web application consists of several main interfaces, including the login page, dashboard page, assessment form, and extraction page. Figure 2 presents the login page used to authenticate users before accessing the system.

Fig. 2. Login Page

After successful authentication, users are directed to the dashboard page, as shown in Figure 3. The dashboard provides access to assessment forms, image data, and user management features.

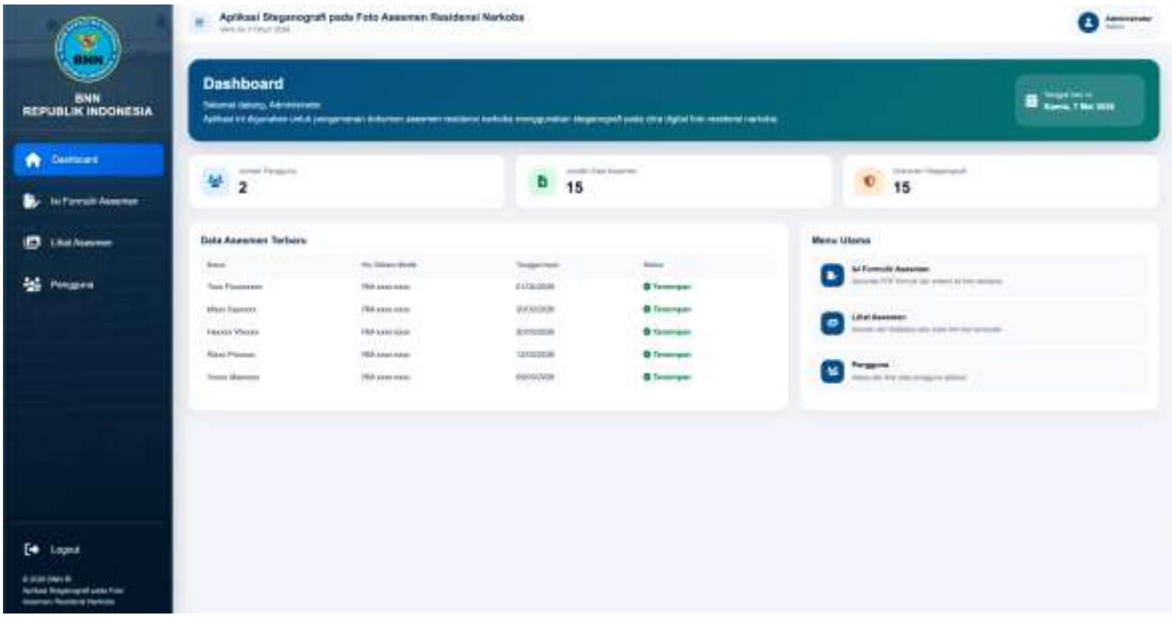


Fig. 3. Dashboard Page

The experimental dataset consisted of nine valid residency images that were used as cover images during the embedding process. Prior to publication, all images were anonymized to preserve privacy and confidentiality. The residency images used in the experiment are presented in Figure 4.

