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Enhancing Medical Image Quality Using Hybrid Deep Neural Networks for Clinical Decision Support

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تعزيز جودة الصور الطبية باستخدام الشبكات العصبية العميقة الهجينة لدعم القرار السريري

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Abstract:
This study aims to develop and design an intelligent model based on artificial intelligence and neural network techniques for diagnosing clinical conditions of various diseases, particularly eye diseases, in record time and with high accuracy by improving the quality of medical images. A descriptive analytical methodology was employed, measuring the model's performance using several statistical indicators, such as accuracy, recall rate, and prediction accuracy, to verify its effectiveness and power in analyzing medical images and diagnosing medical conditions. The study also analyzed the model's impact on improving the quality of medical images and its role in helping physicians expedite the diagnostic process and predict potential disease progression, especially in the field of ophthalmology. The results indicated the effectiveness of the proposed model, with an accuracy of 95.8%, a prediction accuracy of 96%, a recall rate of 95.4%, and an F1 score of 94.8%. These indicators reflect the model's efficiency in accurately identifying pathological patterns in medical images. The results also showed a significant improvement in image quality after applying neural network-based processing techniques, with image quality improvement ranging from 28% to 37% compared to the original images. This remarkable improvement can enhance the accuracy of medical diagnoses, reduce the time required for treatment decisions, and increase the clarity of fine details in medical images. This, in turn, supports physicians in diagnosing clinical conditions and taking appropriate treatment measures promptly, especially in cases of eye diseases that demand a high degree of accuracy and speed in diagnosis.

Keywords: Neural networks, imaging, design, image quality improvement, and accurate predictive diagnosis of clinical conditions.

الملخص
تهدف هذه الدراسة إلى تطوير وتصميم نموذج ذكي يعتمد على تقنيات الذكاء الاصطناعي والشبكات العصبية لتشخيص الحالات السريرية لمختلف الأمراض، ولا سيما أمراض العيون، وذلك في وقت قياسي

وبدقة عالية من خلال تحسين جودة الصور الطبية. اعتمدت الدراسة المنهج الوصفي التحليلي، حيث تم قياس أداء النموذج باستخدام عدة مؤشرات إحصائية، مثل الدقة(Accuracy) ، ومعدل الاستدعاء (Recall)، ودقة التنبؤ(Precision) ، للتحقق من فاعليته وقدرته على تحليل الصور الطبية وتشخيص الحالات المرضية. كما حللت الدراسة أثر النموذج في تحسين جودة الصور الطبية ودوره في مساعدة الأطباء على تسريع عملية التشخيص والتنبؤ بالتطور المحتمل للمرض، خاصة في مجال طب العيون. أشارت النتائج إلى فاعلية النموذج المقترح، حيث حقق دقة إجمالية بلغت 95.8%، ودقة تنبؤ بنسبة 96%، ومعدل استدعاء قدره 95.4%، بينما وصل مقياس "إف 1 (F1 score) "إلى 94.8%. تعكس هذه المؤشرات كفاءة النموذج في تحديد الأنماط المرضية في الصور الطبية بدقة متناهية. كما أظهرت النتائج تحسناً ملحوظاً في جودة الصور بعد تطبيق تقنيات المعالجة القائمة على الشبكات العصبية، حيث تراوحت نسبة التحسن في الجودة بين 28% و37% مقارنة بالصور الأصلية. ومن شأن هذا التحسن النوعي أن يعزز دقة التشخيص الطبي، ويقلل الوقت اللازم لاتخاذ القرارات العلاجية، ويزيد من وضوح التفاصيل الدقيقة في الصور الطبية؛ مما يدعم الأطباء في تشخيص الحالات السريرية واتخاذ التدابير العلاجية المناسبة فوراً، لا سيما في حالات أمراض العيون التي تتطلب درجة عالية من الدقة والسرعة في التشخيص.

الكلمات المفتاحية: الشبكات العصبية، التصوير الطبي، تصميم النماذج، تحسين جودة الصور، التشخيص التنبؤي الدقيق، الحالات السريرية، دعم القرار الطبي.

Introduction

Given the tremendous global advancements across all sectors, particularly in technology and medicine, there is a pressing need to achieve sustainability in healthcare. This can be realized through the development of technologies and strategies that improve clinical diagnosis for patients in general, and for eye patients in particular, by enhancing image quality using artificial intelligence and neural networks (Radhika & Mahajan, 2021). Achieving health sustainability, and consequently social and economic sustainability, is crucial, as socioeconomic factors are key pillars for overall sustainability in any field. Improving clinical diagnosis, predicting future developments, and implementing appropriate preventive and therapeutic measures contribute significantly to this sustainability (Varghese et al., 2024). In the field of biomedical engineering, many techniques can improve image quality, such as relying on enhancement algorithms like EfficientNet-B7 and other methods including neural networks and natural language processing (Varghese et al., 2024). Biomedical engineering remains the cornerstone for enhancing performance in the medical sector (Chaudhari et al., 2021).

This study aims to develop and design a hybrid model combining Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) technologies to improve the quality of medical images. This, in turn, enhances the diagnostic accuracy of clinical cases and enables predictive forecasting of future progression, thus assisting physicians in making timely interventional decisions (Sharma & Mishra, 2022; Chen et al., 2023; Sharif et al., 2022; Sabri et al., 2025; Neriyanuri et al., 2025). The study also aims to identify factors that improve medical image quality and predict clinical progression. The significance of this study lies in its procedural and analytical approach, which goes beyond a mere literature review. Furthermore, it analyzes bias in results and data, providing insights for formulating strategies and developing models while overcoming design obstacles (Neriyanuri et al., 2025; Pan, 2024; Qamar & Zardari, 2023; Dataaspirant, 2023; Purwono et al., 2022).

