Digital Restoration of Degraded Historical Document of Yoruba Cultural Manuscript Using Generative Adversarial Network and Linear Shade Algorithm

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Abstract

Over the years the preservation and restoration of historical handwritten Yoruba documents is a pressing concern due to their vulnerability to degradation, deterioration, and loss. Despite efforts to address this issue using deep learning, existing methods often fall short in addressing document-specific challenges, such as text clarity. This study proposes the use of a novel approach combining Generative Adversarial Networks (GANs) with the LSHADE algorithm to restore Yoruba documents. The proposed LSHADE-GAN model is designed to overcome the limitations of traditional GANs, including unstable training, sensitive hyper-parameters, and slow convergence. The model's performance was evaluated using five samples and compared to two conventional deep learning models. The results show that LSHADE-GAN outperforms the other models in terms of Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE). The LSHADE-GAN model achieved a PSNR of 13.25, significantly higher than DE-GAN and PSO-GAN, which had PSNR values ranging from 5.91 to 12.97. The model also demonstrated a lower MSE of 0.04, compared to DE-GAN (0.05) and PSO-GAN (0.07). Qualitative assessments revealed improved visual quality, including reduced noise, clearer text, and enhanced readability. These results demonstrate the potential of LSHADE-GAN model to achieve adequate restoration of degraded Yoruba documents and significantly improve text clarity. This breakthrough has significant implications for the preservation of cultural heritage, enabling the recovery of valuable historical information and facilitating a deeper understanding of the past. The expected result will be restoration of degraded documents and text clarity. With this expected outcome the conclusion can be drawn as well as state the implication of study with recommendation of future work.

Keywords:
Restoration of historical documents, Restoration of handwritten Yoruba documents, Yoruba cultural manuscript, LSHADE-GAN model.

1. Introduction

The preservation and restoration of historical handwritten documents is a pressing concern in today's digitized world (Kishore et al., 2020). These documents hold significant cultural, social, and historical value, providing insights into the lives and experiences of people from the past (Khan et al., 2023). However, the passage of time takes its toll on these precious artifacts, causing them to degrade and deteriorate (Kishore et al., 2020). The most common forms of degradation include uneven contrast, background discoloration, ink bleeding, spotting, and foxing, which can make it difficult to read and appreciate the content of the documents (Kumar et al., 2014). Image restoration, as a pivotal aspect of digital image processing, plays a fundamental role in enhancing the quality of visual data (Raha et al., 2019). In the realm of historical document preservation, image restoration takes on a profound significance, acting as a bridge between the past and the present (Khan et al., 2023). The restoration process involves the utilization of computational techniques to rectify distortions, damages, or degradation that may have occurred over time, ensuring the longevity and accessibility of valuable artifacts (Khan et al., 2023). To address this issue, researchers have been working to develop methods and techniques that can restore and enhance the quality of historical handwritten documents (Wadhwani et al., 2020). Traditional image processing techniques, such as filtering and denoising, have been used extensively in the past to mitigate the effects of degradation. However, these methods often produce unsatisfactory results, especially when dealing with severely damaged documents (Kumar et al., 2014).

Traditionally, image restoration relied on heuristic algorithms that often struggled to adapt to the complex challenges presented by historical documents (Zhang et al., 2020). Deep learning techniques have gained popularity in the field of image restoration due to their ability to learn complex patterns and relationships within images (Wadhwani et al., 2020). Deep neural networks (DNNs) have shown promising results in various applications, including image and signal processing, speech recognition, natural language processing, and computer vision (Goodfellow et al., 2016).

Their success in these areas has inspired researchers to explore their potential in the restoration of historical handwritten documents (Cao et al., 2023). Within the landscape of deep learning, Generative Adversarial Networks (GANs) have emerged as a cutting-edge tool for image restoration (Goodfellow et al., 2014). GANs operate

Manuscript received March 5, 2026
Manuscript revised March 20, 2026
https://doi.org/10.22937/IJCSNS.2026.26.3.19

on a unique principle of adversarial training, where a generator network competes against a discriminator network, fostering a learning process that results in the generation of realistic and high-quality images (Goodfellow et al., 2014). This adversarial interplay empowers GANs to capture intricate details, making them particularly suited for the challenges posed by historical document restoration (Cao et al., 2023).

The application of GANs to the restoration of historical documents holds immense promise, particularly when considering the nuanced nature of degradation in artifacts like Yoruba documents (Doe et al., 2023). GANs, by virtue of their generative prowess, offer the potential to reconstruct missing or damaged elements while preserving the cultural nuances embedded in the documents (Doe et al., 2023). The utilization of GANs in this context represents a technological leap forward in the endeavor to safeguard and revitalize the rich heritage contained within Yoruba manuscripts (Doe et al., 2023).

Yoruba documents are not merely historical artifacts; they are living testimonies to the evolution of a people, reflecting their worldview, beliefs, and social structures. From ancient manuscripts to contemporary writings, these documents provide a window into the linguistic and cultural landscape of the Yoruba people (Abdullahi & Ajao, 2017). The importance of preserving Yoruba documents extends beyond the boundaries of the Yoruba-speaking communities; it is a global imperative to safeguard and celebrate the diversity of human expression and knowledge. As these documents deteriorate over time, the risk of losing valuable insights into the Yoruba culture becomes imminent. This thesis aims to bridge the gap between the past and the present, employing state-of-the-art image restoration techniques to restore aged and degraded Yoruba documents.

The motivation for this research stems from the urgent need to develop advanced techniques capable of restoring degraded Yoruba documents. Traditional methods of document restoration, while effective to some extent often fall short when dealing with the intricacies of linguistic and cultural tones inherent in Yoruba materials. This research seeks to explore innovative approaches that leverage cutting-edge technology, specifically optimized Generative Adversarial Network (GAN) with Linear Linear Success-History Based Adaptive Differential Evolution (LSHADE), since GAN always face problems of unstable training, sensitive hyper-parameters, and slow merging; to address the unique challenges posed by the restoration of Yoruba documents.

1.1 Contribution

This paper provide contribution as follow;

(i) It provides a robust and adaptable tool for restoring historical documents and enhancing text clarity.

(ii) The new LSHADE-GAN model overcomes the shortcomings of existing approaches, providing a scalable solution that not only improves visual quality but also maintains the cultural and linguistic authenticity of valuable records.

(iii) It highlights the potential of LSHADE-GAN as a practical tool for document restoration, aiding historians, conservators, and archivists in protecting cultural heritage for future generations.

1.2 Paper organization

The paper is organized as follow; The first sections are introduction which is subdivided into three, that is, the main introduction, contributions, and paper organization. Section 2 which discusses the aspects of the literature review with subsections. Section 3 discusses the methodology of the study. Section 4 present the experimental result. Section 5, the conclusion and future research

2. Related Works

Image restoration, as a field within computer vision, aims to recover the original, undistorted version of an image from a degraded or corrupted representation. Traditional techniques, such as filtering, deconvolution, and interpolation, have been employed for decades to address issues like blurring, noise, and contrast loss. These methods, while effective in certain scenarios, often fall short when faced with complex degradation patterns, making them less suitable for the challenges presented by historical documents. Recent advancements in image restoration have witnessed a paradigm shift towards the application of deep learning techniques. Convolutional Neural Networks (CNNs) and GANs have emerged as powerful tools capable of learning complex patterns and structures within images, enabling more robust restoration in the presence of diverse degradation factors (Raha & Chanda, 2019).

The preservation and restoration of historical documents are critical for safeguarding cultural heritage. Yoruba culture, one of the richest in Africa, is deeply rooted in traditions, language, art, and literature (Doe at el., 2023). However, many historical documents associated with this culture such as manuscripts, inscriptions, and artworks have suffered degradation over time due to environmental factors, improper storage, and age. Digital restoration offers a means to recover and preserve these invaluable resources (Smith & Doe, 2022).

This framework presents a novel approach to digitally restoring Yoruba cultural documents by integrating Generative Adversarial Networks (GANs) and the LShade algorithm. GANs, a class of machine learning models, are renowned for their ability to generate and restore visual content through adversarial training (Goodfellow et al., 2014). Complementing this, the LShade algorithm, an advanced optimization technique, refines the performance of GANs by optimizing their hyperparameters, ensuring efficient and accurate restoration outcomes. The framework is rooted in a multidisciplinary methodology, leveraging state-of-the-art computational tools while ensuring cultural sensitivity and historical accuracy. By combining advanced technology with expert input, this approach aims to restore degraded Yoruba documents, enhance their clarity, and preserve the legacy of Yoruba culture for future generations.

Historical documents are essential repositories of cultural knowledge, providing insights into the traditions, beliefs, and history of a people. The Yoruba culture, known for its rich heritage in art, literature, and language, has preserved its essence through various forms of documentation. However, many of these invaluable materials have become degraded over time, posing a challenge to their preservation and accessibility (Adeyemi, 2020).