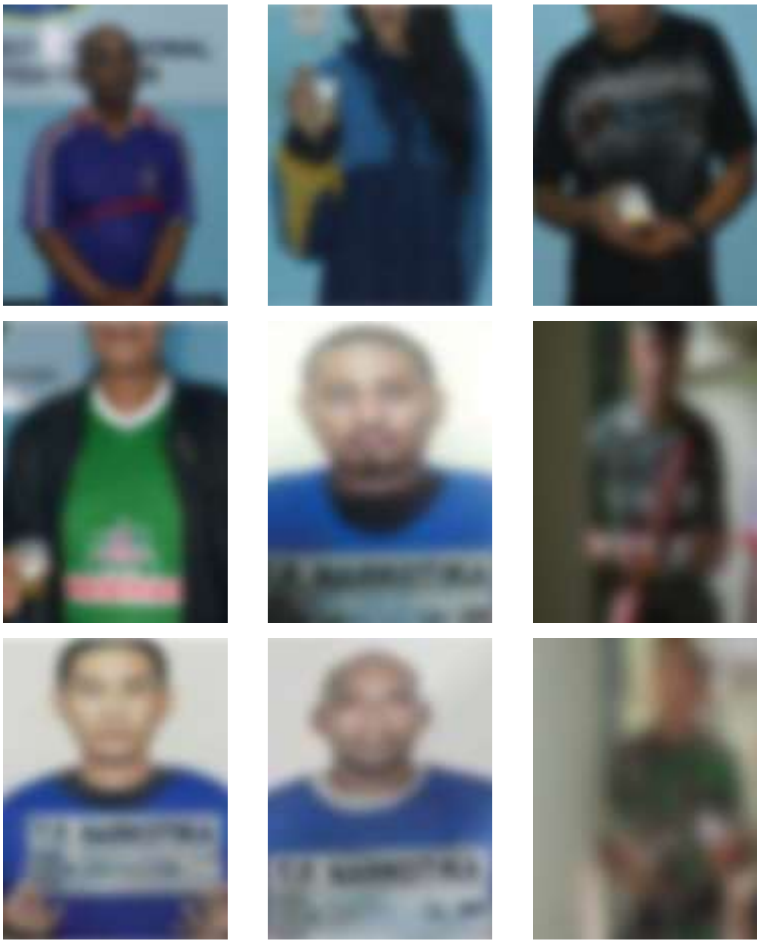


Fig. 4. Residency Images Used in the Experiment

The developed web application provides an interface for entering assessment information and uploading residency images. An example of the assessment form interface is shown in Figure 5.

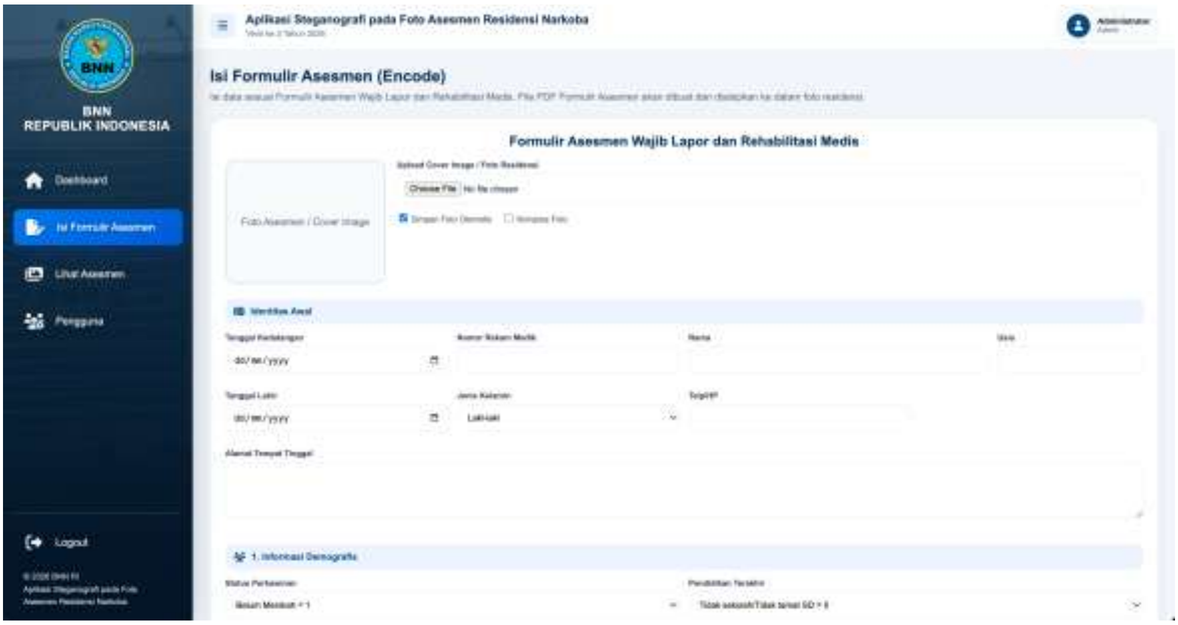


Fig. 5. Assessment Form Interface

After the assessment form was completed, the system automatically generated a PDF document containing the assessment results. The generated PDF was subsequently embedded into the selected residency image. Figure 6 presents an example of an extracted assessment document successfully reconstructed from a stego image.