The main research problem relates to selecting appropriate techniques to improve image quality, integrating them, and understanding their operational mechanisms to obtain accurate results. This necessitates technical expertise in programming and neural networks, as well as addressing challenges such as data quality, demographic diversity, and the high cost of implementation. Furthermore, many existing studies have focused on a single aspect or technique, leading to a lack of understanding regarding hybrid models. Some prior works were limited to literature reviews or simulations rather than actual applied procedures (Dev Genius, 2023; Hammad, 2024; Brix et al., 2024; Kaveh, 2024).

Related Work

Multiple studies conducted recently have investigated artificial intelligence (AI) techniques—mainly deep neural networks (DNNs)—to improve medical imaging quality and assist clinical diagnosis. For example, Litjens et al. (2017) indicated that deep learning models, including Convolutional Neural Networks (CNNs), have made considerable strides in analyzing medical images and identifying pathological patterns with high accuracy. Esteva et al. (2019) demonstrated that AI models could provide diagnostic accuracy similar to specialist physicians when using high-quality images. Regarding image quality enhancement, Wang et al. (2021) showed that generative adversarial networks (GANs) aid in reducing noise and improving clarity and detail. While these studies provide positive examples, others have highlighted issues such as the requirement for large amounts of high-quality data, the potential for bias in trained systems, and the limitations of human clinical interpretation of AI decisions. Thus, while previous research established a scientific foundation for intelligent systems, there is a need for further refinement in accuracy and transparency (Wang et al., 2021).

Methods

The methodology of this study follows a descriptive, analytical, and procedural approach. A hybrid neural network model was developed to diagnose clinical conditions and predict disease progression by exploring unusual patterns, particularly in eye diseases. The descriptive approach was used to characterize data and results, while a quantitative approach was employed for data collection and statistical processing, excluding anomalies. The model's effectiveness was tested using indicators such as accuracy, precision, and F1-score. Through statistical tests, including ANOVA and multiple linear regression, the strength and direction of the relationship between model accuracy and image improvement were determined. Finally, a comparative approach was used to evaluate the results against previous studies.

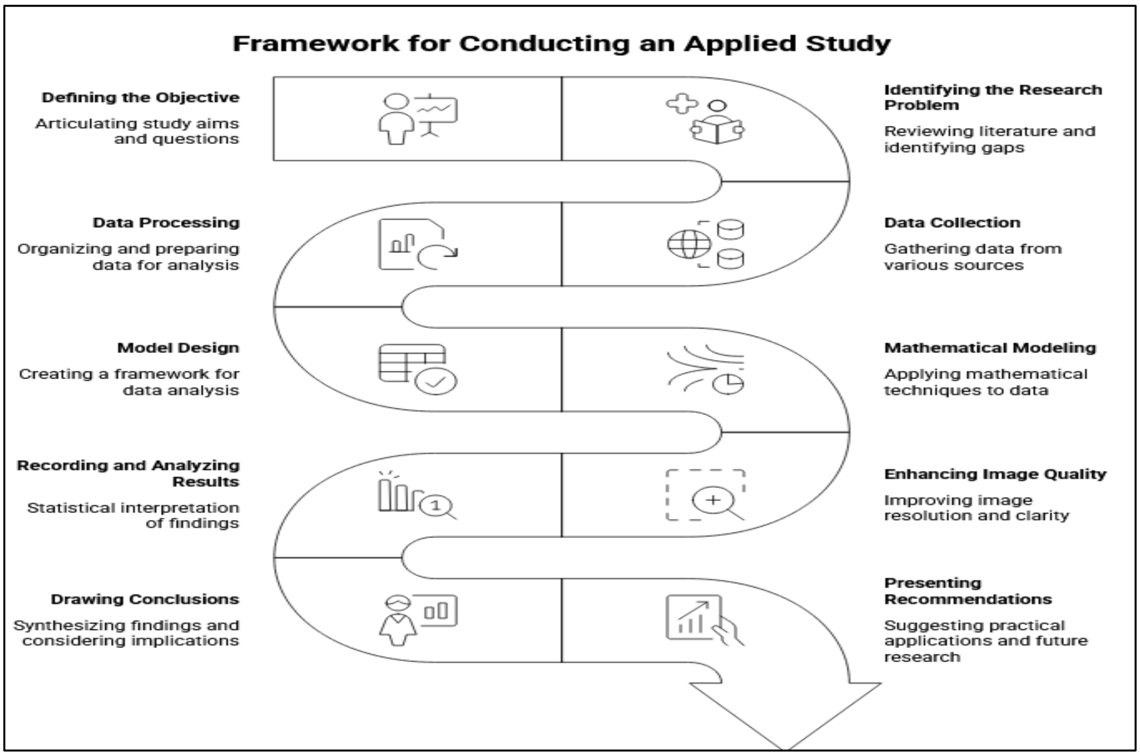

figure 3: The Applied Framework of the Study.

