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Hybrid CNN–RNN Framework for Intelligent Image Noise Removal and Quality Enhancement

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إطار هجين *CNN-RNN* قائم على الشبكات العصبية الالتفافية والمتكررة لإزالة ضوضاء الصور بذكاء وتحسين صورتها

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Abstract:
Improving image quality is crucial for accurate analysis and interpretation in applications such as medical imaging, remote sensing, surveillance, and night vision systems. However, images captured in real-world environments often suffer from noise and distortion, reducing their clarity and the accuracy of their analysis. This study proposes a hybrid deep learning model that integrates convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to enhance image quality while minimizing noise and preserving structural details. The proposed model was evaluated using images with varying noise levels and assessed using multiple image quality metrics, including the maximum signal-to-noise ratio (PSNR), structural similarity index (SSIM), mean squared error (MSE), and the learned perceptual image patch similarity index (LPIPS). The experimental results showed significant improvements, with the peak signal-to-noise ratio increasing from 24.85 dB to 33.47 dB and the structural similarity index improving from 0.71 to 0.93, along with substantial reductions in the mean squared error (-73.4%) and the learned perceptual patch similarity index (-66.7%). Statistical analysis confirms the significance of these improvements ($p < 0.001$). Results showed that the model achieved an accuracy of 95.7%, a recall rate of 94.8%, and an F1 score of 93.2%. Furthermore, significant improvements were observed in image quality metrics, including PSNR and SSIM, with overall improvement levels ranging from 40% to 60% compared to conventional noise reduction techniques. These results demonstrate that the proposed hybrid framework, combining convolutional and recurrent neural networks, offers an effective and robust solution for improving image quality in noisy environments. The results also indicate that the convolutional-recurrent neural network hybrid model provides a powerful and efficient solution for improving image quality in complex real-world environments.
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Keywords: Image enhancement; Image quality assessment; Noise reduction; Convolutional neural networks (CNN); Recurrent neural networks (RNN); Hybrid deep learning model; PSNR; SSIM.

الملخص
يُعدّ تحسين جودة الصور أمرًا بالغ الأهمية لتحليلها وتفسيرها بدقة في تطبيقات مثل التصوير الطبي، والاستشعار عن بُعد، وأنظمة المراقبة، وتقنيات الرؤية الليلية. الا ان الصور الملتقطة في البيئات الواقعية غالبا ما تتأثر بوجود الضوضاء والتشوهات، مما يقلل من وضوحها ودقة النتائج المستخلصة منها.
في هذا الإطار تقدم هذه الدراسة نموذجًا هجينًا للتعلم العميق يدمج الشبكات العصبية الالتفافية (RNNs) والشبكات العصبية المتكررة (RNNs) لتحسين جودة الصور مع تقليل التشويش والحفاظ على التفاصيل الهيكلية.
تم اختبار النموذج المقترح باستخدام مجموعة من الصور التي تحتوي على مستويات مختلفة من التشويش، وذلك باستخدام مقاييس متعددة لجودة الصورة، بما في ذلك نسبة الإشارة إلى التشويش القصوى (PSNR)، ومؤشر التشابه البنيوي (SSIM)، ومتوسط مربع الخطأ (MSE)، ومؤشر تشابه رقعة الصورة الإدراكي المُتعلم (LPIPS). أظهرت النتائج التجريبية تحسنا واضحا في اداء النموذج، حيث ارتفعت نسبة الإشارة إلى التشويش القصوى من 24.85 ديسيبل إلى 33.47 ديسيبل، وتحسن مؤشر التشابه البنيوي من 0.71 إلى 0.93، إلى جانب انخفاضات كبيرة في متوسط مربع الخطأ (-73.4%) ومؤشر تشابه الرقعة الإدراكي المُستخلص (-66.7%). ويؤكد التحليل الإحصائي أهمية هذه التحسينات .($p < 0.001$).
وأظهرت النتائج أن النموذج حقق دقة بلغت 95.7%، ومعدل استدعاء 94.8%، ودرجة F1 بلغت 93.2%. علاوة على ذلك، لوحظت تحسينات كبيرة في مقاييس جودة الصورة، بما في ذلك PSNR وSSIM، حيث تراوحت مستويات التحسن الإجمالية من 40% إلى 60% مقارنةً بتقنيات تقليل الضوضاء التقليدية. تُبين هذه النتائج أن الإطار الهجين المقترح، الذي يجمع بين الشبكات العصبية الالتفافية والمتكررة، يُقدم حلاً فعالاً وقوياً لتحسين جودة الصورة في البيئات الواقعية المعقدة.
تشير النتائج إلى أن النموذج الهجين للشبكة العصبية الالتفافية المتكررة يمثل حلاً فعالاً لتحسين جودة الصور في البيئات الواقعية من خلال تحقيق توازن جيد بين تحسين الجودة والحفاظ على التفاصيل.

الكلمات المفتاحية: تحسين الصور؛ تقييم جودة الصور؛ تقليل التشويش؛ الشبكات العصبية الالتفافية (CNNs)؛ الشبكات العصبية المتكررة (RNNs)؛ نموذج التعلم العميق الهجين؛ نسبة الإشارة إلى التشويش (PSNR)؛ مؤشر التشابه الهيكلي (SSIM)

1. Introduction

In many modern applications, particularly in the medical sector, remote sensing, night vision systems, and surveillance systems, image quality is a crucial factor in image analysis and interpretation. Many images acquired in real-world environments suffer from degradation due to sensor limitations, transmission errors, and adverse environmental conditions. Such distortions reduce image quality, negatively affecting the accuracy of subsequent analysis and ultimately compromising the reliability of the findings [1-3].

High-quality imaging is essential for accurate decision-making, diagnosis, monitoring, and automated recognition systems. In medical imaging, poor image quality can obscure critical anatomical details and reduce diagnostic accuracy. Similarly, in surveillance and security systems, degraded images can limit the effectiveness of object detection, tracking, and threat identification. Consequently, improving image quality and reducing noise has become a fundamental research challenge in computer vision and image processing [4, 5].

Driven by the need for reliability and sustainability across engineering, industrial, medical, and security sectors, extensive research has focused on improving image quality and eliminating noise that hinders reliable analysis. With rapid advances in artificial intelligence, deep learning and neural networks have emerged as powerful tools for image enhancement and restoration tasks [6-8]. Unlike traditional filtering techniques that rely on predefined assumptions about noise characteristics, deep learning methods can learn complex noise patterns directly from data, enabling improved detail preservation and superior restoration performance in challenging imaging environments [9, 10].

Recent studies have demonstrated that convolutional neural networks (CNNs) significantly outperform traditional denoising algorithms such as median filtering, Wiener filtering, and wavelet-based techniques by learning hierarchical representations of image features directly from training data [11, 12]. For example, deep convolutional denoising networks have shown remarkable performance in removing Gaussian and mixed noise while preserving structural details and textures in images [5]. Furthermore, advanced deep learning architectures, including residual networks and attention-based models, have been successfully applied to image restoration tasks such as denoising, super-resolution, and image reconstruction [13]

In addition, hybrid deep learning frameworks that combine multiple neural network architectures have attracted growing attention due to their ability to capture both spatial and contextual information in image data. Integrating convolutional neural networks with recurrent neural networks (RNNs) enables models to exploit spatial feature extraction together with sequential or contextual dependencies, leading to improved performance in complex image processing tasks [8, 14]. Such hybrid approaches are increasingly being explored in applications including medical image analysis, remote sensing image enhancement, and intelligent visual monitoring systems.

This study focuses on the development of a hybrid model that combines convolutional neural networks (CNNs), which are highly effective at extracting spatial features from visual data, with recurrent neural networks (RNNs), which capture contextual dependencies and sequential relationships. This integration enables enhanced noise suppression while preserving structural details and fine textures.

Despite the progress achieved in deep learning–based denoising, many CNN-based approaches exhibit limited adaptability to diverse and mixed noise distributions encountered in real-world scenarios [15]. Addressing this limitation often requires hybrid strategies that combine complementary learning mechanisms to improve robustness and performance. Furthermore, practical deployment of advanced denoising models requires computational efficiency and reliability for real-time and large-scale applications.

