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RESEARCH ARTICLE

CARDIO-3DNet: CORONARY ARTERY RECONSTRUCTION USING DEEP LEARNING FOR ADVANCED MEDICAL IMAGE AND OBJECT-BASED 3D NETWORK

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Abstract – The 3D medical image reconstruction (3D MIR) is important in the diagnosis and analysis of coronary artery disease (CAD), as it presents a detailed picture of the vascular structures. Nevertheless, it is difficult to reconstruct coronary arteries from 2D angiographic images in the presence of noise, low contrast, complex topology of the vessel and loss of spatial information. The current methods are inefficient in preserving the fine vessel structures and continuity, which results in less accuracy in the reconstruction process. In this paper, an advanced DL-based CARDIO-3DNet for 3D coronary artery reconstruction technique has been proposed by incorporating the advanced feature learning and image processing techniques. Preliminary filtering is done with the Optimally Oriented Flux (OOF) filter to obtain better vessel structures, and the coronary arteries are segmented with U-Net to obtain accurate extraction results. Then a 3D Convolutional Neural Network (3D CNN) is used to implement efficient 3D feature extraction and reconstruction. The proposed method is intended to enhance the continuity of the vessels, maintain the spatial distribution, and produce accurate 3D models of coronary arteries. The significance of this work lies in integrating vessel enhancement deep segmentation and hybrid 3D feature learning within a single framework. The proposed method provides improved reconstruction accuracy and can support early diagnosis and clinical decision-making in CAD analysis. The performance of the proposed CARDIO-3DNet is assessed using measures such as accuracy, precision, recall, specificity, and F1-score. Experimental results show that the model has an accuracy of 99.02% and an F1-score of 97.23%, showing that it is effective in 3D medical picture reconstruction of coronary arteries. Moreover, the proposed CARDIO-3DNet increases the AY by 0.79%, 0.52%, 0.39%, and 0.13% over AlexNet, ShuffleNet, SqueezeNet and DenseNet respectively.

Keywords *– 3D Medical image reconstruction, Deep Learning, coronary artery, Optimally Oriented Flux filter, CNN.*

1. INTRODUCTION

This Medical image reconstruction is an important method in medical imaging that enhances image quality and aids in accurate diagnosis [1]. It seeks to recover high-quality images from damaged or low-quality inputs while retaining critical anatomical information [2]. The rising prevalence of coronary artery disease, which is caused by constriction or blockage of the coronary arteries, has increased the demand for better imaging techniques [3]. Deep learning-based reconstruction approaches have demonstrated significant potential for improving image quality while lowering radiation exposure [4]. Furthermore, contemporary imaging technologies such as CT, MRI, PET, and X-ray have significantly enhanced clinical evaluation and therapy planning [5].

The complicated image patterns and the inconsistency of clinical interpretations of SPECT-MPI images still make diagnosis of CAD difficult, and previous approaches to diagnosis lack accuracy [6]. Even the complexity of vascular architecture and the lack of depth information still make the reconstruction of coronary arteries from 2D X-ray angiograms difficult and inaccurate [7]. The registration between coronary arteries in the systolic and diastolic phases is difficult because of cardiac movement, non-rigid deformation, and their structural differences, thus reducing the effectiveness of the current approaches [8]. Medical image segmentation of the coronaries is difficult as the coronary anatomy is variable, there is imaging noise, and the coronary is in normal or diseased condition [9].