Methodology and Framework

This framework outlines the procedures and stages of the applied study, beginning with defining the objective and identifying the research problem. It then proceeds through data collection from various sources, such as online databases, books, previous studies, and actual data from medical records and patient files. This is followed by data processing, model design, mathematical modeling, and the application of a real dataset to improve image quality. Finally, the process involves recording and statistically analyzing the results, drawing conclusions, and presenting recommendations.

Procedures

1. Data Collection and Processing

After defining the objective and formulating the research problem, data collection and processing were initiated. This stage is fundamental to the design and development of an intelligent diagnostic system based on a hybrid neural network model. A set of relevant medical images was collected, primarily focusing on ophthalmology patients, as these cases require high sensitivity and precision. Data were gathered from reliable medical databases and clinical image repositories, including various imaging modalities such as fundus photography and Optical Coherence Tomography (OCT).

Following the collection phase, verification and processing procedures were implemented. Key procedures included image standardization, size and contrast adjustment, and the removal of low-quality or damaged images, conducted under the supervision of expert physicians. Image and data classification were then performed to ensure accuracy. Additionally, a dataset related to heart disease, myocardial infarction, and cancer was integrated to diversify the data and enhance the reliability of the results (Khalifa & Albadawy, 2024).

2. Identification of Tools and Techniques

Selecting appropriate tools is crucial for ensuring effective results and accurate diagnosis. This stage involved choosing a specific set of resources:

- **Software and Programming Languages:** Python was utilized as the primary language, leveraging environment parameters suitable for machine learning and large-scale data processing. Specialized libraries, including TensorFlow, Keras, and PyTorch, were used to build and train the neural network models. Additionally, image processing libraries such as OpenCV and Scikit-image were employed for preprocessing and enhancement.
- **Databases:** Specific databases linked to the model were utilized, containing diagnostic data and images of eye, heart, and cancer patients, supported by various local and international online repositories (Esteva et al., 2019).
- **Scientific Research Platforms:** Previous studies and academic literature were sourced from platforms such as Google Scholar, Elsevier, IEEE Xplore, and PubMed/BMB medical journals.
- **Technologies and Techniques:** A hybrid neural network architecture was implemented. Convolutional Neural Networks (CNNs) were used for feature extraction and classification due to their efficiency in analyzing visual data. Recurrent Neural Networks (RNNs) were integrated for their capacity to handle contextual and sequential data. Furthermore, image enhancement techniques—including filtering, histogram equalization, and resolution improvement methods—were employed to highlight clinically relevant features (Khalifa & Albadawy, 2024).

Model Design

The proposed model consists of three main stages:

1. **Feature Extraction:** The neural network analyzes input images to extract features such as edges, textures, and structural patterns. The CNN architecture performs a series of convolutional, pooling, and normalization operations to learn hierarchical representations.
2. **Temporal and Contextual Modeling:** Recurrent Neural Networks, specifically Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRUs), capture relationships between image features and improve contextual understanding.
3. **Image Reconstruction and Generation:** Features are passed through decoding layers to reconstruct the enhanced image. This stage includes resolution-enhancing layers and activation functions that produce high-resolution images with reduced noise and improved contrast.