FORMULIR ASESMEN WAJIB LAPOR DAN REHABILITASI MEDIS

Tanggal Kedatangan	:		
Nomor Rekam Medik			
Nama		Usia :	
Alamat Tempat Tinggal		Jenis Kelamin :	
Telp/HP			
1. INFORMASI DEMOGRAFIS	1. Status Perkawinan :	Belum Menikah = 1	
		Menikah = 2	
		Duda/Janda = 3	
	2. Pendidikan Terakhir :	Tamat SD = 1	
		Tamat SLTP = 2	
		Tamat SLTA = 3	
		Tamat Akademi = 4	
		Tamat PT = 5	
STATUS MEDIS	1. Riwayat rawat inap yang tidak terkait masalah narkotika		
	Jenis Penyakit	Dirawat Tahun	Lamanya

Fig. 6. Extracted Assessment Document

To evaluate the BNN model, image patches were classified into suitable and unsuitable embedding regions. The resulting confusion matrix is presented in Table 3.

Table 3. Confusion Matrix of the BNN Model

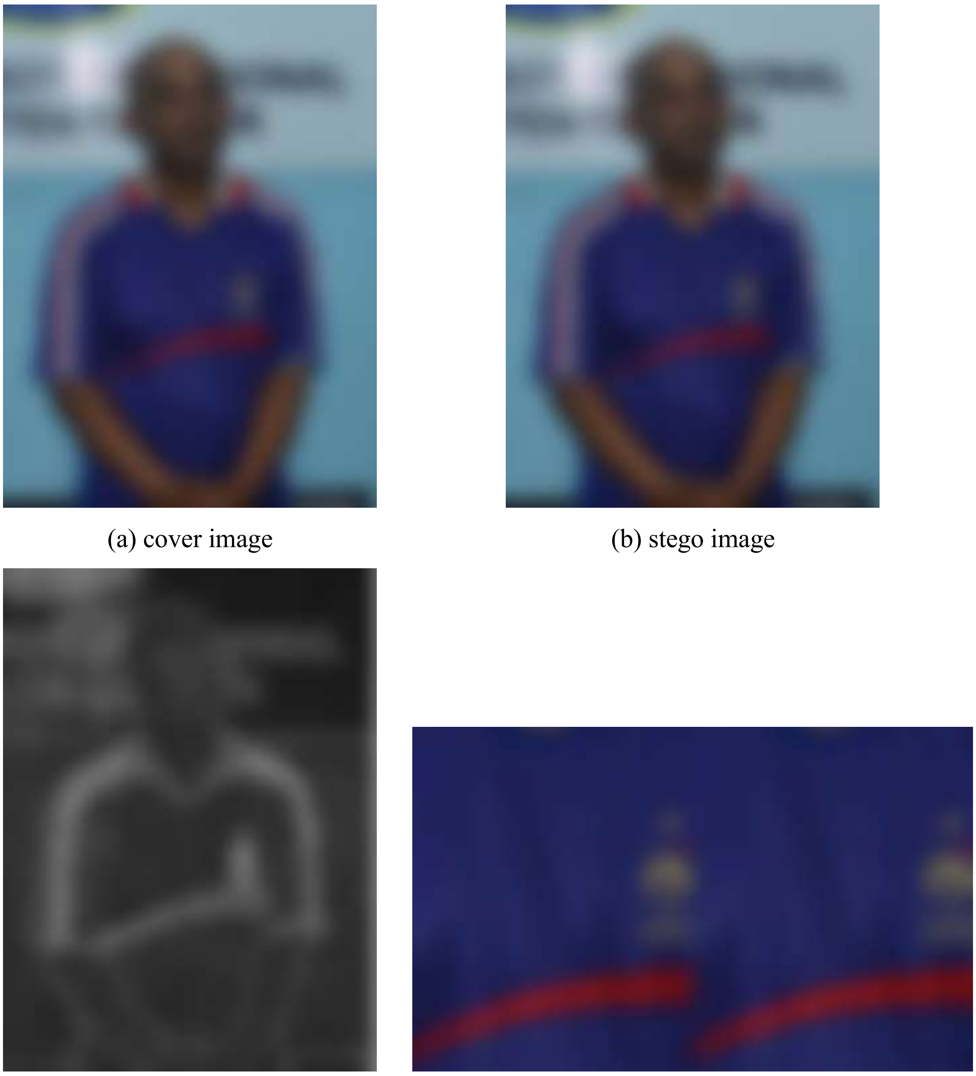
Actual/Predicted	Suitable	Unsuitable
Suitable	83	7
Unsuitable	8	82

Based on the confusion matrix, the classification performance metrics shown in Table 4 were obtained.

Table 4. BNN Classification Performance

Metric	Value (%)
Accuracy	91.7
Precision	91.2
Recall	92.2
F1-Score	91.7

Visual comparison between the original cover image and the stego image is presented in Figure 7. The figure consists of the original image, stego image, amplified difference map, and zoom patch comparison.