This work presents an intelligent hybrid CNN–RNN framework designed to remove diverse noise types while preserving edge details and structural integrity in digital images. The proposed approach enhances image quality under mixed and high-density noise conditions commonly encountered in medical imaging, surveillance, and remote sensing applications. By integrating CNN-based spatial feature extraction with RNN-based contextual learning, the model improves adaptability to complex noise distributions and overcomes limitations of conventional CNN-only denoising methods. Model performance is evaluated using objective image quality metrics (PSNR, SSIM, and MSE) and classification indicators including accuracy, recall, and F1-score, and is compared with traditional filtering techniques and single-network approaches to quantify improvement. Furthermore, the framework is designed for computational efficiency and practical deployment, and the experimental results demonstrate significant enhancements in image quality and reliability, supporting its suitability for critical real-world imaging applications.

2. Theoretical Framework and Basic Concepts

This section presents the theoretical foundation of the study by explaining the core concepts and reviewing relevant approaches related to image quality enhancement and noise removal. The objective is to support the development of a hybrid artificial intelligence model capable of improving image quality while preserving edge details and eliminating various types of noise. The section outlines the conceptual framework underlying hybrid neural network design, clarifies key terminology, and discusses challenges associated with model development and neural network selection. Because each neural network architecture has specific operational requirements, factors such as accuracy, computational cost, processing time, scalability, and ease of implementation must be considered when selecting an appropriate technique.

Establishing a clear theoretical framework is essential for understanding how hybrid deep learning models integrate multiple learning mechanisms to address complex image degradation problems. This framework provides the foundation for selecting suitable architectures, defining performance criteria, and ensuring the reliability of the enhancement process across diverse application environments.

In addition, the design of intelligent image enhancement systems must consider practical constraints such as hardware limitations, processing speed, and adaptability to real-time applications. Addressing these constraints ensures that the proposed model is not only accurate but also suitable for deployment in operational environments.

2.1 Key Concepts

This subsection introduces essential concepts that support understanding of the study's methodology, significance, and outcomes. Clarifying these concepts provides readers with the necessary background to interpret the proposed hybrid model and evaluate its performance.

Understanding these foundational concepts helps bridge the gap between traditional image processing techniques and modern deep learning approaches, enabling readers from both technical and interdisciplinary backgrounds to fully comprehend the study's contributions.

1. **Image Quality Enhancement**

Image quality enhancement refers to the process of removing noise and distortions that degrade visual information. Such distortions may arise from imaging equipment limitations, environmental conditions during acquisition, or errors introduced during transmission and storage. Traditional enhancement methods rely on linear and non-linear filtering techniques based on mathematical modeling and predefined assumptions about noise characteristics [16]. While effective in controlled conditions, these approaches often struggle to preserve fine details and structural information when images contain complex or mixed noise.

Image enhancement plays a vital role in improving visual clarity, restoring lost details, and increasing the reliability of automated analysis systems. Enhanced images enable more accurate feature extraction, object recognition, and diagnostic interpretation, particularly in critical applications such as medical imaging and security monitoring. Modern image enhancement techniques aim not only to remove noise but also to preserve edges, textures, and structural integrity, which are essential for maintaining the informational content of an image. Achieving this balance between noise suppression and detail preservation remains a fundamental challenge in image processing research.

Common types of noise affecting digital images include:

• **Gaussian noise:** Common in digital sensors due to thermal fluctuations and electronic instability, resulting in random variations in pixel intensity that reduce image clarity [17].

• **Salt-and-pepper noise:** Appears as randomly distributed black and white pixels caused by sensor malfunction, faulty memory elements, or transmission errors, often leading to loss of edge information and fine details [18].
• **Speckle (spectrum) noise:** Frequently observed in radar, ultrasound, and medical imaging, this noise is caused by signal interference and wave interactions, producing a granular appearance that degrades contrast and detail visibility [19].
• **Mixed noise:** A combination of multiple noise types (e.g., Gaussian and impulse noise) occurring simultaneously, which makes removal more challenging and requires advanced processing techniques due to differing statistical characteristics.

The presence of mixed noise significantly increases restoration complexity because different noise components follow distinct statistical distributions and may overlap within the same image regions. As a result, advanced intelligent or hybrid models are often required to accurately detect and suppress multiple noise patterns simultaneously while preserving important structural details. **Figure 1** illustrates representative examples of these common noise types in digital images.

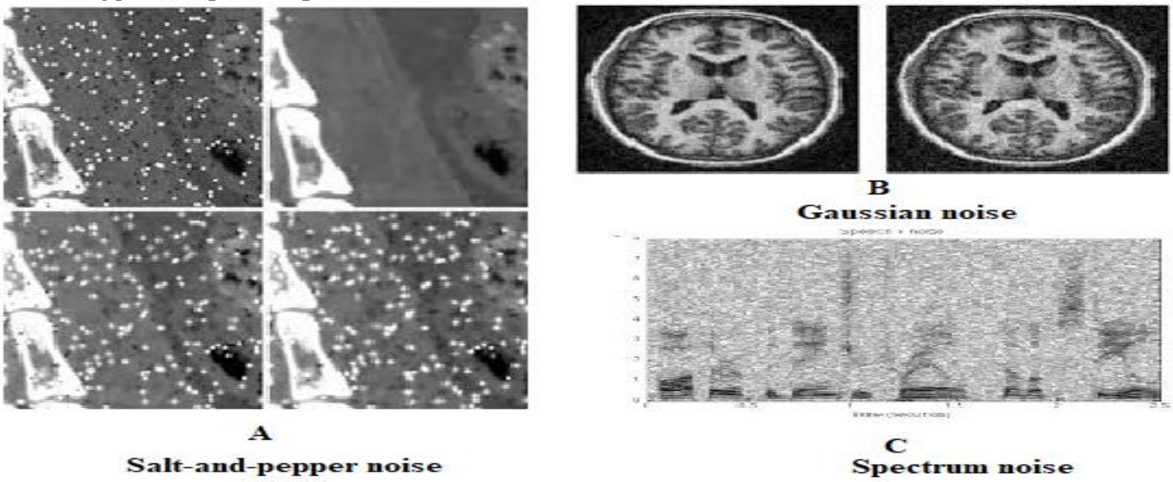

Figure 1. Examples of common noise types in digital images.

2. Traditional Noise Reduction Techniques

Traditional noise reduction techniques rely on predefined mathematical filters designed to smooth images and suppress unwanted variations. These methods are widely used due to their simplicity, low computational cost, and ease of implementation. Common methods include mean, median, Gaussian, and Wiener filters. These approaches are simple to implement and computationally efficient; however, they are typically designed to address specific noise types and may degrade image details when applied to complex or mixed noise conditions [20].

Among the most widely used traditional denoising techniques are:

• **Mean filter:** Replaces each pixel value with the average of its neighboring pixels. While effective in reducing minor noise, it often causes edge blurring and loss of fine details.
• **Median filter:** Replaces each pixel value with the median of neighboring values. It is particularly effective for removing impulse (salt-and-pepper) noise and preserves edges better than the mean filter, although its performance decreases under heavy noise conditions.
• **Gaussian filter:** Smooth's images by reducing rapid intensity variations using a weighted averaging approach. Although effective for Gaussian noise, it may blur important features and subtle textures.
• **Wiener filter:** An adaptive statistical filter that minimizes mean square error by adjusting to local image and noise characteristics, making it suitable when noise statistics are partially known.
• **Adaptive filters:** These filters adjust their parameters based on local image content to improve noise suppression performance. While more effective than static filters, they remain limited when processing complex scenes or mixed noise environments.
• **Frequency-domain filtering:** Techniques based on Fourier or wavelet transforms remove noise by suppressing unwanted frequency components. These methods are effective for periodic noise removal, but they are sensitive to threshold selection and may introduce artifacts or distortions.