The development of artificial intelligence (AI) has produced a promising result in 3D reconstruction of CAD

[10]. Deep Learning (DL) algorithms like CNN and EfficientNet are widely used to detect and classify disease efficiently [11]. Machine Learning (ML) algorithms like Random Forest and Support Vector Mechanism are popularly employed for disease detection and classification [12,13]. These AI-based frameworks reconstruct images by providing rapid object detection and construction. However, many models focus on recreating shape from images rather than dealing with real-life changes such as motion, deformation, or variability in organs, which is why performance suffers in realistic circumstances [14]. Data imbalance and noise present in medical images further affect the reconstruction quality. Additionally, most existing system focus on recreating shapes of the medical images [15]. To address these issues, a novel model-based 3D medical image reconstruction is proposed for precise detection and classification of risk. The key contribution of the proposed is listed as follows,

- To increase the contrast of vessel-like structures and suppress background noise for higher image quality, an Optimally Oriented Flux (OOF) filter is used.
- A U-Net segmentation network is adopted to accurately segment the regions of the coronary arteries, while maintaining the resolution of fine vessels.
- To learn the relationship between the spatial features, a hybrid 3D CNN structure is used for effective 3D feature extraction.
- The proposed framework has the merits of better continuity and structural preservation of the vessel, as well as more accurate reconstruction than traditional reconstruction.
- The performance of the proposed CARDIO-3DNet has been tested with the following metrics, which are used for the efficient classification of 3D MIR: Accuracy, Precision, Recall, Specificity, F1-score, Dice Inde and Jaccard Index.

This paper is organized as follows: The literature review is given in Section 2. In Section 3, the proposed CARDIO-3DNet, a framework for 3D medical image reconstruction of coronary arteries, is described. The results of the experiments and the performance evaluation on the basis of different assessment metrics is discussed in Section 4. The study is concluded in Section 5, which suggests future research directions.

2. LITERATURE SURVEY

Several research have been conducted to reconstruct CAD using a range of DL and ML methodologies. These papers investigate various model architectures, feature extraction approaches, and segmentation techniques for improving reconstruction performance. The next part provides a comparative review of existing methodologies that includes suggested techniques and their achieved accuracies.

In 2025, Chen, Y et al., [16] developed a GVM-Net, a GNN-based model, is utilized for 2D/3D coronary artery registration, with vessel centerline points represented as graph nodes. It was chosen for its ability to record complicated topological relationships and tolerate non-rigid deformation across imaging modalities. Using attention mechanisms and message passing to match features, the model achieves an F1-score of 89.74% on synthetic data and 83.35% on clinical data, exceeding existing techniques.

In 2021, Hwang, M et al., [17] suggested a deep learning-based technique employing a U-Net with a ResNet encoder is used to detect coronary artery endpoints from X-ray coronary angiography. It was chosen for its high feature extraction capacity and is utilized for vessel end identification and 3D reconstruction using template-based matching. The model is highly accurate, with proximal detection rates of up to 97.7% and distal detection rates of up to 94.9% across several arteries.

In 2025, Zhu, L et al., [18] developed a DL image reconstruction (DLIR) technique is combined with ASiR-V to increase CT image quality for coronary artery calcium assessment. It was chosen for its ability to decrease noise while maintaining spatial resolution, resulting in accurate calcium scoring. The approach is used to evaluate patients' Agatston, volumetric, and mass scores. The results demonstrate no significant difference in Agatston scores ($P>0.05$), indicating great consistency with no effect on risk classification.

In 2020 Zamorski et al., [19] utilized a 3D Adversarial Autoencoder (3dAAE) with PointNet architecture for compact representation and reconstruction of 3D point cloud data. The model was used to efficiently learn latent 3D features and improve reconstruction, clustering, and retrieval performance through adversarial learning and Earth Mover's Distance optimization. Experimental findings demonstrated that the proposed network delivered superior performance compared to existing methods.

In 2021 Arndt., et al., [20] employed deep learning-based CT reconstruction techniques to enhance the quality of clinical CT images. The approach was designed to minimize image noise, improve spatial resolution, and provide better diagnostic visualization than traditional filtered back projection (FBP) and iterative reconstruction (IR) methods. The results indicated improved image quality and diagnostic performance, particularly for coronary artery stenosis assessment, while also supporting reduced radiation exposure.