(a) cover image

(b) stego image

(c) difference map

(d) Zoom Patch Comparison

Fig. 7. Visual comparison between cover and stego images: (a) cover image, (b) stego image, (c) amplified difference map, and (d) zoom patch comparison.

The image quality evaluation was performed on all nine residency images used during the experiment. Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index Measure (SSIM) were calculated to assess the impact of the embedding process on image quality. The evaluation results are presented in Table 5.

Table 5. Image Quality Evaluation Results

Image	MSE	PSNR(dB)	SSIM
Residency_1	3.105	43.21	0.976
Residency_2	2.871	43.55	0.979
Residency_3	2.761	43.72	0.981
Residency_4	2.661	43.88	0.982
Residency_5	2.553	44.06	0.984
Residency_6	2.812	43.64	0.980
Residency_7	2.484	44.18	0.985
Residency_8	2.607	43.97	0.983
Residency_9	2.643	43.91	0.982
Average	**2.722**	**43.79**	**0.981**

The image quality results presented in Table 5 are closely related to the embedding region selection performed by the BNN model. By accurately identifying texture-rich regions suitable for data hiding, the BNN minimizes perceptual distortion introduced during the embedding process. Consequently, the resulting stego images achieved high PSNR and SSIM values while maintaining low MSE values.

Since the proposed system was developed as a web-based application, functional testing was conducted using black-box testing. The testing focused on verifying whether the main system functions operated according to the expected requirements, including login authentication, dashboard access, role-based access control, assessment form processing, PDF generation, image upload validation, steganographic embedding, extraction, usage history, and user management access. The system provides two user roles: administrator and staff. The administrator has full access to all menus, including dashboard, assessment form input, assessment viewing, usage history, and user master management. Meanwhile, the staff role is limited to dashboard access, assessment form input, and assessment form viewing.

Table 6. Black-Box Testing Results

No	Tested Function	User Role	Test Scenarrio	Expected Result	Status
1	Login authentication	Administrator/Staff	User enters valid username and password	System grants access to dashboard	Passed
2	Login validation	Administrator/Staff	User enters invalid credentials	System rejects login attempt	Passed
3	Dashboard access	Administrator	Administrator accesses dashboard	System displays dashboard and full menu access	Passed
4	Dashboard access	Staff	Staff accesses dashboard	System displays dashboard with limited menu access	Passed
5	Assessment form input	Administrator/Staff	User inputs assessment data	System saves assessment data correctly	Passed
6	Image upload	Administrator/Staff	User uploads supported image file	System accepts image and displays preview	Passed
7	PDF generation	Administrator/Staff	User submits assessment form	System generates assessment document in PDF format	Passed
8	Upload validation	Administrator/Staff	User uploads unsupported file type	System rejects invalid file	Passed
9	Embedding process	Administrator/Staff	User submits PDF and cover image	System generates stego image	Passed
10	Extraction process	Administrator/Staff	User selects stego image	System reconstructs hidden PDF document	Passed
11	Usage history access	Administrator	Administrator accesses usage history	System displays usage history data	Passed

No	Tested Function	User Role	Test Scenarrio	Expected Result	Status
12	Userr master access restriction	Staff	Staff attempts to access user master menu	System restricts access based on role	Passed

Based on Table 6, all 12 test scenarios were successfully executed. Therefore, the black-box testing success rate was calculated as follows:

$$Success\ Rate = \frac{12}{12} \times 100\% = 100\%$$

The black-box testing results indicate that the main functional components of the web application operated according to the expected workflow. These results support the feasibility of the proposed system as a prototype for assessment document embedding and extraction. However, this functional testing does not replace the need for further application security testing, such as vulnerability assessment, access-control audit, upload security testing, session management testing, and database security evaluation.

Although this study does not present a full quantitative baseline comparison with conventional LSB using MSE, PSNR, and SSIM, implementation observations showed that direct LSB embedding tended to produce larger stego-image file sizes than the proposed BNN-assisted adaptive LSB approach. This condition may occur because conventional LSB inserts data more directly without considering the suitability of local image regions, while the proposed method limits the embedding process to selected regions classified as suitable by the BNN model. Therefore, the BNN-assisted approach can reduce unnecessary embedding operations in less suitable regions and support more controlled data insertion. However, this observation should be interpreted as an implementation-level finding, and further controlled experiments are required to compare conventional LSB and BNN-assisted adaptive LSB using the same payload size, image format, compression setting, and image quality metrics.