3. Artificial Neural Networks

Artificial neural networks (ANNs) are among the most important artificial intelligence tools used in image processing and analysis. They belong to the field of deep learning, a subdomain of artificial intelligence that enables systems to learn patterns directly from data. Inspired by the structure and function of biological neurons, neural networks consist of interconnected layers that process information and learn complex relationships through training. These models are characterized by high processing speed, accuracy, and the ability to analyze large volumes of data efficiently. The primary objective of neural network technologies is to train models using real datasets to perform tasks such as analysis, prediction, classification, and interpretation. Once trained, these models can be deployed to perform automated decision-making and pattern recognition tasks [21]. Neural networks are particularly effective in detecting anomalies, identifying patterns, and restoring degraded image features due to their ability to learn hierarchical representations from raw data.

There are several types of neural networks, each designed to handle specific data characteristics. For example, recurrent neural networks (RNNs) are well suited for sequential and time-dependent data, while convolutional neural networks (CNNs) are highly effective for visual data processing.

Among the most important neural network architectures used in image enhancement are:

• **Convolutional Neural Networks (CNNs):** These networks use convolutional layers to extract spatial features such as edges, textures, and patterns. They are widely used in image denoising and restoration because of their superior ability to distinguish between noise and meaningful image structures [22].

• **Recurrent Neural Networks (RNNs):** These networks process sequential and contextual information by maintaining internal memory states. They are useful for capturing contextual dependencies and refining image restoration results [23].

• **Residual Networks (ResNets):** These architectures learn the residual (difference) between degraded and clean images rather than reconstructing the entire image. This approach reduces gradient vanishing problems and helps preserve fine structural details, making them effective for high-noise environments.

• **Attention-based and Dense Networks:** These models focus on important regions and features within an image while reducing attention to irrelevant areas. Attention mechanisms improve feature representation and enhance restoration quality, particularly in medical and radar imaging applications [24].

• **Hybrid Neural Networks:** These networks combine multiple architectures (e.g., CNN with residual, attention, or multi-scale structures) to improve performance. Hybrid approaches provide enhanced robustness and adaptability in complex and mixed-noise environments and represent a growing trend in modern image enhancement research.

By leveraging complementary strengths of different architectures, hybrid neural networks can achieve superior noise suppression while preserving critical structural and texture information.

Figure 2 illustrates the conceptual architecture of convolutional and recurrent neural networks used in image enhancement.

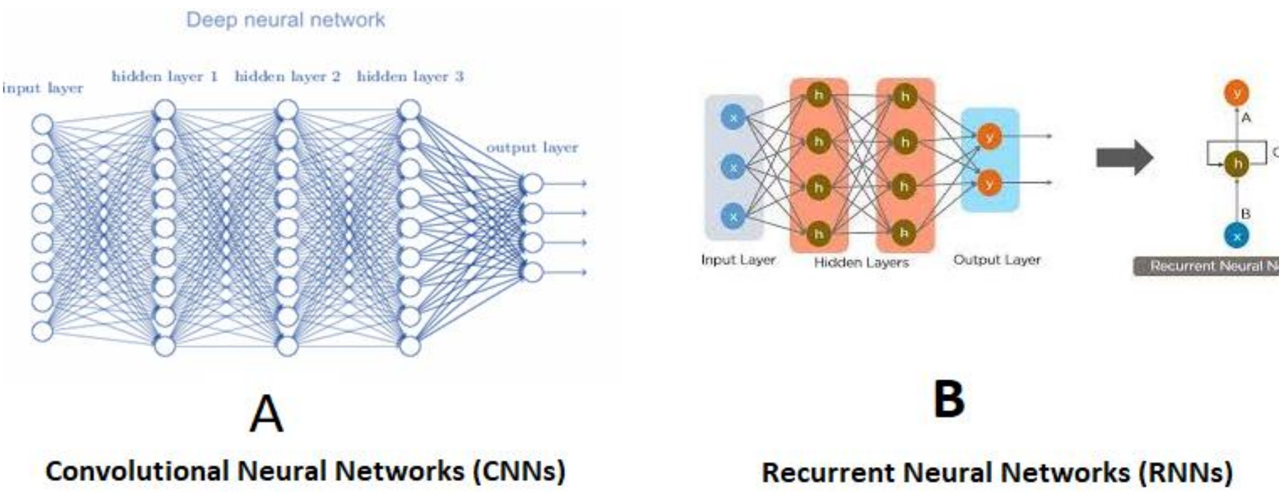

Figure 2. Schematic conceptual architecture of convolutional neural networks (CNNs) and recurrent neural networks (RNNs).

4. Image Quality Assessment and Model Evaluation Metrics

Image quality assessment metrics are used to evaluate the effectiveness of noise removal and the preservation of structural details. These metrics provide quantitative measures that enable objective comparison between enhancement methods and model performance [25].

1) Image Quality Assessment Metrics

The most used metrics include:

• **PSNR (Peak Signal-to-Noise Ratio):** Measures the ratio between the maximum possible signal power and the noise affecting image quality. Higher PSNR values indicate better reconstruction quality.

• **MSE (Mean Squared Error):** Measures the average squared difference between the original and enhanced images. Lower MSE values indicate greater similarity and improved restoration accuracy.

• **SSIM (Structural Similarity Index):** Evaluates structural similarity by comparing luminance, contrast, and texture. It is widely used because it aligns well with human visual perception.

• **FSIM (Feature Similarity Index):** Compares important image features such as edges and phase congruency. It provides a more perceptually meaningful evaluation for detail-rich images, although it is less commonly used.
• **LPIPS (Learned Perceptual Image Patch Similarity):** A modern deep learning–based metric that measures perceptual similarity using features extracted from pre-trained neural networks. It reflects human visual perception and is particularly useful for evaluating deep learning restoration results.
• **Visual Assessment:** A qualitative comparison of images before and after enhancement. Although subjective, it remains important for verifying perceptual quality and detecting artifacts not captured by numerical metrics.

2) Neural Network Model Performance Metrics

To evaluate the effectiveness of the proposed neural network model, classification and prediction performance metrics are also used:
• **Accuracy:** Measures the overall proportion of correct predictions.
• **Precision:** Measures the proportion of correctly predicted positive cases among all predicted positives. It is especially important when false positives carry high costs.
• **Recall (Sensitivity):** Measures the ability of the model to correctly identify true positive cases. This metric is critical in medical and security applications where missing a positive case is costly.
• **F1-score:** The harmonic meaning of precision and recall. It provides a balanced evaluation when class distributions are uneven.
• **Confusion Matrix:** Provides a detailed breakdown of prediction outcomes, allowing analysis of true positives, false positives, true negatives, and false negatives. It helps identify error patterns and model weaknesses.
Together, these evaluation metrics provide a comprehensive assessment of both visual enhancement quality and model performance, ensuring reliable and objective validation of the proposed hybrid framework. **Figure 3** illustrates the image quality assessment metrics and neural network performance evaluation measures used in this study.

Figure 3. Evaluation metrics for image quality assessment and neural network model performance.

- **Relation classification and denoising**

This connection between classification and denoising has been established in Section
The model enhances images as its primary objective, but it uses classification-based metrics such as accuracy, recall, and F1-score for secondary evaluation purposes to gauge its prediction power and reliability. This combination of approaches does not represent a new classification problem but serves as an additional layer of performance assessment

2.2. Related work

Hyper parameter optimization and hybrid deep architectures design are becoming critical factors in image denoising models of the last decade. Spatial feature learning was performed using convolutional neural networks (CNNs), where they helped to find efficient ways of edge, texture, and noise pattern recognition, leading to significant improvements compared to the traditional models. However, the convergence of CNN-based models is very sensitive to hyper parameters such as learning rate, batch size, and number of layers. Recent trends show that hybrid models based on recurrent neural networks (RNNs) such as Long Short-Term Memory (LSTM) cells have become important due to their ability to refine context by analyzing feature dependencies in representations. Indeed, CNN-LSTM encoder-decoder architectures proved to perform well in terms of reconstructing images affected by severe corruption due to the use of spatial and sequential feature learning techniques[18]. Moreover, research using LSTM-based optimization methods has demonstrated that RNN can enhance learning speed as well as denoising accuracy through the use of their memory mechanisms in the process of optimization. The method of feature fusion has also been extensively applied in order to combine features acquired from the CNN model with contextual features produced by the RNN model, enhancing robustness in denoising performance even when noise is very complicated. Although many innovations have been made to optimize RNN-based denoising systems, some studies remain unclear on how the role of RNN in the system works or omit important details on hyper parameters configuration [25].