The literature review revealed that although significant progress has been made in the field of DL-based CT image reconstruction, most methods have been developed to enhance the quality of the reconstructed image and to reduce noise, but they have not been optimized for accurate 3D reconstruction of the complex coronary artery structures. Most methods also lack the ability to maintain the continuity and spatial relationship of fine vessels, which is why these methods are not effective in detailed analysis of coronary artery and diagnosis. For this purpose, a novel CARDIO-3DNet is applied to achieve accurate reconstruction of 3D MIR, addressing these problems.

3. PROPOSED CARDIO-3DNET METHODOLOGY

In this section, a novel CARDIO-3DNet is introduced to detect 3D MIR by reconstructing the medical images from Synthetic Coronary Angiography Dataset. The proposed structural design of CARDIO-3DNet is shown in the figure 1.

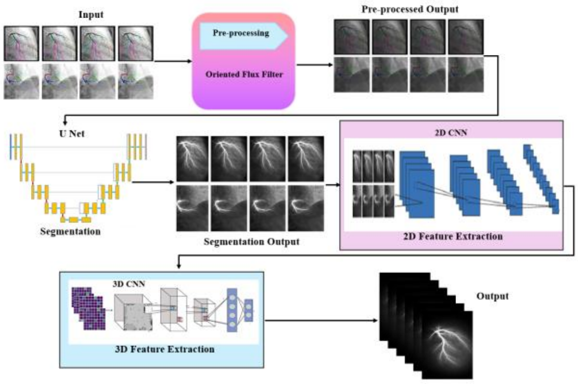


Figure 1: Schematic representation of the proposed CARDIO-3DNet methodology

3.1 Synthetic Angiography Dataset Description

The Synthetic Coronary Angiography Dataset is commonly used for creating and testing 3D reconstruction models using 2D projections. A lot of images for deep learning applications—some 15,000 training images and around 3,800 testing images. The total size of the dataset is around 100-120 MB, making it suitable for experimentation and model training. Images are produced from synthetic 2D X-ray angiography images of the coronary artery architecture, where the coronary artery has a different vessel pattern in each image. Images are generally 256x256 pixels for a compromise between detail and processing speed. Centerline and structural annotations are also provided which are utilized as ground truth for reconstruction tasks. The images depict multi-view angiographic projections, suitable to use for training models in 2D-to-3D coronary artery reconstruction and segmentation.

3.2 Oriented Flux filter (OFF)

Accurate enhancement and recognition of vessel-like features in the three-dimensional (3D) space of the coronary artery architecture in medical images is required to support the reconstruction process. The Optimally Oriented Flux filter (OFF) is a well-known filter for this application that is capable of identifying coronary arteries, which are curvilinear. The OFF filter is inspired by the idea of oriented flux—a measure of the gradient of the image passing through a limited spherical area in a particular direction. For a voxel a, the outward oriented flow along direction $\hat{\rho}$ within a spherical region R_s. is defined as follows:

$$g(a; s, \hat{\rho}) = \iint_{\varrho R_s} (j(a+h) \cdot \hat{\rho})(\hat{\rho} \cdot \hat{q})\, dX \quad (1)$$

This formulation can be stated in matrix format as

$$g(a; s, \hat{\rho}) = \hat{\rho}^T F_{s,a} \hat{\rho} \quad (2)$$

Where $F_{s,a}$ is a symmetric matrix, whose entries are defined as:

$$v_{l,m}^{s,a} = \int\int_{\varrho R_s} j_l(a+s\hat{q}) q_m dX \quad (3)$$

To efficiently compute the flow, convolution-based filtering is applied.

$$v_{l,m}^{s,a} = \psi_{s,l,m}(a) * L(a) \quad (4)$$

Where $\psi_{s,l,m}(a)$ indicates a collection of linear filters constructed from Gaussian derivatives. The optimal vessel direction is achieved by solving the eigenvalue problem.

$$V_{s,a} w_{s,a} = \lambda_{s,a} w_{s,a} \quad (5)$$

The eigenvector corresponding to the fewest eigenvalues establishes the normal plane, whereas the biggest eigenvalue specifies the vessel direction. This procedure emphasizes coronary arteries by boosting curvilinear features and increasing vascular visibility. The improved images are then sent into a U-Net-based deep learning model for segmentation.