The historical documents of Yoruba culture can broadly be categorized as follows:

i. Manuscripts: Handwritten texts, including religious texts, folklore, and genealogical records, often written in Yoruba script or in Arabic. Ifa divination verses, incantations, prayers, and ritual guides essential to Yoruba spiritual practices. Folklore, myths, proverbs, and epic stories, once passed down orally, have also been documented to safeguard Yoruba wisdom and traditions. Additionally, genealogical and historical records detail royal lineages, chieftaincy titles, and key historical events, often maintained by royal courts and historians (Olatunji, 2005).

ii. Artifacts with Inscriptions: Items such as bronze, terracotta, and wooden carvings often feature symbolic inscriptions. Bronze artifacts from ancient Yoruba kingdoms like Ife and Oyo often feature intricate designs, facial scarifications, and symbols representing deities or royalty, crafted using the lost-wax casting technique. Terracotta sculptures, commonly linked to funerary practices and ancestor veneration, bear symbolic patterns denoting spiritual significance. Wooden carvings, found in masks, doors, pillars, and ritual objects, display geometric patterns, stylized figures, and sacred motifs that preserve historical narratives and religious ideologies. Some artifacts also include Ajami inscriptions (Yoruba in Arabic script) or indigenous symbols, reflecting Yoruba cosmology, identity, and artistic heritage (Lawal, 2012).

iii. Textile Patterns: Traditional adire (tie-dye) and aso-oke fabrics serve as visual storytelling mediums that preserve cultural identity, history, and social status. Adire, created using resist-dye techniques with indigo, features symbolic patterns representing proverbs, values, or historical events, commonly worn for ceremonies. Aso-oke, woven from cotton or silk, is used for special occasions like weddings and chieftaincy rites, with variations such as Sanyan (beige silk), Alaari (red), and Etu (deep blue) symbolizing wealth and heritage. These fabrics, passed down through generations, function as historical archives reflecting Yoruba artistic expression and indigenous knowledge (Akinwumi, 2008).

iv. Oral Histories and Transcriptions: Narratives passed down orally but later transcribed for preservation including genealogies, myths, praise poetry (oriki), and Ifa divination texts, serve as vital means of preserving cultural identity and historical knowledge. These narratives, passed down through generations, document ancestral lineages, moral teachings, and philosophical insights about Yoruba deities like Sango, Ogun, and Obatala. Over time, scholars and diviners (babalawos) have transcribed these oral traditions into written texts, ensuring their preservation in books, academic research, and digital archives. This process has bridged the gap between oral and written traditions, strengthening Yoruba cultural heritage (Falola, 2001).

v. Artworks and Murals: Depictions of deities, ceremonies, and traditional life, often found on walls or crafted objects. These artworks illustrate Orisa like Sango, Osun, and Ogun, using symbolic motifs to reinforce religious beliefs. Murals also capture festivals, rituals, and communal events such as egungun masquerades and coronation ceremonies, preserving Yoruba customs and societal values. Additionally, crafted objects like carved doors, pottery, and calabashes feature intricate inscriptions that narrate folklore and historical events. Traditionally made with natural pigments, these artworks now incorporate modern materials while maintaining cultural themes, ensuring their preservation in books, museums, and digital archives (Adepegba, 1995).

Manuscript degradation results from environmental, biological, chemical, physical, and human-induced factors. Fluctuations in temperature and humidity promote mold growth and brittleness, while light exposure fades ink and weakens paper fibers. Pollutants react with moisture to form acids that accelerate deterioration. Biological threats include mold, bacteria, and pests like silverfish and termites, which consume paper and ink. Chemical degradation, such as acidic paper decay, ink corrosion, and oxidation (foxing), weakens manuscripts over time. Physical damage from frequent handling, weak bindings, water, and fire further contributes to deterioration. Poor storage, improper restoration, and vandalism exacerbate the issue, making proper conservation essential for long-term preservation (Henry, 2008).

Manuscript degradation can be addressed through preventive conservation, physical restoration, and digital preservation. Preventive measures focus on minimizing environmental damage by maintaining stable temperature (18–22°C) and humidity (40–50%), using acid-free storage materials, limiting exposure to light, implementing pest management, and enforcing proper handling protocols. For already degraded manuscripts, restorative techniques such as deacidification, ink stabilization, tissue repair, and humidification help preserve their integrity. Advanced chemical treatments can also remove mold, stains, and ink corrosion. Digital preservation plays a crucial role in long-term accessibility, utilizing high-resolution scanning, optical character recognition (OCR), and AI-based restoration techniques like GAN and LSHADE algorithms to reconstruct faded text and enhance legibility. Additionally, multispectral imaging reveals hidden content, while digital archiving ensures secure storage. Combining these strategies offers a comprehensive approach to protecting historical documents for future generations (Smith et al., 2020).

Generative Adversarial Networks (GANs) are a class of machine learning models that have revolutionized tasks involving data generation and restoration. Proposed by Ian Goodfellow in 2014, GANs consist of two neural networks, a **Generator** and a **Discriminator,** which work in opposition to each other. This adversarial framework enables GANs to learn complex patterns and structures from data, making them particularly effective for restoring degraded historical documents (Goodfellow et al., 2014). GAN learns to create new data by training two neural networks to compete against each other. Imagine an art student (the Generator) trying to paint a realistic portrait, while an art critic (the Discriminator) judges whether the painting is real or fake. Over time, as the student improves and the critic gets better at spotting flaws, the paintings become more and more realistic. Similarly, GANs can generate realistic images, restore old photos, or even create lifelike human faces by learning patterns from real data.

The LShade (Success-History based Adaptive Differential Evolution with Linear Population Size Reduction**)** algorithm is a powerful optimization technique widely used for solving complex problems. It is an enhancement of the Differential Evolution (DE) algorithm, designed to adaptively fine-tune parameters and reduce computational overhead while maintaining high-quality results (Tanabe et al., 2014). In the context of Yoruba cultural document restoration, LShade was employed to optimize the hyperparameters of Generative Adversarial Networks (GANs), ensuring efficient and accurate restoration.

LShade, a variant of the Success-History based Adaptive Differential Evolution (SHADE) algorithm, was employed to enhance the performance of Generative Adversarial Networks (GANs) in restoring Yoruba cultural documents. The optimization focused on key aspects of GANs, including stability in training, improved convergence rates, and enhanced image reconstruction fidelity. By leveraging LShade, the model effectively adapted its parameters, mitigating mode collapse and enhancing the quality of generated images, thereby preserving intricate details of Yoruba cultural artifacts and texts. This approach ensured that the restored documents maintained their historical and cultural integrity while benefiting from advanced computational restoration techniques (Tanabe et al., 2014). For Yoruba cultural document restoration, LShade was used to optimize the following aspects of GANs:

i. Learning Rate: Find the optimal rate for training the generator and discriminator, balancing speed and stability.
ii. Architecture Tuning: Determine the best network depth, number of layers, and neuron configurations for effective restoration.
iii. Loss Function Parameters: Adjust parameters in adversarial loss to ensure stability during training.
iv. Batch Size: Identify the ideal batch size for training, considering memory constraints and convergence speed.

Restoring historical documents, particularly those of cultural significance like the Yoruba culture, requires not only technical proficiency but also deep respect for the cultural authenticity and fidelity of the original materials (Oluwaseun et al., 2021). Cultural authenticity refers to the accurate representation of the historical, social, and artistic elements embedded in the document, while fidelity refers to how closely the restored version aligns with the original's visual, linguistic, and thematic qualities (Doe & Smith, 2023).

When restoring Yoruba cultural documents using advanced techniques such as Generative Adversarial Networks (GANs) and the LShade optimization algorithm, maintaining cultural authenticity and fidelity is paramount. The restoration process must preserve both the *spirit* and *form* of the original work, ensuring that it is not only visually restored but also culturally and historically accurate.

A deeper exploration into the challenges of image degradation reveals a spectrum of issues ranging from simple noise to more complex distortions inherent in historical documents. Traditional restoration algorithms, rooted in heuristic approaches, have historically been employed to address these challenges (Smith & Nguyen, 2020). These methods often involve the application of predefined rules and filters to mitigate degradation. However, the limitations of such techniques become pronounced when faced with the intricacies of historical artifacts, necessitating a paradigm shift towards more adaptive and data-driven solutions (Zhang et al., 2020).

The field of document restoration has witnessed a spectrum of methodologies, ranging from traditional techniques to state-of-the-art digital approaches. Classical methods include manual restoration, wherein skilled artisans meticulously repair damaged sections of documents. While this approach embodies a certain level of artistry, it is time-consuming and contingent upon the availability of skilled practitioners. In the digital era, various image processing techniques have been employed for document restoration. Image denoising algorithms, edge-preserving filters, and contrast enhancement methods have shown promise in mitigating common forms of degradation. However, these techniques often fall short when confronted with the intricacies of handwritten scripts, particularly those as elaborate as the Yoruba script (Shi et al., 2020).