3.2 Analysis of Findings

The experimental results demonstrate that the proposed BNN-assisted adaptive LSB steganography system achieved its objective of embedding assessment documents into residency cover images while preserving visual quality. The classification performance shown in Table 4 indicates that the BNN model effectively distinguished suitable embedding regions from unsuitable regions, achieving an accuracy of 91.7%. This result suggests that the model learned image characteristics associated with texture complexity and entropy, which are important factors in adaptive steganography.

Based on the confusion matrix presented in Table 3, the model correctly classified 83 suitable regions and 82 unsuitable regions. Only 15 image patches were misclassified during testing. These results indicate that the proposed BNN model can support embedding region selection and reduce the likelihood of embedding data in visually sensitive image areas. However, because the dataset was constructed from a limited number of images, the classification results should be interpreted cautiously and may require further validation using image-level splitting and larger datasets. The proposed method does not replace LSB; instead, it extends conventional LSB by adding BNN-based embedding region selection. Conventional LSB directly inserts data into image pixels without explicitly considering local image characteristics. In contrast, the proposed method uses BNN-based patch classification to identify suitable regions before applying LSB embedding. This mechanism is expected to reduce perceptual distortion because the embedding process is directed to regions that are less sensitive to visual changes.

The visual comparison shown in Figure 7 further confirms the visual quality preservation of the proposed approach. Although the PDF assessment document was embedded into the residency cover image, the visual appearance of the stego image remained nearly identical to the original cover image. The amplified difference map reveals only minor pixel-level modifications, while the zoom patch comparison demonstrates that local image structures and textures were preserved after embedding. The image quality evaluation presented in Table 5 shows that the proposed method achieved an average MSE of 2.722, PSNR of 43.79 dB, and SSIM of 0.981. PSNR values above 40 dB generally indicate that image distortions are difficult to perceive visually [22]. Similarly, SSIM values approaching 1.0 indicate strong structural similarity between the original and modified images [23]. Therefore, the obtained results demonstrate that the proposed embedding mechanism preserved visual quality effectively.

The black-box testing results also indicate that the developed web application operated according to the expected functional requirements. All 12 tested scenarios were passed, resulting in a functional success rate of 100%. The tested functions included login validation, role-based access for administrator and staff, dashboard access, assessment form input, PDF generation, image upload validation, embedding, extraction, usage history access, and user master access restriction. These results show that the implemented prototype can support the main workflow required for assessment document embedding and extraction.

The findings are consistent with previous studies that integrated artificial intelligence into steganography systems. Previous BNN-based steganography research has shown that Binarized Neural Networks can support image steganography while maintaining acceptable image quality [16]. Other deep-learning-based steganography studies also indicate that adaptive embedding guided by image characteristics can reduce perceptual distortion and improve embedding effectiveness [14], [15], [26]. Nevertheless, this study does not claim complete security validation, because robustness testing, steganalysis evaluation, payload capacity analysis, and formal baseline comparison were not fully conducted.

3.3 Implications of the Results

The results of this study indicate that BNN-assisted adaptive LSB can be used as a prototype approach for embedding assessment documents into residency cover images while preserving visual quality. Under the current experimental conditions, the proposed system demonstrates that lightweight AI can support the selection of suitable embedding regions before LSB-based data insertion. This finding is relevant for document-management contexts where concealment and visual quality preservation are required.

From a system implementation perspective, the proposed application integrates assessment form input, automatic PDF generation, image-based embedding, extraction, usage history, and role-based access into a single web-based workflow. The administrator role supports full system management, including usage history and user master data, while the staff role supports operational functions such as accessing the dashboard, inputting assessment forms, and viewing assessment forms. However, practical deployment in institutional environments requires additional validation, including security testing, privacy compliance review, access-control audit, robustness testing, and evaluation using larger datasets. Therefore, the current findings should be interpreted as prototype-level evidence rather than a complete operational security solution.

3.4 Limitations of the Study

Several limitations were identified during this research. First, the number of available residency images was limited because of confidentiality restrictions and data accessibility considerations. Although a patch-based dataset consisting of 900 image patches was constructed, the dataset was derived from only nine valid images. This condition may limit the generalizability of the BNN model and may introduce potential data leakage if patches from the same image appear in both training and testing subsets. Future studies should apply image-level splitting or cross-validation strategies to provide a more rigorous evaluation. Second, the evaluation was conducted only on residency cover images and PDF assessment documents generated by the developed system. Consequently, the results may differ when applied to other image types, document formats, payload sizes, or operating environments.