3.3 U Net Segmentation

The pre-processed from the OFF filter is then passed to the U-Net architecture for precise segmentation of coronary artery features because it is effective in medical image analysis. U-Net consists of encoder-decoder architecture where the encoder extracts hierarchical features and the decoder regenerate the exact segmentation maps. The segmentation process can be mathematically represented as follows:

$$B = D(E(A)) \quad (6)$$

Here A represents the input image, whereas B represents the segmented output. The encoder extracts multilevel feature maps:

$$E(A) = \{G_1, G_2, G_3, G_4\} \quad (7)$$

Each feature map is created by convolving, activating and pooling operations

$$G_l = \begin{cases} g_{pool}(g_{relu}(g_{conv}(A))) & l = 1 \\ g_{pool}(g_{relu}(g_{conv}(G_{l-1}))) & l = 2,3,4 \end{cases} \quad (8)$$

The decoder recovers the segmentation using features upsampled and concatenated with skip connections.

$$D(E) = \{\hat{G}_4, \hat{G}_3, \hat{G}_2, \hat{G}_1\} \quad (9)$$

The rebuilt feature maps are obtained as follows:

$$\hat{G}_L = \begin{cases} g_{conv}\left(g_{relu}\left(g_{concat}\left(g_{up}(E_4), G_4\right)\right)\right) & l = 4 \\ g_{conv}\left(g_{relu}\left(g_{concat}\left(g_{up}\left(\hat{G}_{l+1}\right), G_{l+1}\ l = 3,2,1\right)\right)\right) \end{cases}$$
(10)

Architecture retains spatial (short-range) information while retaining deep semantic (long-range) information, which allows for a precise localization of coronary arteries. The result is a binary segmentation mask which distinctly divides the regions of the vessels from the background. Following segmentation, 2D CNN will identify meaningful spatial and structural features like edges, textures and vascular patterns.

3.4 2D Feature Extraction

After segmentation, feature extraction is used to extract relevant spatial and structural data from coronary artery images. First, 2D CNN are used to extract local features from segmented layers. The convolution process can be mathematically represented as follows:

$$b_p = \sum_{n=0}^{N-1} a_n h_{p-n} \tag{11}$$

The input image is represented by a, the convolution kernel is h, and b_p is the output feature map. To introduce nonlinearity, the Rectified Linear Unit (ReLU) activation function is used

$$X_{RELU}(n) = \begin{cases} n & if\ n > 0 \\ 0 & if\ n \le 0 \end{cases} \tag{12}$$

Pooling layers are then employed to minimize spatial dimensions while retaining dominating features, resulting in higher computing efficiency.

$$U(a_l) = \frac{e^{a_l}}{\sum_m e^{a_m}} \tag{13}$$

The retrieved 2D features from many slices are then combined into a volumetric representation for 3D analysis. To improve global feature learning, a Vision Transformer (ViT) is used with CNN features. While CNN detects local spatial patterns, ViT models long-range interdependence by converting image patches into sequences

3.5 3D Feature Extraction

In this section, a 3D CNN is used to gather spatial and depth-related information from volumetric medical images in order to effectively extract 3D features of coronary artery architecture. Unlike conventional 2D CNNs that process slices on an individual basis, 3D CNNs examine height, breadth, and depth data all at once using three-dimensional kernels. In 3D CNN, the convolution operation is stated as follows:

$$b_m = \sum_a \sum_b \sum_c I(a,b,c) K(u-a, v-b, k-c) \tag{14}$$

where $I(a,b,c)$represents the input 3D volume, Kdenotes the 3D convolution kernel, and $y_m$is the generated feature map. To enhance the learning capability of the model, the extracted features are passed through the ReLU activation function, introducing non-linearity.