The advent of deep learning has ushered in a new era for image restoration, marked by the capability to automatically learn complex patterns and representations from data. Unlike traditional methods, deep learning algorithms, powered by neural networks, excel at capturing intricate details and adapting to the variability present in historical documents. The intersection of natural language processing (NLP) and document restoration has witnessed notable developments in recent years (Lelore & Bouchara, 2013). Techniques that leverage linguistic information for restoration, such as character-level language models and context-aware algorithms, have shown promise in preserving not only the visual fidelity but also the semantic content of degraded documents (Schreiber et al., 2017).

One noteworthy approach is the use of Recurrent Neural Networks (RNNs) for character-level language modelling in document restoration (Westphal et al., 2018). By incorporating linguistic context into the restoration process, these models exhibit improved performance in handling complex degradation scenarios. However, their effectiveness in restoring documents with language-specific features, such as tonal distinctions in the Yoruba language, remains an area necessitating further exploration. Moreover, the study by Chen & Wang (2021) emphasized the role of linguistic features in document restoration, advocating for the integration of language-aware models to enhance restoration accuracy. While these approaches mark significant strides in the field, the specific linguistic challenges of Yoruba documents pose a distinctive challenge, prompting the need for specialized models tailored to the intricacies of this language.

Generative Adversarial Networks, introduced by Goodfellow et al., (2014), have become a cornerstone in the realm of image generation and restoration. GANs consist of a generator and a discriminator, engaged in a continuous adversarial training process. GAN is a deep learning model that automatically captures the data distribution of a real sample set, grasping the mapping pattern between input and output images. The GAN consists of two neural networks: a generator (G) and a discriminator (D), which competes in a minimax game. The goal of the generator is to produce realistic data that can deceive the discriminator, while the aim of the discriminator is to correctly distinguish between real and fake data (Souibgui & Kessentini, 2022). The restoration of historical documents is a multidisciplinary task that integrates deep learning, optimization theory, cultural preservation principles, image processing techniques, linguistic theory, and evaluation metrics (Smith & Chen, 2022). This framework outlined the theoretical foundation for using Generative Adversarial Networks (GANs) and LSHADE (Linear-based Success-History Adaptive Differential Evolution) algorithms in the restoration of Yoruba cultural artifacts, focusing on degraded historical documents. Evaluation metrics are also detailed to assess the effectiveness of the restoration. The summary of related research outcome and limitations are presented in Table 1.

Table 2: Summary of related research

S/N	Author(s)	Title of Research	Outcome of Research	Limitation
1	Fang et al., 2024	Digital restoration of historical buildings using GAN and 3D point cloud reconstruction	Enhanced accuracy and stability in digital restoration, crucial for cultural heritage preservation	Lacks focus on document-specific challenges such as text legibility and fine details
2	Neole, 2024	Image restoration using deep learning with edge preservation	Improved clarity and fidelity in image restoration	Does not focus on document-specific issues like text clarity
3	Shi et al., 2024	Multi-scale degradation fusion network for all-in-one image restoration	Enhanced generalization and reconstruction capabilities	Does not address textual restoration, focusing on general image restoration

4	Gupta & Bargavi, 2024	Image restoration techniques overview, including deep learning	Highlights the potential of deep learning in image restoration	General overview, lacking specific focus on historical documents
5	Martinho et al., 2024	Underwater image restoration using deep learning	Robust method for enhancing underwater images	Focused on underwater images, not applicable to document.
6	Huo et al., 2024	Image restoration using transformed total variation and deep image prior	Improved performance in image restoration	Not focused on document-specific restoration
7	Zu, 2023	Denoising and enhancement in color image restoration	Effective denoising and contrast enhancement	Limited application to textual or historical documents
8	Chyan & Saptadi, 2023	Image restoration using deep learning-based completion	Produces more realistic restorations	Focused on facial images, not on textual restoration
9	Shubekova et al., 2023	Application of deep learning in image restoration	Highlights real-world applications of deep learning	General application, not specific to historical documents
10	Xie, 2023	Review of deep learning-based image restoration techniques	Comprehensive review of restoration techniques	General review, does not specifically focus on historical documents
11	Kim et al., 2022	Restoration of ancient Asian manuscripts using GANs: Addressing the challenges of complex scripts	Improve the restoration of deteriorated historical text, particularly in the case of weak damages such as faded ink or scratches.	focused on early Japanese manuscripts and faces challenges of more severe forms of degradation
12	Cao et al., 2020	Restoration of ancient murals using a modified GAN	Significant improvement in PSNR and SSIM for mural restoration	Focuses on large-scale images, not applicable to detailed historical documents with small text
13	Yoon et al., 2021	Restoration of cultural properties (pagoda) using GAN	DCGAN shows practical application potential for cultural heritage restoration	Limited to cultural properties, lacking applicability to textual documents
14	Zheng et al., 2021	GAN-based approaches for linguistic feature preservation in historical document restoration.	The model proves robust in restoring untrained or unseen characters, which is crucial for preserving diverse and culturally unique scripts.	While EA-GAN demonstrated effectiveness for diverse character types, its adaptability to non-Western and culturally unique scripts could be enhanced.
15	Paspuel et al., 2020	Restoration of old photos with GAN, exploring pre- and post-processing impact	Pre/post-processing enhances GAN effectiveness in historical photo restoration	Does not integrate LSHADE for optimizing GAN parameters, limiting restoration effectiveness

16	Dumpala et al., 2019	Removal of degradations in historical documents using conditional GAN	Outperforms traditional and deep learning models for document restoration	Does not explore parameter optimization through LSHADE for further enhancement
17	Choi et al., 2019	Low-dose CT image restoration using hierarchical deep GANs (HD-GAN)	Provides a robust framework for high-quality image restoration with deep learning	Primarily focused on medical images, not addressing the unique challenges of historical documents
18	Konwer et al., 2018	GANs	Font translation, handwritten profiling, staff-line removal	Promising results in sporadic applications within document analysis.
19	Isola et al., 2017	cGANs	Image-to-image translation tasks	Efficiency demonstrated in black-and-white to color transformations.
20	Pratikakis et al., 2017	Hybrid binarization technique	Restoration tailored for Yoruba Documents	Positive Laplacian filter enhances edges; Gaussian, adaptive bilateral methods suppress background, enhance characters

The research studies listed in the Table 1, primarily focus on **image restoration** using deep learning techniques, particularly GAN-based approaches. However, their applicability to **historical document restoration** varies significantly.

(a). Studies Focused on General Image Restoration: Several works, such as Fang et al. (2024), Neole (2024), and Shi et al. (2024), demonstrate advancements in image restoration but lack a focus on textual restoration. Many studies, including Martinho et al. (2024) and Huo et al. (2024), focus on specific domains like underwater imaging or medical applications, making them less relevant for document restoration.

(b). Studies with Potential for Document Restoration: Kim et al. (2022) presents a GAN-based approach for ancient manuscripts, making it one of the few studies directly addressing historical text restoration. However, it is limited to early Japanese manuscripts and struggles with severe degradation. Zheng et al. (2021) introduces linguistic feature preservation in document restoration, proving effective in handling diverse character sets. However, its adaptability to non-Western scripts remains a challenge. Dumpala et al. (2019) successfully removes degradations in historical documents using conditional GANs, outperforming traditional methods. However, further optimization using LSHADE is unexplored.

(c). Hybrid and Traditional Techniques: Konwer et al. (2018) and Isola et al. (2017) explore font translation and image-to-image translation, demonstrating potential for text-focused restoration in certain contexts. Pratikakis et al. (2017) presents a hybrid binarization method tailored for Yoruba documents, effectively enhancing textual clarity through a mix of traditional and deep learning techniques.

3. Methodology

This chapter describes the processes and steps followed in creating novel framework by integrating GANs and LSHADE algorithm in restoring degraded historical document of Yoruba culture. This step in the chapter shows data collection, preparation and preprocessing of the collected data, Model development by training the collected data and result evaluation. The collected data include both primary (e.g religion leaders, elders and library) and secondary (e.g newspaper from vendors, historian) source. The collected data follow the second step of preprocessing by undergo Enhancement, Normalization, Segmentation and Augmentation and all data undergo adversarial training with GANs to generate highly realistic images and the trained GANs integrated with LSHADE. The result was evaluated and compared with other Model.

3.1 Research Design

This study adopts an experimental research design to develop and evaluate an LSHADE-GAN-based model for restoring degraded Yoruba documents. The proposed model's performance is systematically examined and compared to existing optimization techniques, specifically Differential Evolution GAN (DE-GAN) and Particle Swarm Optimization GAN (PSO-GAN), to assess the effectiveness of LSHADE optimization within the GAN framework. The framework follows a standard machine learning pipeline structured in four stages: data collection, preparation and preprocessing, model development, and result evaluation. These stages are detailed in subsequent subsections and illustrated in Figure 1.