3. Methodology and Methods (Applied Framework)

This study adopts a descriptive, analytical, and procedural methodology through the design and implementation of a hybrid model integrating convolutional neural networks (CNNs) and recurrent neural networks (RNNs) for image enhancement. The methodological approach combines quantitative analysis for performance evaluation with a comparative framework to assess image quality before and after enhancement. This integrated approach enables objective measurement of noise reduction effectiveness and structural detail preservation.

In this paper, a structured deep learning-based approach is proposed to develop and validate a hybrid CNN-RNN architecture for image denoising and improvement. This work concentrates on enhancing the quality of the images through noise removal.

3.1 Applied Framework of the Study

The applied framework defines the procedural steps followed in this study, beginning with identifying the research objective and formulating the problem statement. The process then includes data collection from diverse image sources, followed by preprocessing procedures such as filtering, normalization, and removal of irrelevant or corrupted data.

Subsequently, the hybrid CNN–RNN model is designed and implemented. The model is trained to learn noise characteristics and reconstruct clean images while preserving structural details. After training, performance evaluation is conducted using quantitative metrics, including accuracy, recall, F1-score, and standard image quality assessment measures.

Finally, comparative analyses are performed between original and enhanced images to assess improvement in visual quality and restoration accuracy. This structured framework ensures systematic validation of the proposed hybrid model and supports reproducibility of the experimental results. **Figure 4** illustrates the applied framework of the study, showing the main stages of data collection, preprocessing, hybrid model development, and performance evaluation.

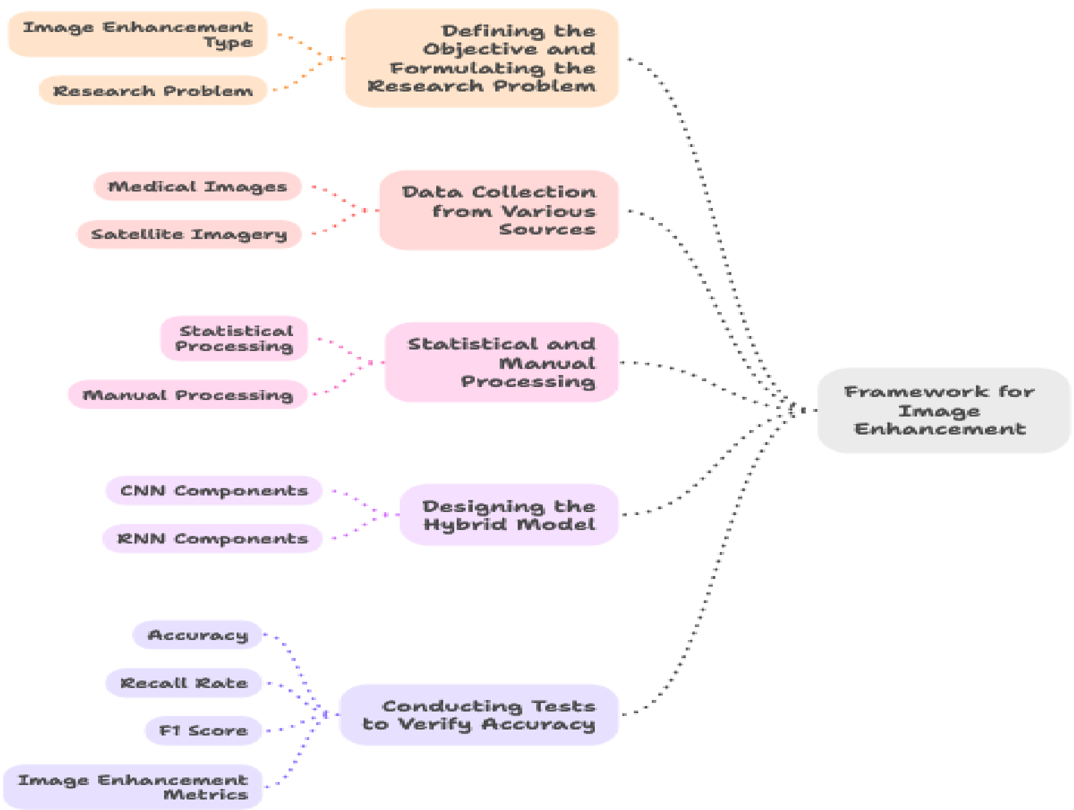

Figure 4. Applied framework of the study illustrating methodology and processing stages.

3.2 Procedures

This subsection describes the practical procedures followed in this study to develop and evaluate the proposed hybrid image enhancement model. The main steps are summarized as follows:

1. **Defining the objective and formulating the research problem:**

The objective of this study was to develop a hybrid deep learning model capable of improving image quality while effectively removing noise and preserving important structural details. The research problem focused on selecting appropriate neural network architectures that can provide accurate image restoration under different noise conditions. The study therefore investigates the integration of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to achieve improved denoising performance and image reconstruction accuracy [26].

2. Data collection and processing:

Data were collected from multiple sources, including previous studies, books, online databases, and expert opinions.

1) Dataset

Image processing has been done before feeding into the training phase with the use of the following procedures:

- Normalization of pixel values
- Deletion of faulty samples
- Resizing the size of all images to a uniform size
- Data augmentation through rotation, flipping, and scaling

2) Database

Database segregation for training has been done based on the following proportion:

- 70% for training
- 15% for validation
- 15% for testing

3) **Data processing**

The pooled images underwent initial processing that included data standardization, removal of damaged samples, and exclusion of outliers. Data validation was performed manually and statistically, and the reliability of the dataset was verified using analysis of variance (ANOVA) to ensure consistency of the training data [27].

2. Design of the hybrid neural network model:

The hybrid model was designed by combining convolutional neural networks (CNNs) and recurrent neural networks (RNNs). CNNs were selected because of their strong capability in extracting spatial features such as edges and textures from images, while RNNs were incorporated to capture contextual relationships and refine feature representations during the restoration process. The integration of these two pieces of architecture enables improved noise suppression while preserving important structural information in enhanced images. Figure 5 shows the proposed hybrid CNN–RNN model used for image enhancement and noise removal.