$$X_{ReLU}(a) = \begin{cases} a & a > 0 \\ 0 & a \le 0 \end{cases} \tag{15}$$

Then, 3D pooling layers are used to minimize dimensionality while retaining crucial volumetric properties. The 3D CNN architecture acquires hierarchical representations of coronary artery structures, such as vessel continuity, branching patterns, and spatial correlations. The network is able to process volumetric data directly in order to better capture inter-slice dependencies and depth information and hence achieve improved feature representation for correct 3D reconstruction and analysis of coronary arteries.

4. RESULT AND CONCLUSION

The result section analyses the performance of the proposed CARDIO-3DNet using common metrics for 3D MIR classification. In this evaluation, we have analyzed several patients with their gathered fundus images between different time intervals. The experiments were performed on a workstation running Windows 10, equipped with an Intel Core i9 processor, 32 GB RAM, and an NVIDIA GPU with CUDA support to accelerate deep learning computations. The proposed model was implemented using Python and developed with widely used deep learning frameworks, including TensorFlow and PyTorch, for efficient 3D medical image reconstruction and analysis. Figure 4 shows the experimental results of the proposed CARDIO-3DNet.

4.1 Performance Analysis

The efficacy of the proposed CARDIO-3DNet performance is measured using metrics such as accuracy (AY), Precision (PN), specificity (SY), recall (RL), F1-score (F1-S), dices Index (DI) and Jaccard Index (JI). The use of CARDIO-3DNet for efficiently segmenting the 3D MIR from medical images leads to more accurate feature extraction and reconstruction.

$$\mathrm{AY} = \frac{\mathrm{T_P+T_N}}{\mathrm{T_P+T_N+F_P+F_N}} \tag{14}$$

$$\mathrm{RL} = \frac{\mathrm{T_P}}{\mathrm{T_P+F_N}} \tag{15}$$

$$\mathrm{PN} = \frac{\mathrm{T_P}}{\mathrm{T_P+F_P}} \tag{16}$$

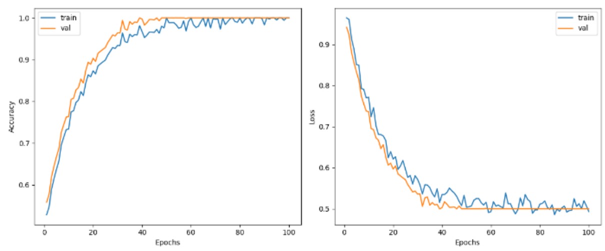
$$\mathrm{SY} = \frac{\mathrm{T_N}}{\mathrm{T_N+F_P}} \tag{17}$$

$$\mathrm{F1-S} = 2 * \frac{\mathrm{PN \times RL}}{\mathrm{PN+RL}} \tag{18}$$

$$DI = \frac{2.\mathrm{T_P}}{2.\mathrm{T_P+F_P+F_N}} \tag{19}$$

$$JI = \frac{\mathrm{T_P}}{\mathrm{T_P+F_P+F_N}} \tag{20}$$

From the above equation (14-20) $\mathrm{T_P}$ represents True Positive, $\mathrm{T_N}$ represents True Negative, $\mathrm{F_P}$ represents False Positive, and $\mathrm{F_N}$ denotes False Negative in the performance analysis of the 3D MIR reconstruction of medical image.