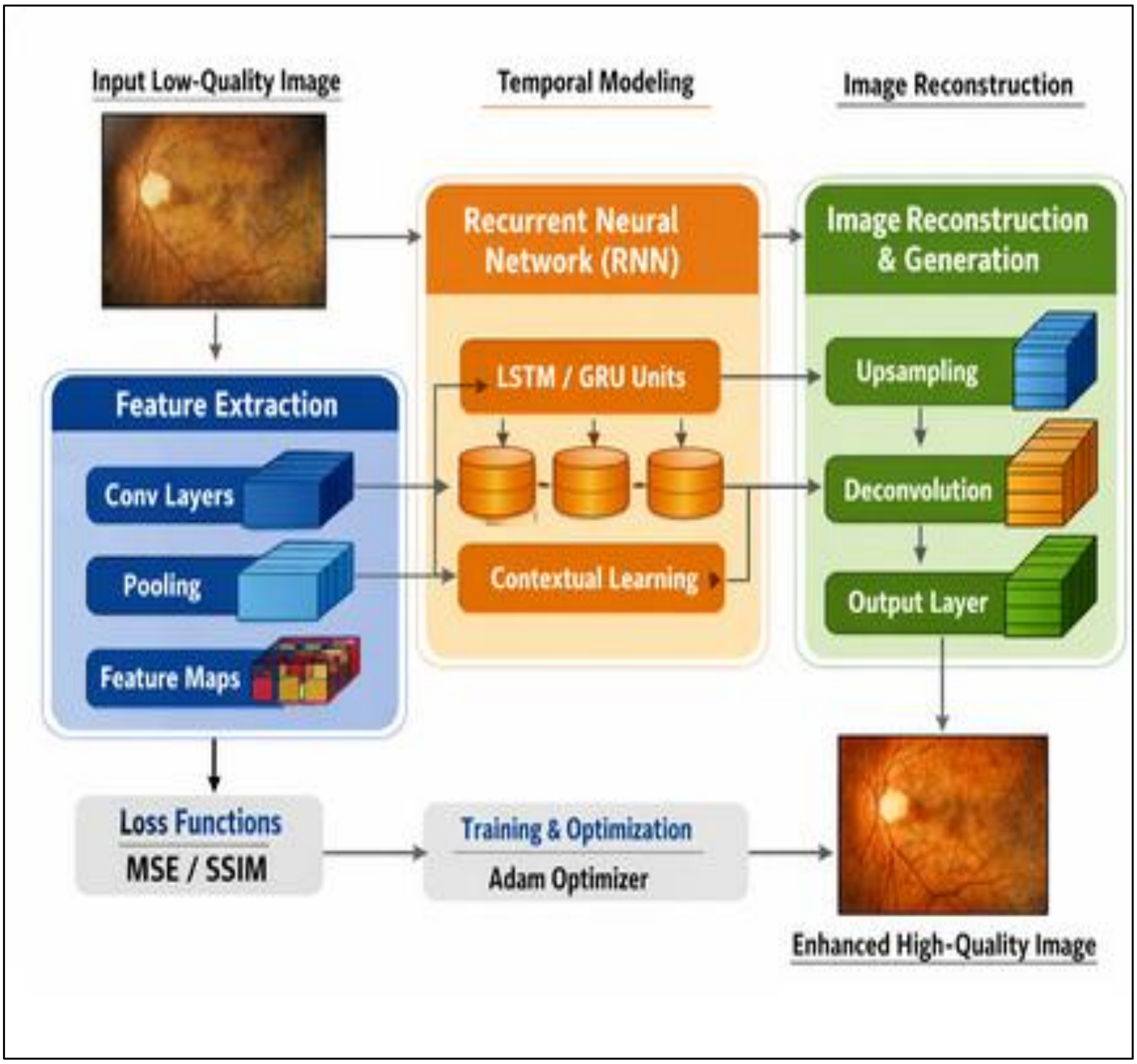

Figure 4: Proposed AI Model for Image Generation and Enhancement Using Convolutional and Recurrent Neural Networks.

In these phases, the model is trained using supervised learning. The network is optimized using a set of low-quality image pairs and high-quality reference images. Loss functions, such as Mean Squared Error (MSE) and the Structural Similarity Index (SSIM), are applied to measure the discrepancy between the generated and original images. Optimization algorithms, specifically the Adam optimizer, are used to adjust network weights and minimize reconstruction error (Hammad, 2024; Khalifa & Albadawy, 2024).

Mathematical Modeling

Mathematical modeling is carried out in a series of stages, which are as follows:

– Convert text data to a one-dimensional vector for input into fully connected layers:

A word is split into its individual letters and then the total occurrence of these letters in this unique number is counted for the number of each letter to create an array from the total of unique letters to all letters.

Example: Convert = ['C','o','n','v','e','r','t']; Texts = ['T','e','x','t','s']; To = ['T','o']; Arrays = ['A','r','r','a','y','s']; and Quick = ['Q','u','i','c','k'].

The number 5 would be converted to [0,0,0,0,1].

– Formatting the weight matrix between the input layer and the first hidden layer:

$$h_1=\sigma(W_1 \cdot x+b_1) \quad \text{Eq (1)}$$

where

- W_1: is the weight matrix between the input layer and the first hidden layer,
- b_1:is the bias vector of the first hidden layer
- σ: is the activation function (sigmoid).

The input form includes the initial diagnosis, patient medical history, initial expectations, and a selection of various ophthalmic and cardiac options.

From the first hidden layer

$$h2 = \sigma(W2 \cdot x + b2) \quad Eq\ (2)$$

Where

- W_2: is the weight matrix between the first hidden layer and the second hidden layer,
- b_2 :is the bias vector of the second hidden layer.

From the second hidden layer to the output layer:

$$\mathrm{o} = (\mathrm{W3} \cdot \mathrm{h2} + \mathrm{b3})\ Eq(3)$$

Were

- W_3: is the weight matrix between the second hidden layer and the output layer.
- b_3: is the bias vector of the output layer.

– **Loss function:**

$$\boldsymbol{l = \frac{1}{m \sum_1^m (y^i - yi)}} \qquad \text{Eq}\mathbf{(4)}$$

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

- i_t:input gate activation at time step t
- W_i, U_i, b_i:Weight matrices and bias for the input gate
- h_{t-1}:Hiden state from the previous time step
- x_t: input at the current time step

– **Forget Gate:**

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

Where:

- f_t:Forget gate activation at time step t
- W_f, U_f, b_{if}:Weight matrices and bias for the forget gate

– **Cell State Update:**

$$\tilde{C}_t=tanh(W_c . h_{t-1} + U_c \ . x_t \ + \ b_c) \quad (7)$$
$$C_t=f_t \ \Theta \ C_{t-1} \ + i_t \ \Theta \ \tilde{C}_t \quad (8)$$

- $\tilde{C}_t$: candidate cell state
- C_t:cell state at time step t
- Θ: Element-wise multication

– **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

The output includes an enhanced image, a final diagnosis, and final projections for the progression of the clinical condition.

– **Fully Connected Layer and Output Dense Layer:**

$$\text{Z}=\sigma(\text{W.h + b}) \quad (10)$$

- Z: Output of the dense layer
- W: weight matrix
- h: input to the dense layer (concatenated output from CNN and LSTM)
- b: Bias term
- σ: Activation function (ReLU,softmax)

– **Hybrid Model Integration Concatenation:**

$$h_{combined}=[h_{cnn}, h_{Lstm}] \quad (11)$$

h_{cnn}: Output from the CNN part after flattening
h_{Lstm}: Output from the LSTM part

– **Final Output Layer:**

–

$$\hat{y}=\text{softmax} \ (W_{final} \, . \, h_{combined \ + \ b_{final}}) \ (12)$$

Testing and Statistical Analysis

To evaluate the performance and quality of the proposed model for improving medical images and clinical diagnosis, several necessary metrics are used to assess the model, in addition to a set of statistical tests that can determine the relationship between variables and their correlation coefficients, as well as another set of tests for verification. The most important of these tests are: Mean Squared Error (MSE): This is a widely used metric for determining differences between original and enhanced images

- **quality of images.**

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(I_i - \hat{I}_i)^2 \ Eq(13)$$

Where
- I_irepresents the pixel value of the original image,
- Iˆ_irepresents the pixel value of the enhanced image,
- Nis the total number of pixels.