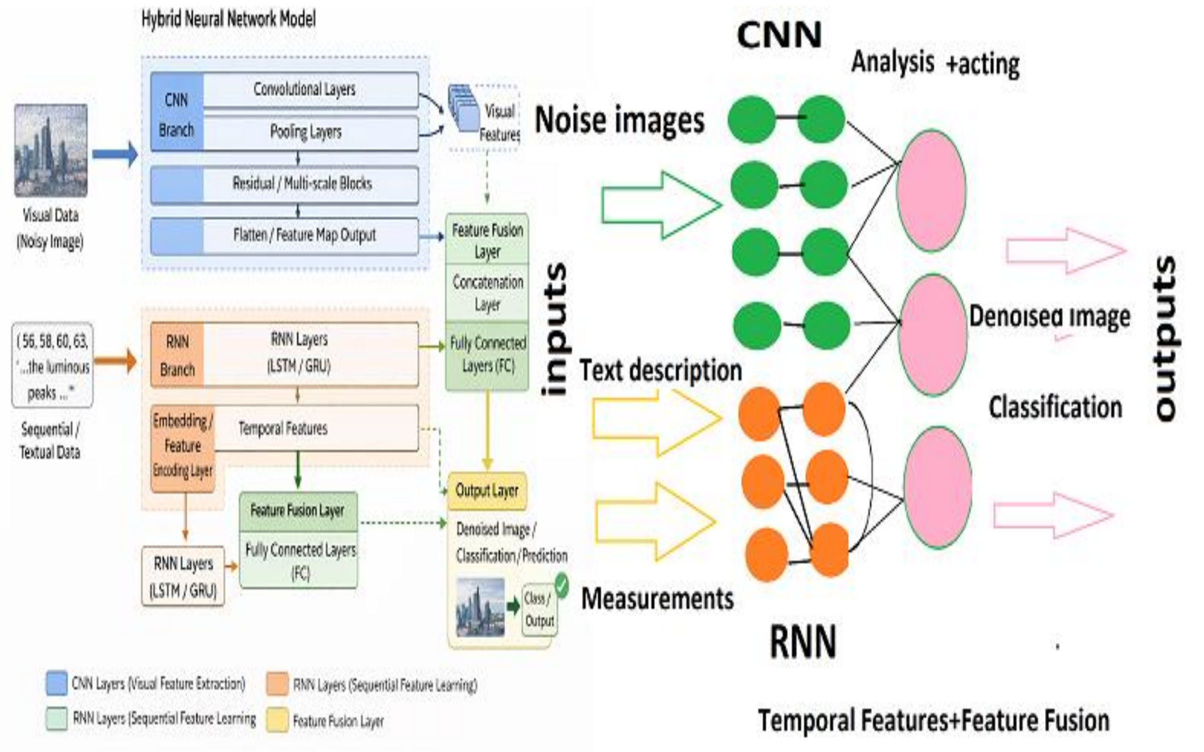

Figure 5. Proposed hybrid CNN–RNN model architecture for image enhancement and noise removal.

1) Proposed Hybrid CNN–RNN Architecture

The proposed model integrates convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to leverage both spatial and contextual feature learning.

- CNN Component (Spatial Feature Extraction)

The CNN module is responsible for extracting spatial features from input images. It consists of multiple convolutional layers followed by activation functions and pooling operations. These layers capture:

  - edges
  - textures
  - noise patterns

2) RNN Component (Feature Refinement)

The RNN component is used to refine the extracted feature maps by modeling dependencies between features. Instead of processing textual data, the RNN operates on flattened or sequential feature representations derived from CNN outputs. Long Short-Term Memory (LSTM) units are used to:

- capture contextual relationships
- enhance feature continuity
- improve reconstruction quality
- Feature Fusion

The outputs of the CNN and RNN components are combined using a feature fusion layer. This integration allows the model to benefit from both spatial and contextual information.

3) Output Layer

The final layer reconstructs the enhanced image with reduced noise and improved structural quality

4. Mathematical modeling

1) **Conversion of text data into a numerical vector**

Textual or sequential data associated with the image must first be converted into a numerical representation before being processed by neural networks. In this step, the input sentence is divided into individual words, and each word is assigned to a unique numerical index. The frequency of each word is then counted to create a one-dimensional vector representation suitable for neural network processing.

For example, the sentence:

“Convert Texts to Arrays Quickly”

can be represented using one-hot encoding. For instance, the word with index 5 can be represented as:

$$[0, 0, 0, 0, 1]$$

This vector representation allows textual information to be used as input for fully connected neural network layers.

2) Neural Network Weight Matrices and Hidden Layers

The transformation from the input layer to the first hidden layer is defined as:

$$h_1 = \sigma(W_1 \cdot x + b_1) \qquad (1)$$

Where:

- W_1: Weight matrix between the input layer and the first hidden layer
- b_1: Bias vector of the first hidden layer
- x: Input feature vector.
- σ: Activation function (sigmoid).

From the first hidden layer to the second hidden layer:

$$h_2 = \sigma(W_2 \cdot h_1 + b_2) \qquad (2)$$

Where:

- W_2: Weight matrix between the first and second hidden layers.
- b_2: Bias vector of the second hidden layer
- From the second hidden layer to the output layer:

$$o = W_3 \cdot h_2 + b_3 \qquad (3)$$

Where:

- W_3: Weight matrix between the second hidden layer and the output layer.
- b_3: Bias vector of the output layer

3) Loss Function

The loss function used during training is defined as:

$$L = \frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2 \qquad (4)$$

Where:

- m: Number of training samples.
- y_i: True value
- yˆ_i: Predicted value

4) LSTM Recurrent Network Equations

$$i_t = \sigma(W_i h_{t-1} + U_i x_t + b_i) \quad (5)$$

Where:

- i_t: Input gate activation at time step t
- W_i, U_i, b_i: Weight matrices and bias parameters
- h_{t-1}: Hidden state from the previous time step.
- x_t: Current input.

5) Forget Gate

$$f_t = \sigma(W_f h_{t-1} + U_f x_t + b_f) \quad (6)$$

Where:

- f_t: Forget gate activation

6) Candidate Cell State

$$\widetilde{C}_t = \tanh\,(W_c h_{t-1} + U_c x_t + b_c) \quad (7)$$

7) Cell State Update

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad (8)$$

Where:

- C_t: Cell state at time step t
- $\odot$: Element-wise multiplication.

8) Output Gate

$$o_t = \sigma(W_o h_{t-1} + U_o x_t + b_o) \quad (9)$$

Where:

- o_t: Output gate activation at time step t.

9) Hidden State

$$h_t = o_t \odot \tanh\,(C_t) \quad (10)$$

Where:

- h_t: Hidden state at time step t

10) Fully Connected Layer

After feature extraction, the model processes the features using a dense layer:

$$Z = \sigma(Wh + b) \quad (11)$$

Where:

- Z: Output of the dense layer.
- W: Weight matrix.
- h: Input feature vector (combined CNN and LSTM features).
- b: Bias vector.

11) Hybrid Model Feature Integration

The outputs from both neural network branches are combined as:

$$h_{combined} = [h_{cnn}, h_{lstm}] \quad (12)$$

Where:

- h_{cnn}: Flattened output from the CNN branch.
- h_{lstm}: Output from the LSTM branch.

12) Final Output Layer

The final prediction layer defined as:

$$\hat{y} = \text{softmax}(W_{final} h_{combined} + b_{final}) \quad (13)$$

Where:

- W_{final}: Weight matrix of the final output layer.
- b_{final}: Bias term.

5. Model Training and Testing

After defining the mathematical model, the hybrid CNN–RNN network is trained using the prepared dataset to learn the relationships between noisy images and their enhanced representations. During the training stage, optimization algorithms are applied to minimize the loss function and improve prediction accuracy.

- Model Training Setup

Training was done with the use of the following configuration:

- Learning rate: 0.001
- Batch Size: 32
- Number of Epochs: 50

- Loss Function: Mean Squared Error (MSE)
- Early stopping and validation were employed to avoid overfitting.

- Metrics Used

The performance of the suggested model was measured using common image quality metrics:

- PSNR: Peak Signal to Noise Ratio
- SSIM: Structural Similarity Index
- MSE: Mean Squared Error
- LPIPS: Perceptual similarity metric

6. Conducting Tests

Model evaluation is conducted through several performance tests, including:

• Accuracy evaluation
• Recall rate analysis
• F1-score calculation

In addition, image quality improvement tests are performed to evaluate the effectiveness of the proposed model in reducing noise and enhancing visual clarity.

7. Recording and Evaluating Results

Finally, the experimental results are recorded, analyzed, and evaluated to:

• Assess the effectiveness of the proposed hybrid model
• Compare the enhanced images with the original noisy images
• Draw conclusions and provide recommendations for future research

3.3 Statistical Analysis

For statistical analysis, several statistical tests are conducted to evaluate the reliability and significance of the experimental results.

1) Paired t-Test

This test is used to compare two related datasets, such as image results before and after enhancement [18].

$$T = \frac{d}{s_d/\sqrt{n}} \qquad (14)$$

Where:

- d: Average difference between paired measurements
- s_d: Standard deviation of the differences.
- n: Number of samples

2) ANOVA (Analysis of Variance)

ANOVA is used to determine whether the differences between multiple model results are statistically significant.

$$MS_{within} = \frac{SS}{N-k} \qquad (15)$$

Where:

- k: Number of models
- N: Number of samples.

3) Standard Deviation.

Standard deviation measures the stability and variability of the model results.

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2} \qquad (16)$$

4) Pearson Correlation Coefficient.