Third, this study focuses on BNN-assisted adaptive LSB and image quality evaluation using MSE, PSNR, and SSIM. A direct quantitative comparison with conventional LSB was not presented in this study. Although implementation observations indicated that conventional LSB tended to produce larger stego-image file sizes than the proposed BNN-assisted adaptive LSB approach, this finding has not yet been evaluated through a controlled baseline experiment. Future work should compare both methods using identical cover images, payload sizes, image formats, and evaluation metrics, including file size, MSE, PSNR, SSIM, payload capacity, extraction success rate, and robustness against image processing operations.

Fourth, robustness testing against image compression, resizing, cropping, and steganalysis attacks was not included in the current evaluation. Therefore, the results should be interpreted as evidence of visual quality preservation and functional prototype feasibility rather than comprehensive steganographic security validation. Fifth, the web application evaluation was limited to black-box functional testing. Although all 12 scenarios were passed, further testing is needed, including vulnerability assessment, authentication security testing, access-control audit, upload security testing, session management testing, and database security evaluation.

4. Conclusion

This study successfully designed and implemented an AI-assisted web-based steganography system for embedding assessment documents into residency cover images. The proposed system combines PDF document generation, image-based steganography, and Binarized Neural Network (BNN)-assisted embedding region selection. The proposed method extends conventional LSB by adding BNN-based patch classification to guide adaptive embedding.

The experimental results show that the system can embed and recover assessment documents while preserving stego-image quality, as reflected in the average MSE of 2.722, PSNR of 43.79 dB, and SSIM of 0.981. The BNN model also achieved an accuracy of 91.7%, precision of 91.2%, recall of 92.2%, and F1-score of 91.7% in classifying suitable and unsuitable embedding regions. In addition, black-box testing on 12 functional scenarios showed that all scenarios were passed, resulting in a functional success rate of 100%. These results indicate that the proposed system can support document embedding and extraction workflows while maintaining visual quality and functional feasibility under the current experimental conditions.

However, the findings should not be interpreted as complete security validation, because robustness testing, steganalysis evaluation, payload capacity analysis, integrity verification, and formal baseline comparison were not fully conducted. Future research is recommended to use larger and more diverse datasets, apply image-level validation, compare the proposed method with conventional LSB under identical experimental conditions, and evaluate robustness against compression, resizing, cropping, and steganalysis attacks. Further web application testing should also be conducted, including vulnerability assessment, access-control audit, upload security testing, and database security evaluation.

References

[1] W. Stallings, *Cryptography and Network Security: Principles and Practice*, 8th ed, Global ed, New York: Pearson, 2023.

[2] A. Kahate, *Cryptography and Network Security*, 4th ed. New Delhi, India: McGraw-Hill Education, 2019.

[3] B. Schneier, *Applied Cryptography: Protocols, Algorithms, and Source Code in C*, 20th Anniversary ed. Indianapolis, Hoboken: John Wiley & Sons, 2017.

[4] G. Widjaja, "Privacy And Security In Digital Communications: Challenges And Solutions In Cyberspace", *Prosiding Seminar Nasional Indonesia,* Adisam Publisher, vol. 3, no. 1, pp. 26-33, Feb. 2025.

[5] N. F. Johnson, Z. Duric, and S. Jajodia, *Information Hiding: Steganography and Watermarking-Attacks and Countermeasures: Steganography and Watermarking : Attacks and Countermeasures*. Boston, MA, USA: Kluwer Academic Publishers, 2001.

[6] J. Fridrich, *Steganography in Digital Media: Principles, Algorithms, and Applications*. Cambridge, U.K.: Cambridge University Press, 2009.

[7] K. Bennet, "Linguistic steganography: Survey, analysis, and robustness concerns for hiding information in text", *CERIAS Tech Report*, Purdue University, Tech. Rep., 2004.

[8] A. S. Fadel, R. D. Saputra, Y. Fatma, and R. N. Putra, "Security analysis of text steganography using the least significant bit (LSB) method in digital images", *Jurnal CoSciTech (Computer Science and Information Technology)*, vol. 5, no. 1, pp. 36-41, Apr. 2024,https://doi.org/10.37859/coscitech.v5i1.6759.