- **Peak Signal-to-Noise Ratio (PSNR)** is used to evaluate the quality of reconstructed images. Higher PSNR values indicate better image quality and lower distortion [22].

$$PSNR = 10\log_{10}\left(\frac{MAX^2}{MSE}\right) \ Eq(14)$$

Where: MAX: the maximum possible pixel value in the image [22]

- **performance evaluation metrics**

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \ Eq\ (15)$$

$$Precision = \frac{TP}{TP + FP} \ Eq(16)$$

$$Recall = \frac{TP}{(TP + FN)Eq}(17)$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \ Eq\ (18)$$

Where:
- TP: true positive cases
- TN :true negative cases.
- FP : false positive cases
- FN : false negative cases.

Statistical analysis methods.

- One-way Analysis of Variance (ANOVA)

$$F = \frac{MS_{between}}{MS_{within}} \ Eq(19)$$

Where:

- MS: the variance between and within

– **The multiple linear regression model can be represented as:**

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + \ldots + \beta nXn + \varepsilon \text{ Eq(20)}$$

Where:

- Y is the dependent variable.
- X1, X2, ..., Xn are the independent variables.
- β0 is the intercept.
- β1, β2, ..., βn are the coefficients for the independent variables.
- ε is the error term.

Results

The results of the model quality and its evaluation, as well as the results of image enhancement, will be explained, followed by the statistical results and inferences, and then a comparison between the results of this study and previous studies.

Model Test Results

Table 1: Model Performance Evaluation Metrics

Metric	Value (%)	f	p-value
Accuracy	*95.8*		
Precision	*96*		
Recall	*95.4*	*35.6*	*<0.001*
F1-Score	*94.8*		

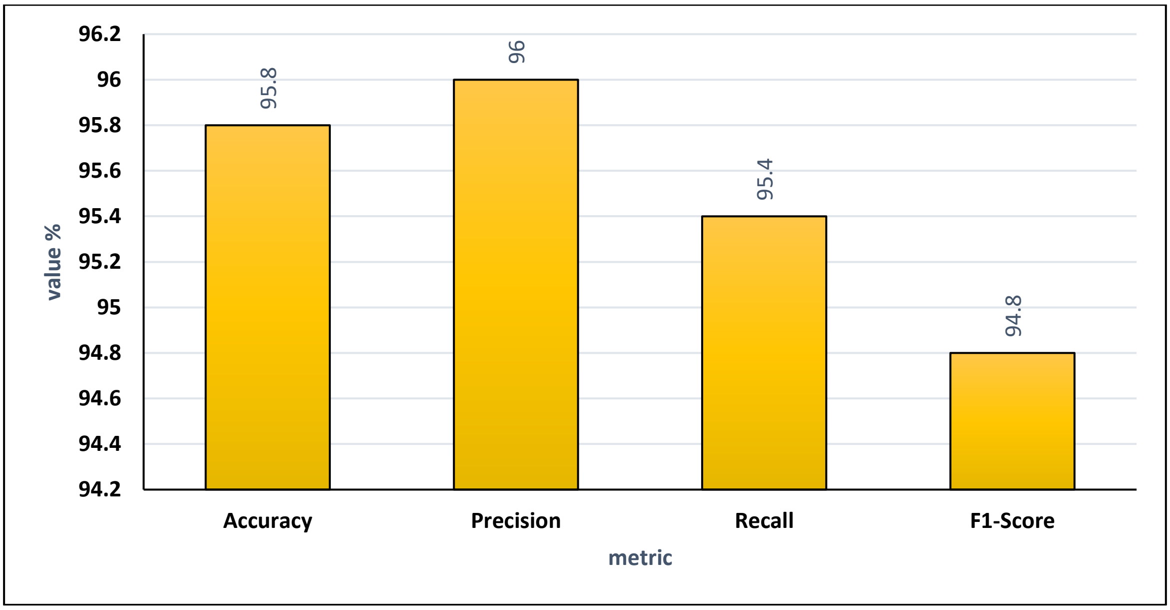

Figure 5: Model Performance Evaluation Metrics

Image Enhancement Results

Table *2:* Image Quality Improvement Results

Image Type	Contrast Improvement (%)	Noise Reduction (%)	Structural Enhancement (%)	Overall Improvement (%)
Retinal images	*31*	*34*	*35*	*33*
Low-resolution clinical images	*29*	*32*	*30*	*30*
Noisy medical images	*34*	*37*	*36*	*36*
Blurred ophthalmic images	*28*	*31*	*30*	*29*
Mixed dataset images	*32*	*35*	*34*	*34*