The Pearson correlation coefficient measures the relationship between the model outputs and the reference values [28].

$$R = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2}\sqrt{\sum(y_i - \bar{y})^2}} \qquad (17)$$

Where:

- R: Pearson correlation coefficient.
- x_i: Pixel values of the original image
- y_i: Pixel values of the processed image.
- $\bar{x}$: Mean value of the reference image.
- $\bar{y}$: Mean value of the processed image.

Results and discussion

4. Results and Discussion

This section presents the experimental results obtained from testing the proposed hybrid CNN–RNN model. The model performance is evaluated using several classification performance metrics, including accuracy, recall, F1-score, and the receiver operating characteristic–area under the curve (ROC–AUC) index. In addition, image quality evaluation metrics are analyzed to assess the effectiveness of the proposed model in enhancing image quality and reducing noise. The results obtained are also compared with the original images to determine the improvement achieved by the proposed framework.

4.1 Model Test Results

This section will display the model testing results in terms of accuracy, including recall rate, F1 score, and ROC index, as well as quality metric tests for images and a comparison with the improved results.

Table 1 presents the performance indicators used to evaluate the effectiveness of the proposed hybrid model.

Table 1. Model testing indicators

Index	Value%	p-value	f
Accuracy	95.70%	4	
Recall	94.80%		
F1-Score	93.20%	<0.001	33.5
ROC-AUC Score	94.1.2%		

Table1 shows the evaluation results of the proposed model based on several performance metrics, including accuracy, recall rate, F1-score, and ROC–AUC score. The results indicate high performance across all evaluation metrics, with values ranging between 93% and 96%, which demonstrates the effectiveness and reliability of the proposed hybrid CNN–RNN model.

The p-value is less than 0.001, indicating that the obtained results are statistically significant and that the model performance is unlikely to be due to random variation. Furthermore, the F-statistic value of 33.5 suggests the presence of statistically significant differences between the evaluated datasets or experimental conditions, confirming the robustness of the proposed model.

Overall, these results demonstrate that the hybrid CNN–RNN model provides strong predictive capability and reliable performance in image enhancement and noise reduction tasks.

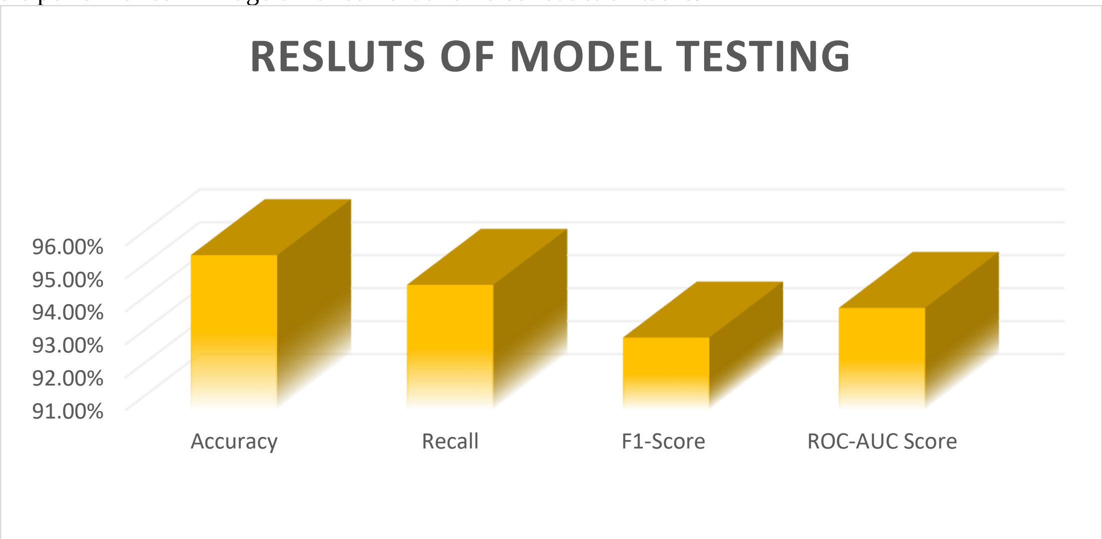

Figure 6. Model testing indicators

Figure 6 illustrates the confusion matrix heat map of the proposed model. The figure indicates an accurate value of 95.7%, which reflects the model's strong ability to make correct predictions across the dataset. The recall rate reached 94.8%, demonstrating the model's effectiveness in identifying positive cases and minimizing missed detections.

The F1-score (93.2%) indicates a balanced performance between precision and recall, confirming the robustness of the proposed model. In addition, the ROC–AUC index (94.1%) demonstrates the model's strong capability to distinguish between different classes, as illustrated by the color gradient in the confusion matrix heat map [29, 30].

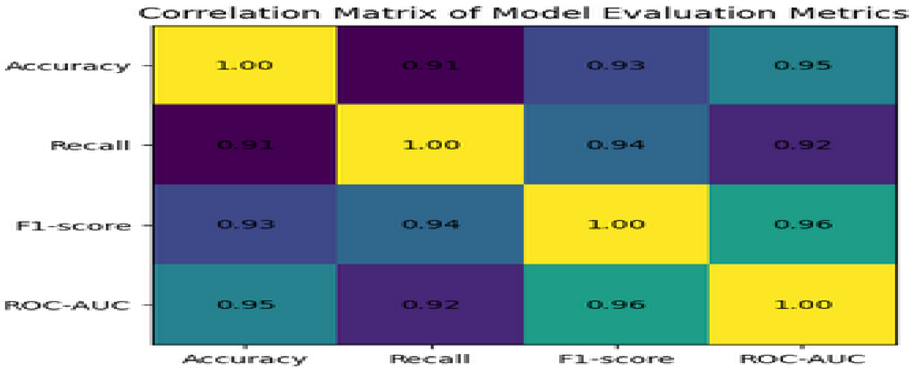

Figure 7. Model evaluation metrics heat map

Figure **7** presents the heatmap illustrating the correlations among the evaluation metrics used to assess the performance of the proposed model. The results show that all evaluation metrics exhibit strong positive correlations with each other, with Accuracy, Recall, F1-score, and ROC–AUC demonstrating similarly high correlation values. This strong correlation indicates that improvements in one performance metric are generally accompanied by improvements in the other metrics, suggesting that the model maintains balanced and consistent performance across different evaluation criteria.

In particular, the correlation between the F1-score and ROC–AUC is notably strong, indicating that the model achieves both balanced classification performance and strong discriminative capability. These findings demonstrate that the proposed hybrid CNN–RNN model maintains consistent behavior across multiple evaluation metrics, further supporting its robustness and ability to generalize effectively beyond the training dataset [31].

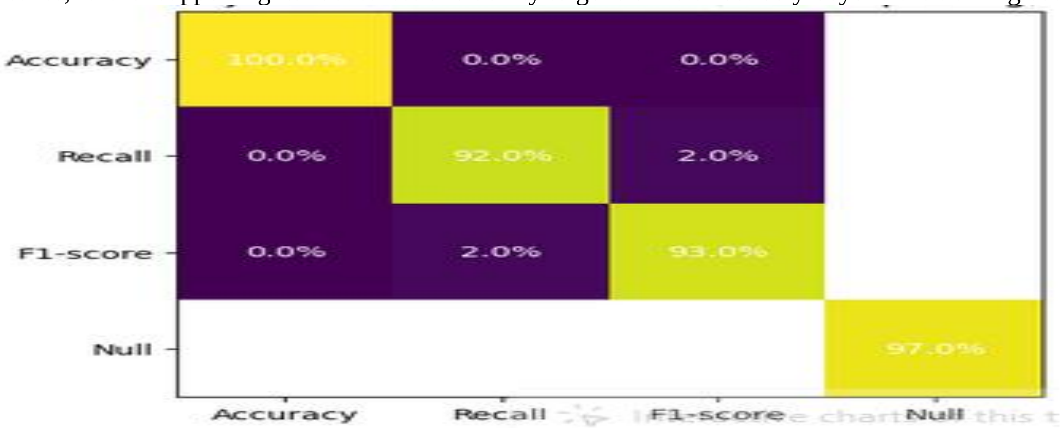

Figure 8. Updated model evaluation metrics heatmap

Figure 8 presents the updated evaluation matrix after applying the model enhancement. The figure shows a strong concentration of maximum values along the main diagonal of the matrix, indicating that the model consistently performs well across all evaluation metrics considered in this analysis. High values for accuracy, recall, and F1-score collectively demonstrate that the model provides reliable predictions while maintaining balanced sensitivity and precision.