(a) (b)

Figure 2: Training and Validation of the proposed CARDIO-3DNet model (a) Accuracy Curve (b) Loss curve

Figure 2 depicts the training and validation performance of the proposed CARDIO-3DNet over 100 epochs. The accuracy graph in figure 2(a) demonstrates an increasing epoch in training and validation accuracy during the early learning period that demonstrates effective model convergence. The precise correlation of training and validation indicates good generalization capacity with low overfitting. The loss graph in figure 2(b) indicates a steady drop in both training and validation loss values as the period increases which indicates better learning efficiency. From this analysis these curves demonstrate the robustness and stability of the proposed CARDIO-3DNet for achieving reliable 3D MIR reconstruction results.

4.2 Comparative Analysis

Different metrics are used to provide a comparison of the proposed CARDIO-3DNet with the existing approaches. The performance of conventional models was analyzed to show the effectiveness of CARDIO-3DNet in 3D medical image reconstruction. Overall, Table 1 presents the comparative results of the various segmentation methods.

Table 1: Comparison of Segmentation Networks

Network	DI	JI
FCN	0.80	0.82
SegNet	0.88	0.86
U Net	**0.97**	**0.94**

Table 1 shows the comparison of segmentation models using DI and JI, where JI is used to measure the accuracy of the overlap between the predicted and ground-truth regions. U Net had the best performance of DI with 0.97 and JI with 0.94, showing superior feature representation and border localization due to long range dependencies. Overall, the findings suggest that the proposed U Net enhance the segmentation accuracy when compared with other Networks.

Table 2: Comparison of different DL Networks with MobiEffi Net

Network	AY (%)	PN (%)	SY (%)	RL (%)	F1-S (%)
AlexNet	98.24	97.15	96.07	97.17	95.42
ShuffleNet	98.51	97.56	96.21	97.62	96.12
SqueezeNet	98.63	98.07	96.86	98.15	96.85
DenseNet	98.89	98.11	97.64	98.27	97.01
3D CNN (Ours)	**99.02**	**98.37**	**97.76**	**98.54**	**97.23**

Table 2 compares the effectiveness of various existing networks in extracting 3D MIR with the proposed model. AlexNet has lower accuracy of 98.24% because of its restricted feature extraction capability, but ShuffleNet and SqueezeNet increase accuracy by 98.51% and 98.63% through lightweight and efficient learning. DenseNet improves performance by 98.89% allowing for better feature reuse and deeper information flow. The proposed 3D CNN achieves the maximum accuracy of 99.02% and F1-score of 97.23% by allowing excellent extraction of both local and global features characteristics for enhanced 3D MIR. The proposed CARDIO-3DNet increases the AY by 0.79%, 0.52%, 0.39%, and 0.13% over AlexNet, ShuffleNet, SqueezeNet and DenseNet respectively.

Table 3: Accuracy Comparison of Existing and Proposed CARDIO-3DNet model

Authors	Methods	Accuracy (%)
Chen, Y et al., [16].,	GVM-Net	89.74
Hwang, M et al., [17].,	U-Net with ResNet	97.7
Zhu, L et al., [18].,	DLIR	94.06
Zamorski et al., [19]	3dAAE	96.48
Proposed (Ours)	**CARDIO-3DNet**	**99.02**

Table 3 shows the comparison of the proposed CARDIO-3DNet achieved the highest accuracy of 99.02%, outperforming existing methods such as SVM, CNN, Mask R-CNN, and Attention-based U-Net. Traditional techniques showed lower performance due to limited feature extraction and segmentation capability. The improved accuracy of the proposed method is achieved through effective vessel enhancement, precise segmentation, and robust deep feature learning. The proposed CARDIO-3DNet exceeds all other approaches with 99.02% accuracy due to its accurate reconstruction process. The proposed CARDIO-3DNet has higher accuracy by 9.33%, 1.33%, 5.01% and 2.56% better than GVM-Net, U-Net with ResNet, DLIR and 3dAAE respectively.