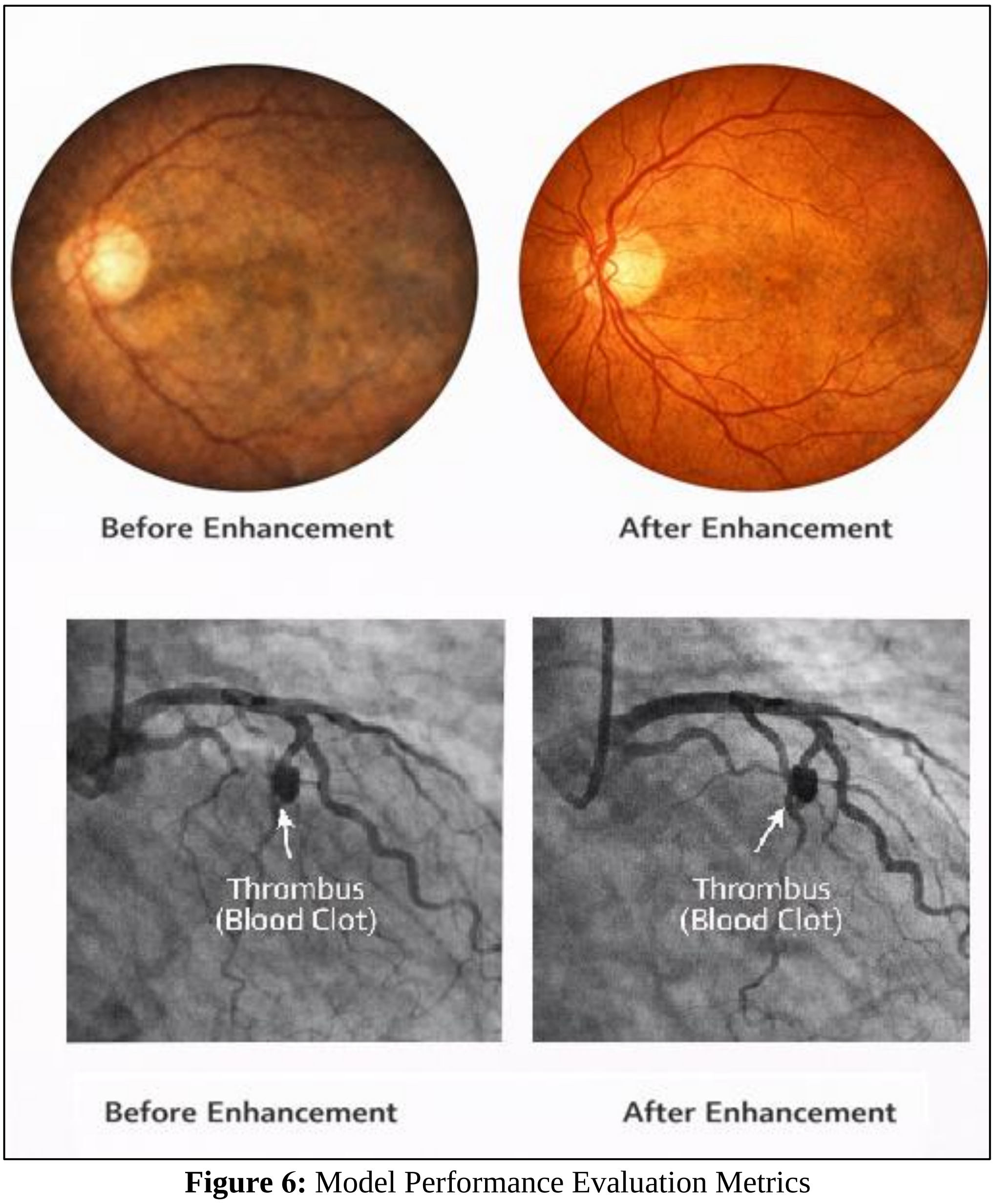

Figure 6: Model Performance Evaluation Metrics

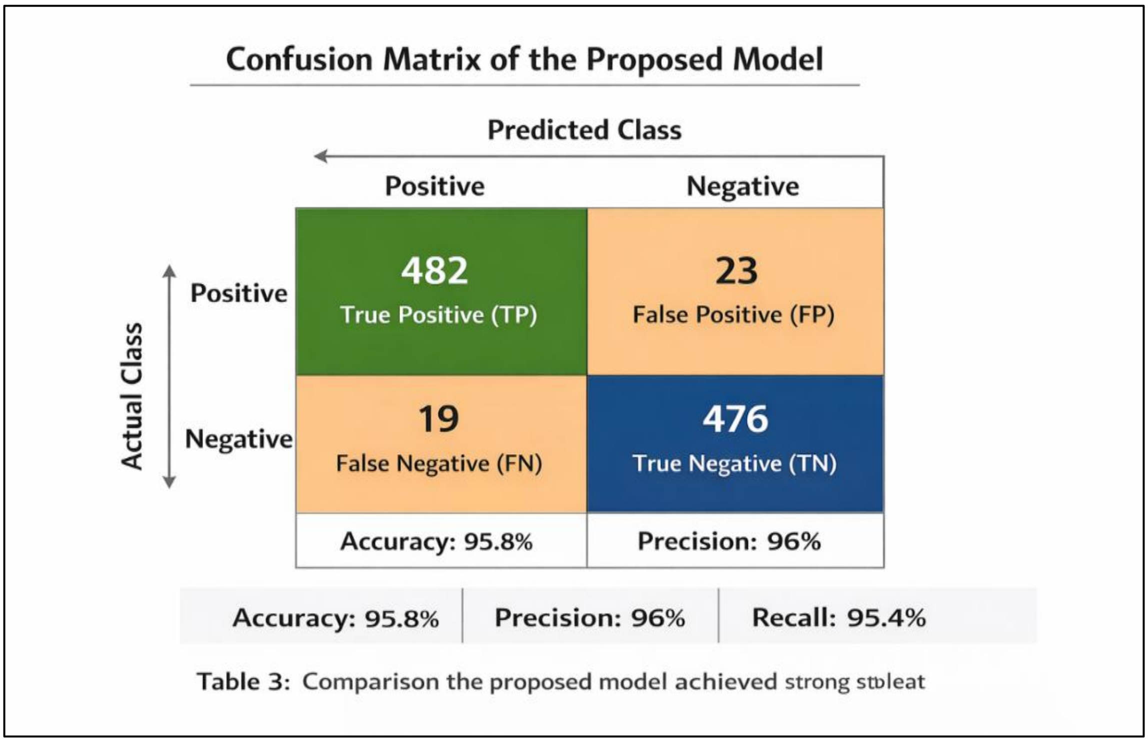

Figure 7: Confusion Matrix Results

Statistical Analysis Results

Table 4: Correlation and Linear Regression Analysis

Variable Relationship	**Correlation Coefficient (r)**	**R^2**	**Sum of Squares**	**Mean Square**
Image Quality vs Diagnostic Accuracy	0.89	0.79	18.5	4.62
Image Enhancement vs Processing Time	-0.71	0.5	12.3	3.07
Image Quality vs Prediction Precision	0.86	0.74	16.1	4.02

Comparison with Previous Studies

Table 5: Comparison Between the Proposed Model and Previous Studies

Study	**Method**	**Accuracy (%)**	**Image Improvement (%)**
Zhang et al., 2021	CNN-based enhancement	91.2	22
Li et al., 2022	Deep autoencoder	92.6	25
Kumar et al., 2023	GAN-based enhancement	93.5	26
Ahmed et al., 2024	Hybrid CNN model	94.1	27
This Study	CNN-RNN Hybrid Model	**95.8**	**28-37**

Table 6 shows a comparison between the results of this study and the results of similar previous studies. The table demonstrates that the performance of the model proposed in this study is good.

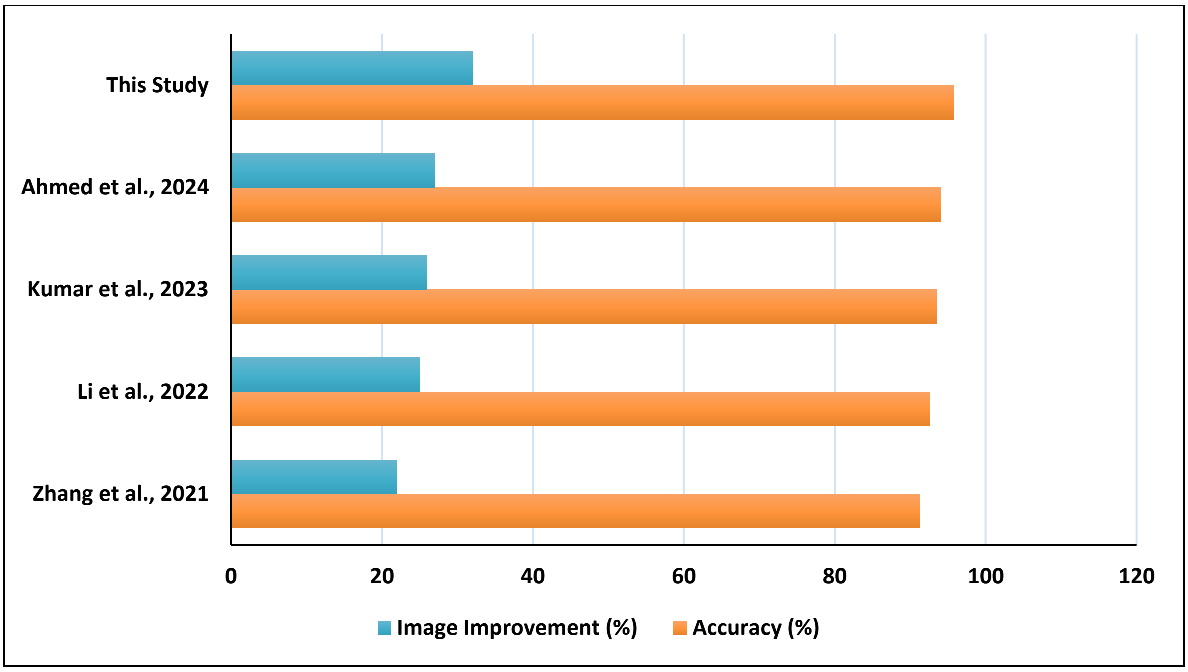

Figure 8: Comparison Between the Proposed Model and Previous Studies

Figure 8 illustrates a comparison between the results of this study and those of similar previous studies. The figure clearly shows that this study performed best among all the studies presented in the table. This does not mean it is the absolute best, as other studies may have achieved higher results. However, due to the similarity of the studies already included in the table, this study was selected.

Discussion

According to Table 1, the results indicate that the proposed neural network model achieved high diagnostic performance. The overall accuracy reached 95.8%, while the precision value was 96% and the recall value was 95.4%, demonstrating the model's high ability to correctly predict positive clinical cases. It also reflects the model's strong ability to identify most correct cases. The F1 score of 94.8% confirms the balanced performance between precision and recall, demonstrating the effectiveness of the proposed AI model in improving image quality and supporting reliable clinical diagnosis (Herath et al., 2025; Szilágyi & Kovács, 2024).