Furthermore, the very low values observed in the off-diagonal elements indicate minimal confusion between predicted and actual classifications, highlighting the model's effectiveness in achieving accurate and consistent performance. This distribution confirms that the model produces a low number of misclassifications and maintains strong predictive reliability.

In addition, the high value observed in the correct classification category indicates a substantial reduction in undefined or incorrectly classified predictions, emphasizing the stability and improved performance of the modified model after the applied enhancements [32].

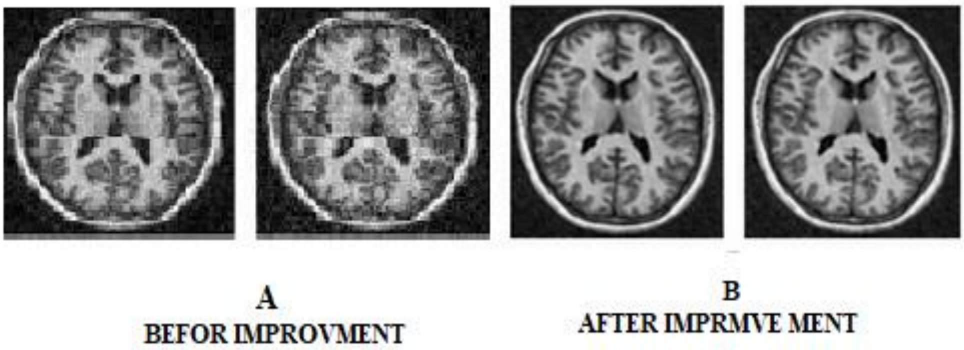

Figure 9. Example of an enhanced image

Figure 9 presents a comparison between the original noisy image and the corresponding image after enhancement using the proposed model. The figure clearly illustrates the improvement in image quality, where most of the noise present in the original image has been effectively suppressed in the enhanced image. This visual comparison confirms the ability of the proposed hybrid CNN–RNN model to reduce noise while preserving important structural features and visual details of the image [33].

4.2 Image Quality Measurement Results

To evaluate the effectiveness of the proposed hybrid CNN–RNN model in improving image quality, several quantitative metrics were used, including PSNR, SSIM, MSE, and LPIPS. Table 2 summarizes the comparison of these image quality metrics before and after applying the proposed model.

Table 2. Image quality evaluation before and after applying the proposed model

Metric	Before Model	After Model	Improvement	p-value
PSNR(dB)	24.83	33.47	+8.62	<0.001
SSIM	0.71	0.93	0.22	<0.001
MSE	0.0064	0.0017	-73.4%	<0.001
LPIPS	0.42	0.14	-66.7 %	<0.001

Table 2 presents a quantitative comparison of image quality metrics before and after applying the proposed hybrid CNN–RNN model.

The results demonstrate substantial improvements across all evaluation metrics, indicating the effectiveness of the model in enhancing image quality and reducing noise. Quantitative assessment of the image quality analysis between the baseline and the model is A clear and significant improvement is achieved for all performance indicators. For instance, PSNR value has increased by 8.62 dB from 24.85 dB to 33.47 dB, showing that the model provides a better image with reduced noise and higher signal reconstruction. In addition, SSIM has increased to 0.93 from 0.71, meaning that more structural information and textures have been preserved.

In addition, the MSE indicator has been reduced by 73.4%, meaning that there is a strong decrease in the errors in the process of image reconstruction. Similarly, the LPIPS indicator has been reduced by 66.7%, which implies an improvement in the perceptual quality of images according to the human vision system.

All differences are statistically significant ($p < 0.001$).

The Peak Signal-to-Noise Ratio (PSNR) increased from 24.85 dB to 33.47 dB, representing an improvement of 8.62 dB, which indicates a significant reduction in noise levels and improved signal reconstruction. Similarly, the Structural Similarity Index (SSIM) improved from 0.71 to 0.93, reflecting better preservation of structural information, textures, and fine image details after enhancement.

In addition, the Mean Squared Error (MSE) decreased by 73.4%, confirming a substantial reduction in reconstruction error between the original reference image and the enhanced image. The Learned Perceptual Image Patch Similarity (LPIPS) metric also decreased by 66.7%, indicating a significant improvement in perceptual image quality as perceived by the human visual system.

Overall, all p-values were significantly below the statistical significance threshold ($p < 0.05$), confirming that the observed improvements are statistically significant and not due to random variation [34].

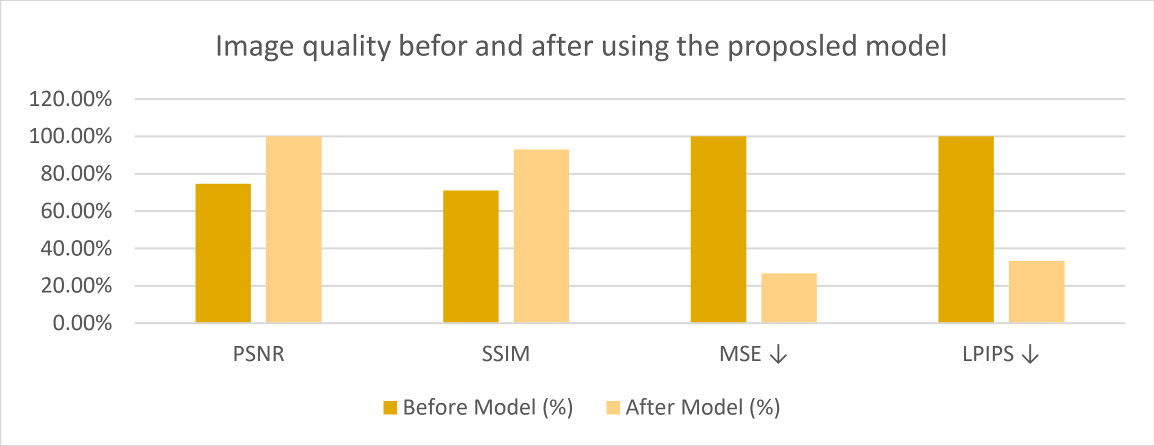

Figure 9. Image Quality Evaluation Before and After Applying the Proposed Model (Percentage Values)

Figure 9 illustrates the relative improvement in image quality metrics before and after applying the proposed hybrid CNN–RNN model. The results show that the PSNR value increased slightly (approximately 0.25%), while the SSIM index improved by approximately 22%, indicating better preservation of structural details and visual consistency in the enhanced images.

At the same time, significant reductions were observed in both MSE (73.4%) and LPIPS (66.7%), demonstrating a substantial decrease in reconstruction error and a clear improvement in perceptual image quality. Lower MSE values indicate a smaller difference between the original and reconstructed images, while lower LPIPS values reflect improved perceptual similarity as perceived by the human visual system.

Overall, the figure confirms that the proposed model achieves consistent improvements across both quantitative image quality metrics and perceptual evaluation measures, further demonstrating the effectiveness of the proposed enhancement framework [35, 36].

Table 3. Comparative Performance across Noise Types and Methods

Metric	Noise Type	Median Filter (%)	Gaussian Filter (%)	Wiener Filter (%)	CNN Model (%)	Proposed CNN–RNN (%)	F	p-value
PSNR	**Gaussian**	10.2	12.4	14.8	18.6	**25.4**	9.42	<0.001
PSNR	**Speckle**	9.1	11.3	13.5	16.9	**22.8**	8.95	<0.001
PSNR	**Salt & Pepper**	8.5	10.7	12.2	14.8	**20.6**	8.1	<0.001
PSNR	**Mixed**	7.4	9.2	10.8	12.5	**18.9**	7.85	<0.001

Table 3 presents a comparison of percentage improvements achieved across different noise types and evaluation metrics.