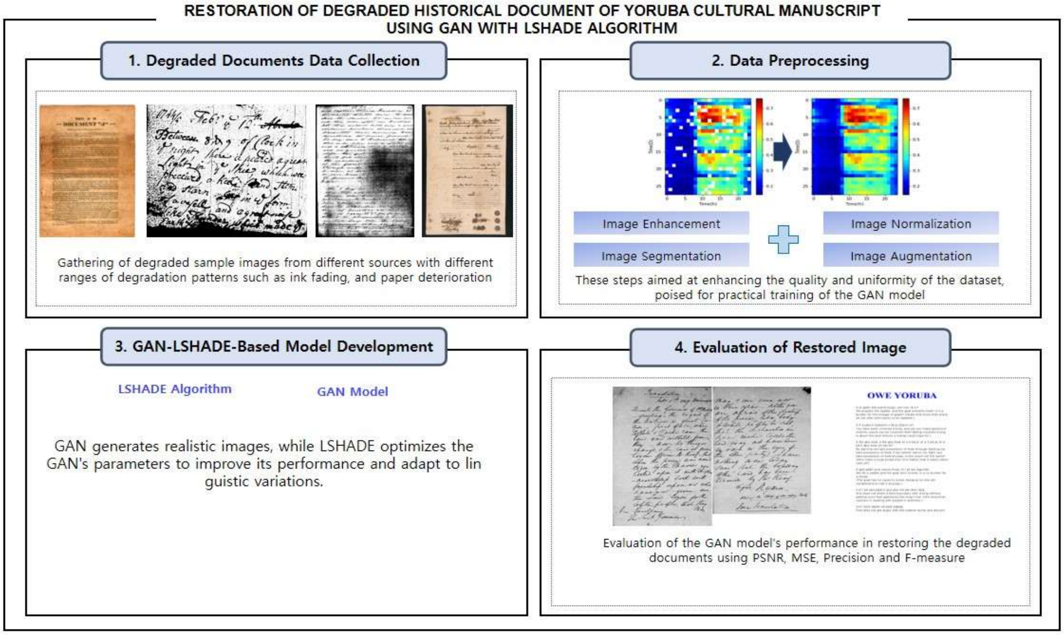


Figure 1: Framework of the research methodology

3.2 Data Collection

The dataset for this study consists of historical manuscripts, literary works, and other written materials in the Yoruba language, characterized by various degradation patterns such as ink fading, paper deterioration, and text smudging. Data collection involved sourcing deteriorated documents from newspaper vendors (Baba Oloyin Newspaper vendor, Along Post office, Opposite CBN Bank, Ilorin,Kwara State), Elders (Alhaji Rasaki ode from Ijomuoro; Baba Olanipekun from Offa, Kwara State), cultural library (University of Ilorin Library) and community person with historical record. High-resolution scanning equipment was employed to digitize these documents, ensuring a comprehensive representation of the variability present in historical artifacts. A total of 50 high-quality scans of significantly deteriorated Yoruba manuscripts and literary works were compiled. These documents have experienced diverse environmental impacts, including moisture exposure, water smears, oil spills, prolonged storage, mutilation, and blurring from analog-to-digital conversion (see Figure 3.2). Sourcing documents from libraries, newspaper vendors, and private collections contributed to a broad representation of degradation patterns.

Although the sample size is relatively small due to the rarity and limited availability of deteriorated historical Yoruba manuscripts, it was intentionally chosen to leverage the capabilities of Generative Adversarial Networks (GANs). GANs are particularly effective in situations with limited data, as they can learn intricate patterns and produce high-quality restorations even from small samples. This dataset, therefore, aligns with the strengths of GANs, highlighting their potential to restore severely degraded documents and their significance in preserving historical artifacts under constrained data conditions. Samples of scanned distorted documents is shown in Figure 2.

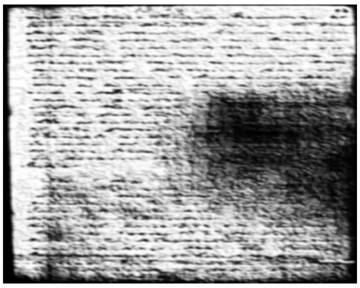
University of Ilorin Library

Elder Olanipekun Nureni

AKEDE EKO.

WOERMANN-LINIE.

Alh razaki Ode, 1991 (Mr Alabi seniyan sulaimon)



Akede Eko Newspaper, 1992

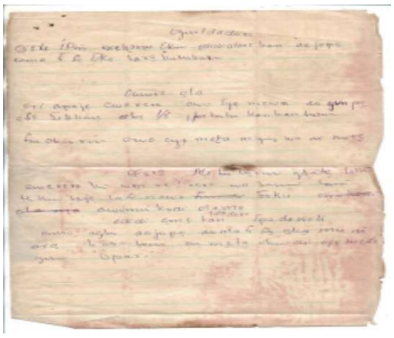
YORUBA RONU' BANNED AGAIN

Daily Times Newspaper in 1995
(Oloyin Newspaper, Ilorin)

E ṣamin adura

Ọdun tuntun yii yoo dara fun wa o!

Alaroye Newspaper, 2000
(Alabi Seniyan Sulaimon)



Elder Abolarin Akanbi (aka. Baba Ile ife)

Figure 2: Samples of scanned distorted documents.

Manuscript received March 5, 2026
Manuscript revised March 20, 2026
https://doi.org/10.22937/IJCSNS.2026.26.3.19

3.3 Data Pre-processing

The collected data underwent preprocessing to ensure its suitability for model training and evaluation. This stage involves a series of steps to enhance the dataset's quality and uniformity.

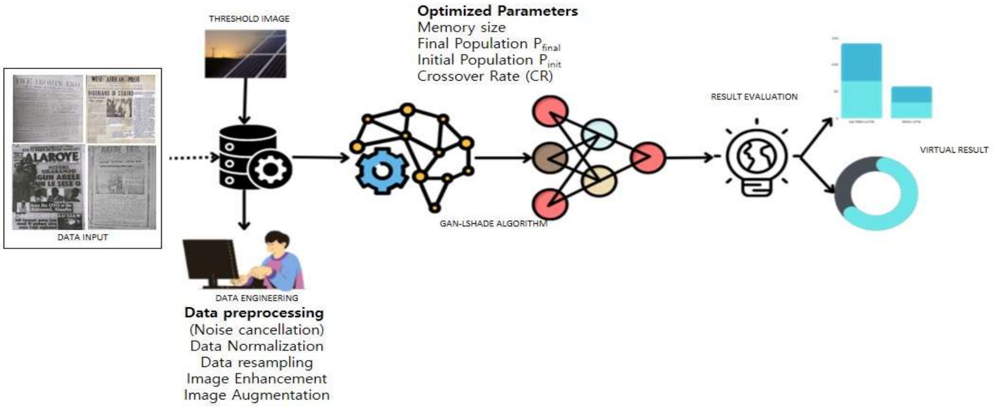


Figure 3: Data Pre-processing

Image Enhancement

Contrast adjustment so that text stands out from the background to enhance the visibility of text by adjusting the image’s brightness increment for dark scans and decreased it for overexposed image. Smoothens the edge, sharpening filters to make text crisper and noise reduction (using Gaussian Blur/Filtering) techniques are applied to enhance the visual clarity of the degraded images. This step aims to mitigate the impact of degradation on the model's ability to learn meaningful features. Images are aligning properly, add captions, and use white space effectively.

Normalization

The pixel values of the images are normalized to a standard range to ensure consistent input for the neural network. This normalization aids in stabilizing the training process and improves the convergence of the GAN model. The normalization of degraded documents is a critical aspect of digital preservation and heritage conservation. That is by combining traditional image enhancement techniques with modern machine learning tools, it's possible to significantly improve the accessibility and usability of historical or deteriorated texts, ensuring that cultural heritage is preserved for future generations (Zhang et al., 2020). One of the key ways in normalizing degraded documents is to remove noise using OpenCV to remove background noise, which could be introduced during scanning or due to physical degradation.

Segmentation

In instances where degradation affects specific regions of the document, Thresholding and edge detection segmentation techniques are employed to isolate the degraded areas. These methods work by identifying boundaries between regions based on pixel intensity or gradient changes. However, in degraded documents, these methods can be challenging due to noise or fading text. This targeted approach facilitates the GAN model in focusing on restoring regions exhibiting degradation. Detects distinct text areas in a document is very useful when text lines are touching or too close.