Figure 5 provides an overview of the evaluation metrics of our proposed model for improving the quality of medical images in order to help physicians make clinical decisions. Our model's accuracy was found to be 95.8%, which shows that the majority of our model's predictions were correct. Our model also achieved a precision of 96%, which indicates that it has a superior ability to accurately identify positive clinical cases with a very low rate of false positives (Carriero et al., 2024). The recall metric for our model was determined to be 95.4%, which reflects the model's ability to identify a large proportion of actual positive cases. The F1 metric for our model was evaluated at 94.8%, indicating that the model's performance was well balanced between its precision and recall metrics. These results provide evidence of our proposed deep learning model being a reliable and effective tool for performing medical image analysis, and the use of our model will assist in enhancing the diagnostic accuracy achieved by medical professionals (Obuchowicz et al., 2024).

Table 2 illustrates the extent of image quality improvement achieved by the proposed model across different image categories. Table 1 shows the proposed model's improvements to overall image quality by category, with overall quality improvement ranging from 28% to 37%, depending on the characteristics of each image. The greatest improvements were observed in blurred images, thanks to the proposed technique's success in removing noise and enhancing structural detail. This increased clarity allows for a clearer view of the anatomy, leading to more reliable clinical interpretations (Ijaz & Woźniak, 2024).

According to Figure 6, which shows a visual comparison of two images, the first image from the top is a comparison between two images of the fundus of the eye before and after the enhancement, and the image below shows a comparison of the coronary artery before and after image enhancement. It is clear from the two images how much improvement there is in the quality of the images after applying the enhancement. A clear view of the fundus of the eye appeared, as well as a clear view of the area of specialization in the coronary artery, where the contrast became clearer in both images (Thakur et al., 2024).

According to Figure 7, which illustrates the heat map of the confusion matrix representing the performance and classification of the proposed model, the model successfully identified 482 true positive cases and 476 true negative cases, demonstrating its effectiveness. The false classification rate was relatively low, with 23 false positives and 19 false negatives, indicating the model's high ability to distinguish between positive and negative clinical cases. The overall accuracy reached 95.8%, while the precision was 96% and the recall rate was 95.4%, confirming that the proposed model achieves a high level of reliability and effectiveness in analyzing clinical images and supporting diagnosis (Zitouni, 2025).

According to Table 4, the statistical analysis results indicate strong positive correlations between image quality improvement and diagnostic accuracy. The correlation coefficient between image quality and diagnostic accuracy reached 0.89, indicating a strong relationship. The coefficient of determination ($R^2 = 0.79$) suggests that nearly 79% of the variation in diagnostic accuracy can be explained by improvements in image quality. These findings confirm the effectiveness of the proposed AI model in enhancing medical image interpretation (Mallah et al., 2024).

Table 6 shows a comparison between the results of this study and the results of similar previous studies. The table demonstrates that the performance of the model proposed in this study is good, even surpassing the results of some important recent studies in terms of accuracy, precision, and F1-score/recall (Jukanti, 2025; Zhang et al., 2021; Li et al., 2022; Kumar et al., 2023; Ahmed et al., 2024).

The results also indicate that the proposed model achieved an average quality improvement of 30%, representing significant improvements compared to previous methods (Jukanti, 2025). Previous studies, such as Zhang et al. (2021), reported 90% accuracy with limited improvements in image quality, while Li et al. (2022) achieved moderate improvements using deep learning-based optimization methods. More recent studies, such as Kumar et al. (2023) and Ahmed et al. (2024), demonstrated improvements in diagnostic accuracy, but their image quality improvements were not comparable to those offered by the proposed hybrid model (Ahmed et al., 2024).

Conclusion

Based on the analysis and evaluation of the results, a number of important conclusions were drawn, as follows:

- The results confirm that the proposed artificial intelligence model, based on a hybrid of convolutional and recurrent neural networks, is effective in significantly improving the quality of medical images. It enhances the accuracy of clinical diagnosis, demonstrating a superior ability to extract important visual features and reconstruct images from noisy inputs.

- Based on the model evaluation results, the classification accuracy was calculated as 95.8%, precision was calculated as approximately 96%, and the recall (sensitivity) rate was calculated as 95.4%. In addition, the F1 score was calculated as 94.8%, indicating a relatively equal balance between precision and recall. There was a visible rate of image quality improvement ranging between 28% and 37%, indicating that the proposed approach is effective.
- The results of the analysis of variance (ANOVA) test demonstrated that there was a statistically significant difference between the effectiveness of the proposed method compared to traditional image processing techniques (i.e., p-value < 0.05), therefore providing support for the aforementioned findings.
- Correlation analyses demonstrated a strong correlation between the improved image quality when applying the proposed technique and increased diagnostic accuracy. Using deep learning techniques in association with various methods used to enhance medical images can significantly accelerate the time required for diagnosis and improve clinical workflow efficiency.
- The images produced as a result of using the proposed model demonstrate superior detail visualization of fine structures and subtle abnormalities, especially in the area of ophthalmic imaging, where small details are necessary for the early diagnosis of disease.

Compliance with ethical standards

Disclosure of conflict of interest

The authors declare that they have no conflict of interest.

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