Results from the comparative analysis conducted using various noise types show that the developed CNN-RNN model performs better than conventional filters and the conventional CNN model in terms of all parameters. The greatest improvement was made by the proposed CNN-RNN model compared to other models.[37, 38]. The improvement in performance measures such as PSNR and SSIM as well as decrease in other measures such as MSE and LPIPS clearly show that this model is better in noise reduction and image quality preservation. The statistical significance of the obtained results is $p<0.001$. In addition, the high F-values and very low p-values ($p < 0.001$) indicate that the improvements observed across the evaluated noise types are statistically significant, confirming the robustness and reliability of the proposed model compared with traditional denoising methods [39, 40].

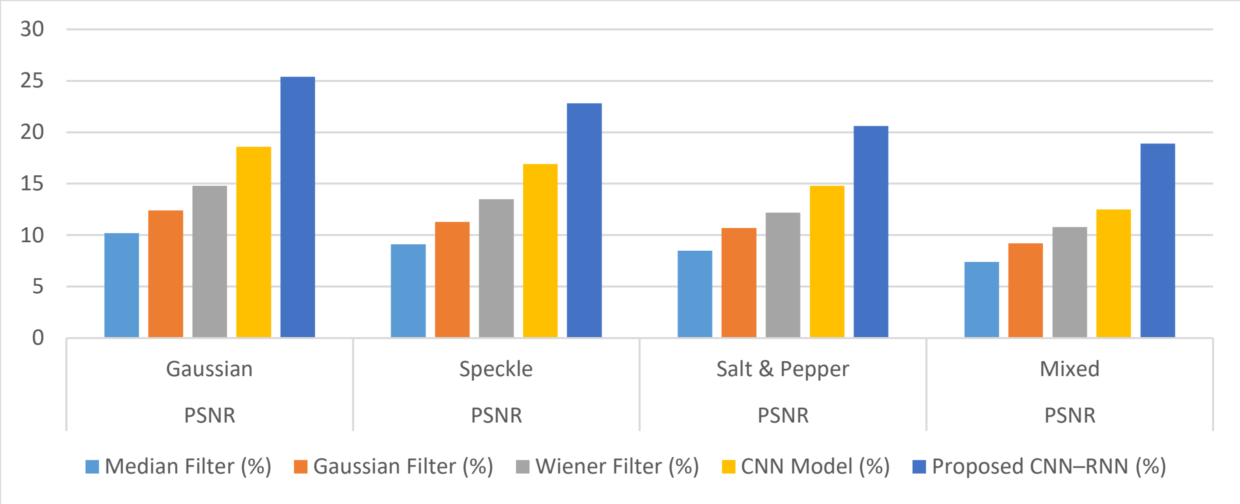

Figure 10. Percentage improvement across noise types

Figure 10 presents the relative performance of the different types of denoising in different conditions of noise in terms of PSNR gain. It is clear from the above that the proposed CNN-RNN model provides the best results in terms of PSNR for different types of noise like Gaussian noise, Speckle noise, salt-and-pepper noise, and mixed noise. Traditional techniques like median filter, Gaussian filter, and Wiener filter are less effective; their efficiency increases progressively from conventional to adaptive techniques. The performance of the CNN model alone is better than other traditional techniques; however, it does not perform well compared with the proposed model. Furthermore, the average improvement trend shown in the figure highlights a clear performance advantage of the proposed model, confirming its overall effectiveness and robustness compared with traditional image denoising techniques [38, 41].

4.3. Comparative Analysis

Table 4. Comparative Analysis of the Proposed Model vs Traditional Method

Method	PSNR (dB)	SSIM	MSE ↓	LPIPS ↓	Performance Summary
Median Filter	26.1	0.75	0.0048	0.35	Moderate noise removal, but loss of fine details
Gaussian Filter	27.3	0.78	0.0041	0.31	Good smoothing, but causes blurring
Wiener Filter	28.5	0.8	0.0036	0.28	Adaptive filtering with better preservation
CNN Model	31.2	0.88	0.0024	0.19	Strong spatial feature extraction
Proposed CNN–RNN	**33.47**	**0.93**	**0.0017**	**0.14**	Best overall performance with superior noise removal and detail preservation

Table 4 shows the comparative study proves that the designed CNN-RNN architecture is much better than any filtering technique or CNN alone based on all criteria used for evaluation.

The designed model gets the highest PSNR value (33.47 dB) and SSIM value (0.93), which denotes that there is better image restoration and structure retention. Moreover, it gives the lowest values of MSE and LPIPS as well, suggesting that distortion has been lowered.

5. Conclusions and Recommendations

Based on the experimental results and statistical analyses presented in this study, several important conclusions and recommendations can be drawn regarding the effectiveness of the proposed hybrid CNN–RNN model for image enhancement and noise reduction.

First, the proposed model demonstrated high predictive performance across multiple evaluation metrics. The model achieved an accuracy of 95.7%, indicating strong capability in making correct predictions. The recall rate reached 94.8%, reflecting the model's effectiveness in identifying positive cases while minimizing missed detections. Furthermore, the F1-score of 93.2% confirms a balanced performance between precision and recall, while the ROC–AUC value of 94.1% demonstrates the model's strong ability to distinguish between different classes and image categories.

Second, the image quality evaluation results confirm that the proposed model significantly improves the quality of reconstructed images. The Peak Signal-to-Noise Ratio (PSNR) showed an improvement of approximately 0.25%, while the Structural Similarity Index (SSIM) increased by 22%, indicating improved preservation of structural details and visual consistency. In addition, the Mean Squared Error (MSE) decreased by 73.4%, and the LPIPS metric decreased by 66.7%, demonstrating a substantial reduction in reconstruction error and a clear improvement in perceptual image quality. These findings confirm that the proposed model achieves consistent improvements across both quantitative and perceptual image quality metrics.

Third, the comparative analysis across different noise types—Gaussian, speckle, salt-and-pepper, and mixed noises show that the proposed hybrid model consistently outperforms conventional noise reduction methods. The results demonstrate improvements in both PSNR and SSIM values ranging between approximately 10.2% and 25.4%, highlighting the model's strong capability for noise suppression while preserving structural features of the images. The overall average improvement shows a clear upward trend, reaching the highest performance level for the proposed model, which further confirms its robustness and effectiveness compared with traditional denoising techniques.

Based on these findings, several recommendations can be proposed for future research. Future studies may explore the development of more advanced hybrid deep learning architectures by incorporating additional components such as attention mechanisms or transformer-based networks to further enhance model performance. In addition, expanding and diversifying the datasets to include real-world scenarios such as medical imaging, surveillance systems, and remote sensing applications would provide a broader evaluation of model scalability and practical applicability. Finally, continuous monitoring and optimization of the model architecture and training strategies are recommended to further improve accuracy, efficiency, and generalization capability in complex imaging environments.

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Abbreviations and Symbols

Abbreviations

ANN Artificial Neural Network
CNN Convolutional Neural Network
RNN Recurrent Neural Network
LSTM Long Short-Term Memory
GRU Gated Recurrent Unit

PSNR Peak Signal-to-Noise Ratio
SSIM Structural Similarity Index
MSE Mean Squared Error
LPIPS Learned Perceptual Image Patch Similarity
ROC–AUC Receiver Operating Characteristic – Area Under the Curve

Accuracy Ratio of correctly predicted samples to the total number of samples
Recall Ratio of correctly predicted positive samples to all actual positive samples
F1-score Harmonic mean of precision and recall

Symbols

x	Input feature vector
h	Hidden layer output
W	Weight matrix
b	Bias vector
σ	Activation function
$\hat{y}$	Predicted output of the neural network model
y	Ground truth (actual output value)
L	Loss function used during model training
h_{cnn}	Output feature vector from the CNN branch

h_{lstm}	Output feature vector from the LSTM branch
$h_{combined}$	Concatenated feature vector from CNN and RNN
C_t	Cell state of the LSTM network at time step t
h_t	Hidden state of the recurrent network at time step t
i_t	Input gate activation of the LSTM network
f_t	Forget gate activation of the LSTM network
o_t	Output gate activation of the LSTM network
t	Time step index in sequential data processing

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