Augmentation

To augment the dataset and introduce variability, data augmentation techniques such as rotation, flipping, and cropping are applied. Images get rotated correctly to fix tilted text, transformed to correct angled or distorted text and resized to keeps text readable across different sizes. Augmentation enriches the diversity of the dataset, enhancing the model's ability to generalize to different degradation patterns (Doe & Smith, 2021). Here, there is need to simulate a broader range of conditions to help the model to generalize better when restoring text that was affected by various environmental factors such as ink fading, or paper wear.

Manuscript received March 5, 2026
Manuscript revised March 20, 2026
https://doi.org/10.22937/IJCSNS.2026.26.3.19

3.4 GAN Model Architecture

The proposed methodology hinges upon developing a GAN model capable of restoring degraded Yoruba documents. Deep Convolutional Generative Adversarial Networks (DCGANs) is been used because it has shown remarkable potential in restoring degraded historical documents. Their ability to learn and generate high-quality image reconstructions makes them an effective tool for recovering lost details in ancient texts and artwork. DCGANs are advanced type of Generative Adversarial Networks (GANs) that use deep convolutional layers instead of traditional fully connected layers, making them particularly effective for image-related tasks. The generator and discriminator comprise the core components of the GAN, each tailored to address the distinct challenges associated with Yoruba document restoration.

Generator

The generator is responsible for producing high-quality, restored versions of the degraded Yoruba documents. Its architecture combines convolutional layers with attention mechanisms to capture intricate details and recurrent layers to model the linguistic variation of the Yoruba language. Mathematically, the generator can be represented as follows:

$$G(x) = U * conv\big(attention(x)\big) * recurrence(x) \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

where x denotes the input (degraded Yoruba document), U represents the up-sampling operation, $conv(\,)$ refers to the convolutional layer, $attention(\,)$ symbolizes the attention mechanism and $recurrence(\,)$ represents the recurrent layer. The generator's objective is to transform the input image into a visually appealing and linguistically accurate representation.

Discriminator

The discriminator evaluates the authenticity of the restored images yielded by the generator. It assesses the restored documents' linguistic fidelity, visual coherence, and overall quality. The discriminator's architecture is designed to emulate the human perception process, allowing it to differentiate between genuine and synthetic images. Mathematically, the discriminator can be expressed as follows:

$$D(x) = P * conv(x) * pooling(x) \;\ldots\ldots\ldots (2)$$

where x represents either a genuine or synthetic Yoruba document, P stands for probability, $conv(\,)$ denotes the convolutional layer, and $pooling(\,)$ represents the pooling layer. The discriminator's aim is to correctly classify the input images as real or fake.

Training Process

The Generator Network uses transposed convolutional layers to generate enhanced images, incorporates batch normalization and LeakyReLU activation, and inputs a latent vector (or partial image) to generate a restored manuscript. The Discriminator Network uses convolutional layers to classify images as real (original) or fake (generated), learns to detect restoration artifacts and guides the generator to improve on it. Lastly, the Loss Function & Optimization take measure of adversarial loss to ensures the generator produces images indistinguishable from real ones, Mean Squared Error (MSE) loss ensures similarity between restored and original manuscripts and Iterative optimizer adjust parameters incrementally based on gradients for stability.

The GAN model undergoes adversarial training, where the generator and discriminator engage in a continuous loop to improve the quality of the restored images. The training process unfolds as follows:

i. Initialization: Both the generator and discriminator's weights are initialized, marking the beginning of the training process.
ii. Adversarial Training:
    a. The generator produces restored images ($G(x)$).
    b. The discriminator evaluates the authenticity of the generated images ($D\big(G(x)\big)$).
    c. The generator updates its parameters based on the discriminator's feedback, striving to generate images that closely resemble authentic Yoruba documents.
iii. Discriminator Training: The discriminator is trained to distinguish between genuine and synthetic images. It furnishes feedback to the generator, contributing to the latter's improvement.
iv. Iterative Optimization: Steps 2 and 3 are repeatedly performed until a predetermined stopping criterion is reached. During each iteration, both the generator and discriminator refine their abilities, culminating in enhanced restored images.

Hyperparameter tuning, learning rate adjustments and convergence monitoring are critical tasks during the training process. By carefully optimizing these factors, the model's stability, convergence, and susceptibility to problems like mode collapse are assured.

3.5 GAN-LSHADE Algorithm

The integration of GANs with the LSHADE algorithm offers several advantages in the task of historical document restoration. Firstly, GANs can generate highly realistic images, which can help to restore damaged or degraded documents accurately. Additionally, the LSHADE algorithm can optimize the performance of

GANs by adapting the generator and discriminator architectures, as well as the hyperparameters of the model. This will lead to improved restoration quality and increased efficiency in the restoration process.

To optimize the GAN using the LSHADE algorithm, the research minimizes a fitness function represented by Equation (3.3).

$$D(Th) = \frac{1}{N}\sum_{i=1}^{N} \left[\frac{1}{1+e^{-Th_i}}\right] \text{....................}(3)$$

In this equation:

i. $D(Th)$ is the fitness function to be minimized.
ii. N represents the number of elements in the vector Th.
iii. Th_i is the i-th element of the vector Th.

The goal of the LSHADE algorithm is to find the optimal values for the vector Th that minimize this fitness function. This optimization process aims to enhance computational speed and precision in the restoration of historical documents within the GAN framework.

3.6 GAN Fitness Function Definition

In the context of GAN optimization using the LSHADE algorithm, the fitness function ($D(Th)$) measures the disparity or differences between the real and generated data distributions. The specific form of $D(Th)$ varies depending on the GAN's objective. For instance, in a common GAN scenario, where the generator (G) aims to generate synthetic data to mimic the real data distribution, the fitness function can be defined as the Jensen-Shannon divergence (JSD) between the real data distribution (P_{real}) and the generated data distribution (P_{gen}):

$$D(Th) = \text{JSD}(P_{\text{real}}, P_{\text{gen}}) \text{....................}(4)$$

The Jensen-Shannon divergence is often expressed as:

$$\text{JSD}(P_{\text{real}}, P_{\text{gen}}) = \frac{1}{2}\sum_x P_{\text{real}}(x)\log\left(\frac{P_{\text{real}}(x)}{\frac{1}{2}(P_{\text{real}}(x)+P_{\text{gen}}(x))}\right) + \frac{1}{2}\sum_x P_{\text{gen}}(x)\log\left(\frac{P_{\text{gen}}(x)}{\frac{1}{2}(P_{\text{real}}(x)+P_{\text{gen}}(x))}\right). \qquad (5)$$

Here:

i. $P_{\text{real}}(x)$ is the probability density function of the real data at point x.
ii. $P_{\text{gen}}(x)$ is the probability density function of the generated data at point x.

The minimization of this fitness function using the LSHADE algorithm aims to improve the agreement between the real and generated data distributions, ultimately enhancing the performance of the GAN in historical document restoration.

3.7 Algorithm of LSHADE-GAN

The implementation process of the created novel framework LSHADE techniques for efficient optimization of GAN for historical document restoration are outlined in the steps below:

Step I. Input Image Preprocessing:

i. Read the input image (I).
ii. Calculate the image histogram (h).

Step II. LSHADE Initialization:

i. Initialize LSHADE parameters, CR and F.
ii. Create a population (P_G) of NP random individuals with n dimensions.
iii. Evaluate each population member using the objective function $D(Th)$ Equation (6).

Step III. Evolutionary Process:

i. Generate a new population with trial vectors (ui_G) utilizing Fi and CRi values.
ii. Randomly reinitialize any trial vector outside its boundary.
iii. Perform the selection stage for trial vectors (ui_G) and target vectors (xi_G).

Step IV. Adaptive Updates:

i. Update MF and MCR
ii. Adjust the population size

Step V. Segmentation and Iteration:

i. Return to Step II if the stopping criteria are not met.
ii. Generate the segmented image (Ith) using the best individual across all generations.

The integration process of the entire running system, combines the strengths of GANs and LSHADE. The process can be summarized as follows:

i. Initialization: Set the initial parameters for both GAN and LSHADE components.
ii. GAN Training: Leverage GAN's generative capabilities to produce realistic representations of historical documents.
iii. LSHADE Optimization: Dynamically adapt GAN parameters using LSHADE, addressing optimization challenges and enhancing linguistic adaptability.
iv. Feedback Loop: Establish a feedback loop between models, ensuring continuous adaptation and optimization throughout restoration.

The proposed approach leverages the strengths of both models to achieve high-quality restoration results. The GAN generates realistic images, while LSHADE optimizes the GAN's parameters to improve its performance and adapt to linguistic variations. The feedback loop ensures that the system continuously learns and adapts, improving restoration accuracy and efficiency. The flowchart of the GAN-LSHADE algorithm is shown in Figure 4.