5. CONCLUSION

The paper presents a dl-based CT image reconstruction approach to improve the quality of clinical CT images. The method reduces image noise, enhances spatial resolution, and improves visualization compared to traditional reconstruction techniques such as filtered back projection and iterative reconstruction. The study demonstrated that DL reconstruction provides better diagnostic image quality and supports accurate clinical analysis while potentially reducing radiation exposure. The performance of the proposed CARDIO-3DNet was validated with AY, PN, RL, SY, F1-S, DI and JI respectively. From the experimental result indicate that the proposed CARDIO-3DNet has a high reconstruction accuracy as 99.02%, F1-Score as 97.23% DI as 0.97 and JI as 0.94 respectively. The proposed CARDIO-3DNet has higher accuracy by 9.33%, 1.33%, 5.01% and 2.56% better than GVM-Net, U-Net with ResNet, DLIR and 3dAAE respectively. The proposed work can be further enhanced by incorporating advanced transformer-based architectures and graph neural networks for the enhancement of spatial feature learning and vessel connectivity analysis. Future studies can be extended by using large-scale and heterogeneous clinical datasets for real-time 3D reconstruction to further improve generalization and robustness. Furthermore, multimodal medical imaging data that are either computed tomography, magnetic resonance imaging or angiography can be fused together in order to obtain more accurate and detailed coronary artery reconstruction and diagnosis.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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S. Prince Samuel is a dedicated researcher and academician with a strong foundation in Electronics, Embedded Systems, and advanced applications of Image Processing and Machine Learning. His academic journey began with a Bachelor of Engineering in Electronics and Instrumentation Engineering, Karunya University which laid the technical groundwork for his career. With a keen interest in embedded technologies and intelligent systems, he pursued a Master of Technology in Embedded Systems, Karunya University gaining specialized expertise in system design, hardware–software integration, and real-time applications. His academic pursuits culminated in a Ph.D. in Image Processing and Machine Learning, where he explored innovative methodologies for data-driven solutions, pattern recognition, and automation across multidisciplinary domains. Samuel's research contributions span across funded projects, publications, and applied innovations. He has successfully executed multiple research projects supported by national and state-level funding agencies, including the Department of Science and Technology (DST), the Tamil Nadu State Council for Science and Technology (TNSCST), and the Indian Council of Medical Research (ICMR). These projects highlight his ability to translate theoretical research into practical applications, particularly in healthcare technologies, biomedical instrumentation, and intelligent monitoring systems. His work has consistently focused on developing affordable, efficient, and reliable solutions that address real-world challenges. In the realm of Image Processing, Samuel has worked extensively on algorithms for feature extraction, image segmentation, and classification techniques, with applications in medical diagnostics, industrial automation, and security systems. His integration of Machine Learning models into image-based systems has enabled predictive analytics, pattern detection, and decision-making support tools. These contributions reflect his multidisciplinary approach, combining engineering principles with artificial intelligence to achieve impactful outcomes. Samuel's expertise is well-documented through his conference and journal publications at national and international levels. His papers cover a wide spectrum, from technical advancements in embedded system design to innovative applications of artificial intelligence in biomedical engineering. These publications have established him as a recognized voice in his research community, while also enabling collaborative opportunities with scholars, industry experts, and healthcare professionals. Beyond individual research, Samuel has been actively engaged in mentoring and guiding students, encouraging them to participate in research initiatives, technical presentations, and publications. He emphasizes the importance of bridging the gap between academia and industry, preparing students to adapt to rapidly evolving technological trends. His involvement in interdisciplinary collaborations reflects his vision of integrating electronics, computing, and biomedical sciences to drive innovation.With a strong combination of technical expertise, research experience, and academic leadership, Prince Samuel continues to contribute significantly to the fields of Embedded Systems, Image Processing, and Machine Learning. His work, supported by esteemed funding bodies and validated through impactful publications, demonstrates his commitment to advancing technology for societal benefit. Looking ahead, his research endeavors are directed towards developing next-generation intelligent systems, expanding the applications of AI in healthcare, and fostering innovation-driven education and research.

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