[9] M. Ahmad, E. Al-Qhtani, A. Samak, A. Ibrahim, M. Elloumi, A. Ahmed, "Deep Learning-Based Steganalysis for Detection and Classification of Possible Hidden Content in Images," *Fusion: Practice and Applications*, vol. 17, no. 2, pp. 377-393, 2025. doi: https://doi.org/10.54216/FPA.170228.

[10] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge, MA, USA: MIT Press, 2016.

[11] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*, 4th ed. New York, NY, USA: Pearson, 2018.

[12] M. Courbariaux, Y. Bengio, and J. P. David, "BinaryConnect: Training deep neural networks with binary weights during propagations", *Advances in Neural Information Processing Systems*, 2016, pp. 3123-3131, doi: https://doi.org/10.48550/arXiv.1511.00363.

[13] M. Courbariaux, I. Hubara, D. Soudry, R. El-Yaniv and Y. Bengio, "BinaryNet: Training deep neural networks with weights and activations constrained to +1 or −1," arXiv preprint arXiv:1602.02830, 2016, doi: https://doi.org/10.48550/arXiv.1602.02830.

[14] A. Tripathi, A. B. Pandey, S. Moudgil, A. K. Rajpoot, B. K. Gupta and V. Khemchandani, "A Deep Learning Approach to Image Steganography and Steganalysis", *Eksplorium*, vol. 46, no. 1, pp. 1192-1206, May. 2025.

[15] D. Polisetty and S. W. A. Rizvi, "GAN-Based Adaptive Image Steganography", *International Journal of Computer Applications*, vol. 187, no. 6, pp. 45-50, May. 2025, doi: http://doi.org/10.5120/ijca2025924951.

[16] S. Prayoga, S. N. Putri, and J. Hidayat, "Aletheia : Sistem Steganografi berbasis Binarized Neural Network untuk Media Gambar Digital", *SISTEMATIK*, vol. 2, no. 1, 2025, doi: https://doi.org/10.64847/sistematik.v2i1.114.

[17] M. D. Gall, J. P. Gall, and W. R. Borg, *Educational Research: An Introduction*, 8th ed. Boston, MA, USA: Pearson, 2007.

[18] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks", *Communications of the ACM*, vol. 60, no. 6, pp. 84-90, May. 2017, doi: https://doi.org/10.1145/3065386.

[19] S. S. Haykin, *Neural Networks and Learning Machines*, 3rd ed. New York, NY, USA: Pearson, 2009.

[20] M. Rastegari, V. Ordonez, J. Redmon, and A. Farhadi, "XNOR-Net: ImageNet Classification Using Binary Convolutional Neural Networks", *Proc. European Conference on Computer Vision (ECCV)*, pp. 525-542, Aug. 2016, doi: https://doi.org/10.48550/arXiv.1603.05279.

[21] T. Fawcett, "An introduction to ROC analysis", *Pattern Recognition Letters*, vol. 27, no. 8, pp. 861-874, Jun. 2006, doi: https://doi.org/10.1016/j.patrec.2005.10.010.

[22] Pujianto, "Model Keamanan Pesan pada Video Menggunakan Metode One's Complement Cryptography Dan Track Free Atom Steganography 1", *Jurnal TELEMATIKA MKOM*, vol. 9, no. 3, nov. 2017, doi: https://doi.org/10.36080/telematikamkom.541.

[23] M. Wulandari, "Index Quality Assesment Citra Terinterpolasi (SSIM Dan FSIM)", *JUTEI (Jurnal Terapan Teknologi Informasi),* vol. 1, no. 1, Apr. 2017, doi: https://doi.org/10.21460/jutei.2017.11.5.

[24] A. Suheri, S. Widaningsih, and A. Nazihah, "Implementation of smoothing and noise reduction for digital image quality enhancement using neighborhood operations," Media Jurnal Informatika, vol. 17, no. 2, pp. 293–304, 2025, doi: 10.35194/mji.v17i2.5893.

[25] C. M. Bishop, *Pattern Recognition and Machine Learning*. New York, NY, USA: Springer, 2006.

[26] B. Song, P. Wei, S. Wu, Y. Lin, and W. Zhou, "A Survey on Deep-Learning-Based Image Steganography" *Expert Systems with Applications*, vol. 254, Art. no. 124390, 2024, doi: 10.1016/j.eswa.2024.124390.