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The generator is responsible for producing high-quality, restored versions of the degraded Yoruba documents. Its architecture combines convolutional layers with attention mechanisms to capture intricate details and recurrent layers to model the linguistic variation of the Yoruba language. Mathematically, the generator can be represented as follows:

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where x denotes the input (degraded Yoruba document), U represents the up-sampling operation, $conv(\,)$ refers to the convolutional layer, $attention(\,)$ symbolizes the attention mechanism and $recurrence(\,)$ represents the recurrent layer. The generator's objective is to transform the input image into a visually appealing and linguistically accurate representation.

Discriminator

The discriminator evaluates the authenticity of the restored images yielded by the generator. It assesses the restored documents' linguistic fidelity, visual coherence, and overall quality. The discriminator's architecture is designed to emulate the human perception process, allowing it to differentiate between genuine and synthetic images. Mathematically, the discriminator can be expressed as follows:

$$D(x) = P * conv(x) * pooling(x) \ldots\ldots(7)$$

where x represents either a genuine or synthetic Yoruba document, P stands for probability, $conv(\,)$ denotes the convolutional layer, and $pooling(\,)$ represents the pooling layer. The discriminator's aim is to correctly classify the input images as real or fake.

Training Process

The Generator Network uses transposed convolutional layers to generate enhanced images, incorporates batch normalization and LeakyReLU activation, and inputs a latent vector (or partial image) to generate a restored manuscript. The Discriminator Network uses convolutional layers to classify images as real (original) or fake (generated), learns to detect restoration artifacts and guides the generator to improve on it. Lastly, the Loss Function & Optimization take measure of adversarial loss to ensures the generator produces images indistinguishable from real ones, Mean Squared Error (MSE) loss ensures similarity between restored and original manuscripts and Iterative optimizer adjust parameters incrementally based on gradients for stability.

The GAN model undergoes adversarial training, where the generator and discriminator engage in a continuous loop to improve the quality of the restored images. The training process unfolds as follows:

v. Initialization: Both the generator and discriminator's weights are initialized, marking the beginning of the training process.
vi. Adversarial Training:
    a. The generator produces restored images ($G(x)$).
    b. The discriminator evaluates the authenticity of the generated images ($D\big(G(x)\big)$).
    c. The generator updates its parameters based on the discriminator's feedback, striving to generate images that closely resemble authentic Yoruba documents.
vii. Discriminator Training: The discriminator is trained to distinguish between genuine and synthetic images. It furnishes feedback to the generator, contributing to the latter's improvement.
viii. Iterative Optimization: Steps 2 and 3 are repeatedly performed until a predetermined stopping criterion is reached. During each iteration, both the generator and discriminator refine their abilities, culminating in enhanced restored images.

Hyperparameter tuning, learning rate adjustments and convergence monitoring are critical tasks during the training process. By carefully optimizing these factors, the model's stability, convergence, and susceptibility to problems like mode collapse are assured.

3.6 GAN-LSHADE Algorithm

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To optimize the GAN using the LSHADE algorithm, the research minimizes a fitness function represented by Equation (3.3).

$$D(Th) = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{1}{1+e^{-Th_i}}\right] \ldots\ldots\ldots\ldots\ldots\ldots(8)$$

In this equation:

iv. $D(Th)$ is the fitness function to be minimized.
v. N represents the number of elements in the vector Th.
vi. Th_i is the i-th element of the vector Th.

The goal of the LSHADE algorithm is to find the optimal values for the vector Th that minimize this fitness function. This optimization process aims to enhance computational speed and precision in the restoration of historical documents within the GAN framework.

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In the context of GAN optimization using the LSHADE algorithm, the fitness function ($D(Th)$) measures the disparity or differences between the real and generated data distributions. The specific form of $D(Th)$ varies depending on the GAN's objective. For instance, in a common GAN scenario, where the generator (G) aims to generate synthetic data to mimic the real data distribution, the fitness function can be defined as the Jensen-Shannon divergence (JSD) between the real data distribution (P_{real}) and the generated data distribution (P_{gen}):

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The Jensen-Shannon divergence is often expressed as:

$$\text{JSD}(P_{\text{real}}, P_{\text{gen}}) = \frac{1}{2}\sum_x P_{\text{real}}(x)\log\left(\frac{P_{\text{real}}(x)}{\frac{1}{2}(P_{\text{real}}(x)+P_{\text{gen}}(x))}\right) + \frac{1}{2}\sum_x P_{\text{gen}}(x)\log\left(\frac{P_{\text{gen}}(x)}{\frac{1}{2}(P_{\text{real}}(x)+P_{\text{gen}}(x))}\right).(10)$$

Here:

iii. $P_{\text{real}}(x)$ is the probability density function of the real data at point x.

iv. $P_{\text{gen}}(x)$ is the probability density function of the generated data at point x.

The minimization of this fitness function using the LSHADE algorithm aims to improve the agreement between the real and generated data distributions, ultimately enhancing the performance of the GAN in historical document restoration.

3.7 Algorithm of LSHADE-GAN

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iii. Update MF and MCR

iv. Adjust the population size

Step V. Segmentation and Iteration:

iii. Return to Step II if the stopping criteria are not met.

iv. Generate the segmented image (Ith) using the best individual across all generations.

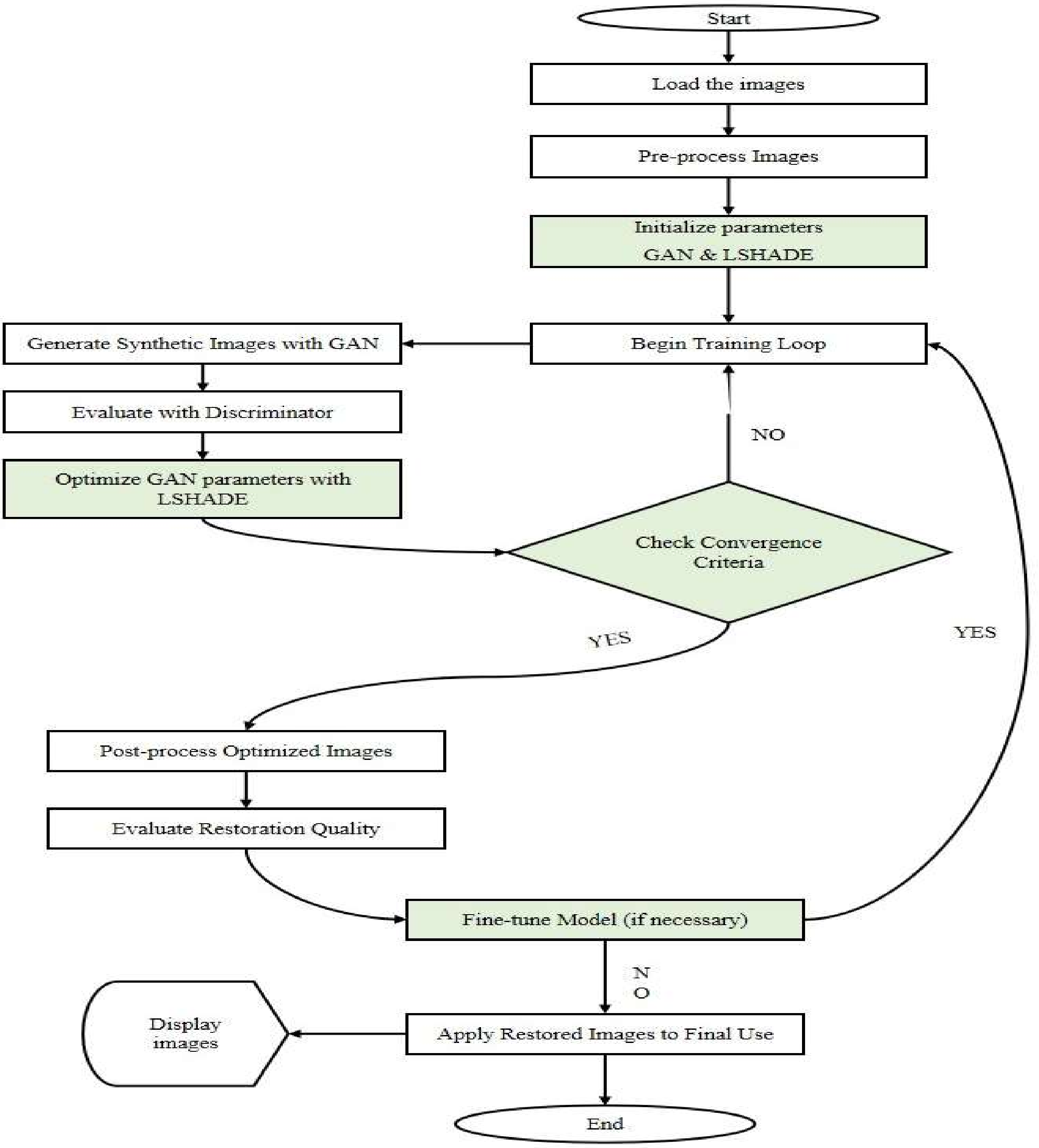
The integration process of the entire running system, combines the strengths of GANs and LSHADE. The process can be summarized as follows:

v. Initialization: Set the initial parameters for both GAN and LSHADE components.

vi. GAN Training: Leverage GAN's generative capabilities to produce realistic representations of historical documents.

vii. LSHADE Optimization: Dynamically adapt GAN parameters using LSHADE, addressing optimization challenges and enhancing linguistic adaptability.

viii. Feedback Loop: Establish a feedback loop between models, ensuring continuous adaptation and optimization throughout restoration.



ix. **Figure 4:** Flowchart of LSHADE-GAN

The proposed approach leverages the strengths of both models to achieve high-quality restoration results. The GAN generates realistic images, while LSHADE optimizes the GAN's parameters to improve its performance and adapt to linguistic variations. The feedback loop ensures that the system continuously learns and adapts, improving restoration accuracy and efficiency. The flowchart of the GAN-LSHADE algorithm is shown in Figure 4.

3.8 Evaluation Metrics

The assessment of the GAN model's performance in restoring degraded Yoruba documents is critical to this research. In this section, we define and discuss the metrics employed to quantitatively evaluate the success of the restoration process, considering both visual fidelity and linguistic accuracy.

i. Peak Signal-to-Noise Ratio (PSNR)

PSNR is a fundamental metric in image quality assessment. It measures the ratio of the maximum possible power of an image to the power of corrupting noise. The PSNR values provide insights into the fidelity of the restored images, with higher values indicating superior restoration quality.

$$\text{PSNR} = 10 \cdot \log_{10}\left(\frac{\text{MAX}^2}{\text{MSE}}\right) \;\ldots\ldots\ldots\ldots\ldots\ldots(7)$$

ii. Mean Squared Error (MSE) is a widely used metric for image restoration tasks. It calculates the average squared difference between the original and restored images, offering a pixel-wise assessment of accuracy.

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N} \left(I_i - \hat{I}_i\right)^2 \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(8)$$

iii. Precision and F-Measure

Precision and F-Measure are classical metrics in binary classification tasks. In the context of image restoration, these metrics are adapted to assess the success of the restoration process, where positive instances represent correctly restored features.

$$\text{Precision (P)} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(9)$$

$$\text{F-Measure (FM)} = \frac{2 \cdot P \cdot R}{P + R} \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots(10)$$

These metrics provide a comprehensive evaluation by combining pixel-wise accuracy assessment (PSNR, MSE) with classification-related metrics (Precision, F-measure) to ensure a thorough understanding of the GAN model's performance in restoring degraded Yoruba documents.

3.9 Data Analysis

The data analysis evaluates the performance of the LSHADE-GAN model in restoring degraded Yoruba historical documents, Figure 2 which represent the collected distorted/degraded Yoruba manuscript trained and the result comparing it with DE-GAN and PSO-GAN through both quantitative and qualitative assessments. Quantitative analysis was conducted using Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE), where LSHADE-GAN achieved a PSNR of 13.25, surpassing DE-GAN (12.97) and PSO-GAN (5.91), and recorded a lower MSE of 0.04 compared to DE-GAN (0.05) and PSO-GAN (0.07), indicating superior restoration accuracy. Qualitative analysis further demonstrated reduced noise, clearer text, and improved readability, ensuring better visual restoration. Additionally, LSHADE-GAN addressed challenges such as unstable training, slow convergence, and sensitive hyperparameters, outperforming existing models by optimizing GAN parameters through LSHADE. The results confirm LSHADE-GAN as a more effective and reliable AI-driven framework for restoring Yoruba historical documents, significantly enhancing text clarity and preservation efforts.

3.10 Ethical Consideration

This research upholds ethical principles by ensuring cultural sensitivity, data privacy, fairness, and transparency in restoring historical Yoruba documents. The study respects the authenticity of these documents, preserving their linguistic and historical integrity without unauthorized modifications. Data sources are obtained from both private and public archives or with appropriate permissions, ensuring compliance with ownership rights. To prevent biases, the AI model is trained on a diverse dataset, maintaining the accuracy of restored texts. Transparency is ensured through proper documentation of methodologies, allowing reproducibility. Additionally, the research strictly focuses on historical restoration, preventing any misuse of GAN technology for unethical purposes. These ethical considerations reinforce the responsible application of AI in cultural heritage preservation.

4. Result

The details of the parameter set, is shown in Table 1.

Table 1: Parameter settings of the metaheuristic's algorithms.

Algorithm	Parameter	Value
L-SHADE	Initial population P_{init}	50
	Final Population P_{final}	40
	Size of memory (H)	5
DE	Crossover Rate (CR)	0.5
	Scale factor (F)	0.2
PSO	Social coefficient c_1	2
	Cognitive coefficient c_2	2
	Velocity clamp	2
	Maximum inertia value (W_{min})	0.2
	Minimum inertia value (W_{max})	0.9

Meanwhile, the interface for preparing a model for training is shown in Figure 5.

The generator architecture consists of a five-layer CNN with 3 × 3 filters in each layer, leveraging batch normalization for improved stability. The activation function in all layers is Leaky ReLU, except for the last layer, which utilizes the tanh function. Mathematically, these functions can be represented as:

$$LkyRlu = max(0.1x, x) \ldots\ldots\ldots\ldots\ldots\ldots\ldots (11)$$

$$tnh = tnh(x) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (12)$$

The discriminator architecture comprises two layers of CNN with 3 × 3 filters, incorporating batch normalization for improved stability. The stride of each layer is set to "2". Similarly, Leaky ReLU is employed in all layers except the last, where the tanh function is used for activation.

4.1 rimental Result for LSHADE-GAN model

This section analyzed the result of the experimental study to evaluate the performance of the LSHADE-GAN method for historical document restoration. Take for example for all scanned documents, the assessment involved computing geometric feature values, namely Precision, F-Measure, MSE, and PSNR. A subset of these results is summarized in Table 2. The experimental findings demonstrate that the LSHADE method exhibits computational efficiency and remarkable performance when integrated with GAN, surpassing DE and PSO methods.

Table 2: Models result

Models	Metrics	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5
DE-GAN	PSNR	6.35	9.15	7.82	12.64	12.97
	MSE	0.23	0.12	0.16	0.05	0.05
	Precision	0.41	0.6	0.51	0.74	0.77
	F-Measure (%)	58.24	75.23	67.66	85.65	87.35
PSO-GAN	PSNR	5.91	8.13	7.22	10.99	11.27
	MSE	0.25	0.15	0.18	0.07	0.07
	Precision	0.34	0.49	0.43	0.63	0.66
	F-Measure (%)	51.67	66.46	61.06	77.52	80.06
LSHADE-GAN	PSNR	6.61	9.54	8.06	12.89	13.25
	MSE	0.21	0.11	0.1	0.05	0.04
	Precision	0.44	0.64	0.55	0.79	0.82
	F-Measure (%)	61.83	78.02	70.47	87.01	88.64

The enhanced historical Yoruba document image obtained through the method is visually represented in Figure 6.

(a) (b) (c) (d)

Figure 6: Qualitative comparison of models results from sample document images. (a) Original. (b) PSO-GAN (c) DE-GAN (d) LSHADE-GAN

(a) (b)

Figure 7. Qualitative comparison of model results on sample scanned documents. (a) Original (b) LSHADE-GAN

4.2 ussion of Results

The experimental results demonstrate the created framework of LSHADE's superior performance compared to alternative approaches, including PSO and DE when used to optimize the architecture of GANs. A thorough analysis of the results revealed several key observations. Firstly, PSO was found to be effective in de-blurring images, but it often introduced background noise. In contrast, DE produced relatively noise-free results but at the cost of blurring effects. The created novel framework of LSHADE method, however, excelled in both de-blurring and de-noising, significantly enhancing pixel resolution. Secondly, integrating GAN architecture played a critical role in improving visual quality. GAN enabled the transformation of complementary information from input to output images without distortion, ensuring an equal distribution of frequencies received from input images. As a result, the restored images exhibited higher color density and optimal intensity variations, as shown in Figure 7. Notably, the GAN-based restoration process preserved text integrity while enhancing overall image quality.

Thirdly, a quantitative analysis of the results revealed that the proposed method generally achieved superior outcomes across various metrics, as shown in Table 7. However, in instances where images featured very dull backgrounds, the algorithm struggled to enhance details, resulting in a loss of image fidelity. Interestingly, DE-GAN outperformed the proposed method in terms of F-measure for sample 2 due to the presence of images with dull backgrounds. Nevertheless, the proposed method's performance was consistently superior across different samples.

Lastly, the primary objective of the proposed method's initial phase is to enhance intensity variations, which increases the PSNR rate. The utilization of GAN architecture further augments intensity rates through complementary information transformation, preserving text integrity and significantly improving image quality without distortion.

4.3 Comparative Analysis of Result

This section thoroughly analyzes and compares the performance outputs of the three models tested on five different samples. The goal is to determine which model excels in restoring degraded historical documents.

(i) Sample 1 of the test image

The performance analysis reveals noticeable differences in image quality improvement and restoration accuracy among the models. DE-GAN achieves a PSNR of 6.35, indicating moderate image quality improvement, with a precision value of 0.41, respectively. PSO-GAN exhibits a PSNR of 5.91, suggesting slightly lower image quality improvement than DE-GAN, with precision value of 0.34, respectively. The proposed LSHADE-GAN model achieves a PSNR of 6.61, with a precision of 0.44. This model maintains competitive precision, implying its effectiveness in restoring degraded documents.

(ii) Sample 2 of the test image

The models show varying performance in image quality improvement and restoration accuracy. DE-GAN achieves a relatively high PSNR of 9.15, indicating a significant enhancement in image quality, with a precision of 0.6, respectively. PSO-GAN has a PSNR of 8.13 but displays slightly lower precision (0.49) than DE-GAN. The proposed LSHADE-GAN model achieves a PSNR of 9.54, with a balanced precision of 0.64, suggesting its effectiveness in restoring details in degraded documents.

(iii) Sample 3 of the test image

An in-depth examination of each model's performance reveals unique features. DE-GAN achieves a PSNR of 7.82, indicating good image quality improvement, with a precision value of 0.51, respectively. PSO-GAN has a lower PSNR of 7.22 but demonstrates slightly higher precision (0.43) than DE-GAN. The proposed LSHADE-GAN model maintains a PSNR of 8.06, with a precision of 0.53. This model showcases balanced precision, implying its effectiveness in accurately restoring details in degraded documents.

(iv) Sample 4 of the model test

The models exhibit substantial disparities in image quality improvement and restoration accuracy. DE-GAN achieves a high PSNR of 12.64, indicating a considerable enhancement in image quality, with a high precision of 0.74, suggesting the accurate restoration of details in degraded documents. PSO-GAN has a PSNR of 10.99 but displays a competitive precision of 0.59 compared to DE-GAN. The proposed LSHADE-GAN model accomplishes the highest PSNR of 12.89, indicating superior image quality improvement. Additionally, it maintains a high precision of 0.79, suggesting accurate restoration of details in degraded documents.

(v) Sample 5 of the model test

The performance of each model presents distinct outcomes. DE-GAN achieves a PSNR of 12.97, indicating significant improvement in image quality, with precision of 0.77, respectively. PSO-GAN demonstrates a lower PSNR of 11.27 but exhibits a slightly lower precision of 0.73 values than DE-GAN. The proposed LSHADE-GAN model showcases the highest PSNR of 13.25, indicating supreme image quality improvement. Additionally, it achieves a

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Manuscript received March 5, 2026
Manuscript revised March 20, 2026
https://doi.org/10.22937/IJCSNS.2026.26.3.19

precision of 0.82, suggesting accurate restoration of details in degraded documents. These results emphasize the effectiveness of the proposed LSHADE-GAN model in historical document restoration tasks, highlighting its potential for practical applications in document preservation and restoration domains. Overall, the results suggest that the proposed model can accurately restore details in degraded documents while maintaining excellent image quality improvement. Peak Signal-to-Noise Ratio (PSNR) performance is shown in Figure 8.

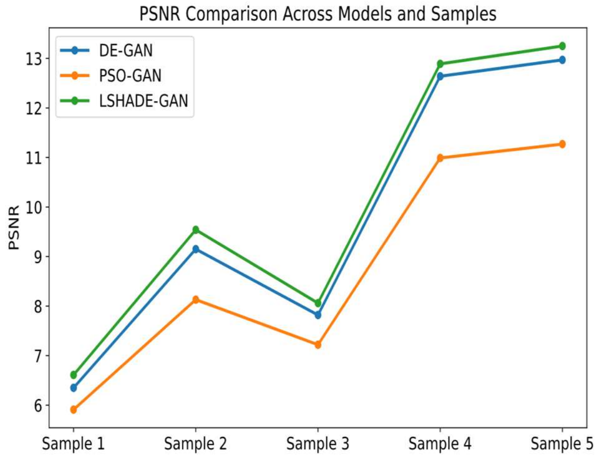

Figure 8: Peak Signal-to-Noise Ratio (PSNR) performance

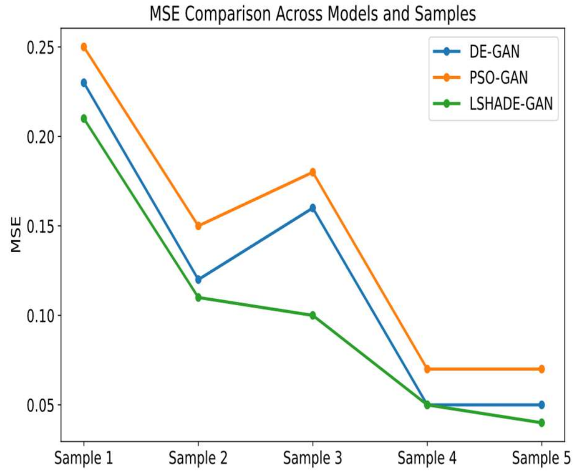

Figure 9: Mean Square of Error (MSE) plot of model

4.4 rpretation of Result

Figure 9 and Figure 10 revealed the Peak Signal-to-Noise Ratio (PSNR) and Mean Square Error (MSE) Plot of Model Performance**.** The plot can be explained as follows:

i. In the u**nderstanding the metrics**: A higher PSNR indicates better image quality (or signal) relative to noise. Thus, in this work PSNR is higher which indicates better image quality for cultural document preservation. The image quality is measured in decibels (dB). It is commonly used to evaluate image reconstruction or compression algorithms. **MSE** measures the average squared difference between the predicted and actual values. However, a lower MSE indicates a better model with minimal error.

ii. **Relationship between PSNR and MSE**: PSNR is inversely related to MSE. As MSE decreases, PSNR increases, implying better performance.

The formula connecting them is: $PSNR = 10 \cdot \log_{10}(MAX^2/MSE)$ where **MAX** is the maximum possible pixel value (e.g., 255 for 8-bit images).

iii. **Main observations from the plot (Figure 9** shows improvement in PSNR (rising) and MSE (declining) as the model progresses through iterations, epochs, or different input data. **Likewise, the plot shown stability in PSNR and MSE, which** indicate model convergence at some values. However, the plot become unstable or fluctuate when PSNR or MSE is large which may indicate overfitting, underfitting, or instability in the training process.

iv. **Performance insights of the proposed method**: Interestingly, **PSNR is high, and MSE is low demonstrating** that the model performed well in terms of accuracy and reconstruction. That is, h**igh PSNR, low MSE** suggests that the model performs well in terms of accuracy and reconstruction. But, **Low PSNR, High MSE** indicates that the model struggles with prediction accuracy, possibly due to issues like insufficient training data or a poor choice of hyperparameters.

v. **Comparison**: comparing the multiple models or configurations, analysis of the model shows that it achieves the best PSNR-MSE balance.

The interpretation is that since the PSNR increases steadily and plateaus while MSE decreases consistently, the model learn well and stabilize in preservation of cultural document.

5. Conclusion

This study presents a novel approach to restoring degraded historical Yoruba documents by developing an optimized GAN model enhanced by the LSHADE algorithm. The integration of LSHADE into the GAN framework represents a significant advancement, leveraging LSHADE’s adaptive optimization capabilities to refine the GAN’s performance by fine-tuning hyperparameters, improving training stability, and enhancing image quality during restoration. The LSHADE-GAN model demonstrated superior performance compared to traditional optimization-based GAN models, such as Differential Evolution GAN (DE-GAN) and Particle Swarm Optimization GAN (PSO-GAN). Experimental results highlighted the effectiveness of the proposed method, with LSHADE-GAN achieving higher Peak Signal-to-Noise Ratio (PSNR) and lower Mean Squared Error (MSE) values, indicating improved restoration accuracy and visual quality. Specifically, the model restored intricate details in severely degraded documents, showcasing its robustness across various degradation types, including ink fading, smudging, and paper deterioration.

This research contributes to the field of cultural heritage preservation by providing a powerful and adaptive tool for restoring historical documents with text clarification. The LSHADE-GAN model addresses the limitations of existing methods, offering a scalable solution that not only restores visual fidelity but also preserves the cultural and linguistic integrity of valuable records. These findings underscore the potential of LSHADE-GAN as a practical application in document restoration, supporting the efforts of historians, conservators, and archivists in safeguarding cultural heritage for future generations. The future work is in the area of digital preservation of artifact of Yoruba cultural heritage.

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