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Research Article

Multi-Layered Model Approach (MLMA) For Heart Vein Blockage Detection Using Gated Recurrent Unit (GRU) and Denoising Autoencoders (DAES)

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ABSTRACT

Cardiovascular diseases (CVD) continue to be the leading cause of death worldwide, and sophisticated diagnostic techniques must be developed to detect and treat them early. This study analyzed vein blockages in the heart and proposed an ensemble model for the early diagnosis of heart problems. Venous blockages can be found using non-invasive imaging techniques, frequently suggesting cardiovascular abnormalities. Using a Coronary Computed Tomography Angiography (CCTA) dataset that includes normal and abnormal cardiac cases, the pre-trained 3D convolutional neural network (3D-CNN) model can learn complex patterns linked to early-stage cardiac problems. To improve the accuracy and dependability of the detection process, the proposed ensemble model incorporates several algorithms, including the segmentation-based threshold method, feature extraction-based form descriptors, and the vessel tracking algorithm (VTA). The ensemble model consisted of several base models, each focusing on a distinct area of vein blockage investigation. Feature extraction techniques extract pertinent information from medical imaging data, such as angiograms and vascular scans. The ensemble model, which uses the combined decision-making ability of several algorithms, including shape descriptors, is fed to the retrieved features. The proposed ensemble model performed better than the individual models and conventional diagnostic techniques regarding early detection accuracy. Moreover, analysis of the feature importance scores improves the interpretability of the model and sheds light on the crucial markers of cardiac anomalies. The suggested ensemble model has a significant potential clinical impact because early identification of cardiac problems enables prompt intervention and better patient outcomes. Finally, the proposed method combines the multi-layer approach with gated recurrent units (GRU) and a Denoising Autoencoder (DAE) to find abnormalities in angiography images. The effectiveness of the suggested method demonstrates a high rate of disease diagnosis and accuracy for specified angiography images.

Keywords: Cardiovascular Diseases, Vessel Tracking Algorithm, Coronary Computed Tomography Angiography, 3D Convolutional Neural Networks, Gated Recurrent Unit, Denoising Autoencoder.

INTRODUCTION

Heart failure is a widespread and complicated medical ailment that places a heavy strain on the global healthcare system. Comprehensive and effective methods for studying and managing heart failure are becoming increasingly important as the prevalence of this condition increases. With the abundance of patient data that may be used to improve our understanding of heart failure, electronic health records (EHRs) have become a potent instrument that revolutionizes healthcare delivery and research. This illness is characterized by the inability of the heart to pump blood effectively, resulting in symptoms such as exhaustion, despair, and retention of fluid. It is a complex illness that is affected by several variables, such as comorbidities, lifestyle, genetics, and cardiovascular disorders. Integrated and holistic approaches that use a large quantity of patient data stored in electronic health records (EHRs) are required to address heart failure. With the ability to digitally record a patient's medical history, diagnosis, prescriptions, test results, and treatment plans, EHR has become essential to contemporary healthcare. A real-time, longitudinal picture of patient health is made possible by integrating EHRs into heart failure research, leading to more precise evaluations of the course of the disease, the effectiveness of treatment, and general patient management. EHR provides smooth information sharing between medical professionals and promotes cooperation and coordination in treating heart failure. Healthcare workers can make well-informed judgments and provide a more comprehensive view of a patient's health status by having easy access to pertinent clinical data, thanks to the interoperability of EHR systems. Because EHRs enable academics and healthcare organizations to analyze large cohorts of individuals with heart failure, they play a critical role in population health management. Identifying trends, risk factors, and disparities—made more straightforward by this population-level approach— will guide the development of preventive policies and public health interventions.

On the other side, cardiovascular diseases (CVDs) are still a significant source of morbidity and death worldwide, and new methods of comprehending and treating these intricate medical problems are required. Big data technologies have recently completely changed the healthcare industry by providing previously unheard-of opportunities to analyze enormous datasets and gain insights into cardiovascular health. Clinicians, researchers, and decision-makers must effectively visualize healthcare data's increasing volume, velocity, and variety. Cardiology has used big data analytics to improve treatment plans, prognosis, and diagnostics. However, communicating and interpreting cardiovascular data is difficult because of the vast amount and complexity of the data. Visualization is a powerful tool for distilling intricate patterns, relationships, and trends within these datasets, facilitating a more intuitive understanding of healthcare professionals. From imaging data to EHR and genomics, amalgamating diverse data sources requires sophisticated visualization techniques to unlock actionable insights.

A. *Objectives*

- The proposed approach combines image processing and deep learning algorithms.
- Detection of abnormal vein blockage from the given input samples.
- Develop a multi-layered model combining GRU and DAEs for heart-vein blockage detection.
- The temporal modeling capabilities of the GRU were utilized to analyze sequential physiological data.
- Employ DAEs to enhance feature extraction and denoise input signals, thereby improving the robustness of the model.
- The performance of the proposed model was evaluated using benchmark datasets and compared with existing methods.
- It focuses on tracking the blood-tracking vessel status by using the proposed VT algorithm.
- Investigate the interpretability of the model to provide insights into the features contributing to blockage detection using VTA.

LITERATURE SURVEY

Akhtar et al.'s study [11] aims to conduct a thorough risk assessment of CAD software used in hepatic resection procedures, emphasizing potential difficulties, weaknesses, and safety issues. A multifaceted approach to risk assessment was used, including simulation-based analysis, expert interviews, and literature review. With emphasis on hepatic resection procedures, this study considered both the technical features of the CAD software and its incorporation into the clinical workflow. Technical, clinical, regulatory, and operational aspects were used to group the potential concerns. Potential false positives or negatives were discovered while evaluating CAD software algorithms, necessitating ongoing improvement and validation. A novel approach for segmentation of the left ventricle using magnetic resonance images was developed by Dakua et al. [12] to advance the field of cardiac image processing. Precise division of the left ventricle is necessary to measure cardiac output, evaluate the condition of the heart, and identify early stages of cardiovascular anomalies. The proposed methodology that has been suggested combines deep learning architectures, machine learning algorithms, and state-of-the-art image processing techniques to improve the accuracy and productivity of left ventricle segmentation. In Bizopoulos et al.'s [13] discussion on applying deep learning models in cardiac imaging, it was noted that GAN and CNN have shown impressive results in feature extraction, picture synthesis, and image segmentation. These developments have increased diagnostic skills, making it possible to identify cardiac irregularities more precisely and better comprehend complex cardiovascular disorders. Moreover, this study delves into the function of deep learning in electrocardiogram (ECG) interpretation, demonstrating its capacity to identify minute irregularities, forecast arrhythmia, and aid in risk assessment. The enhanced accuracy of predictive models can be attributed to the effective handling of temporal dependencies in ECG data by recurrent neural networks (RNNs) and attention mechanisms. A DL method was proposed by Wu et al. [14] to customize a general ECG heartbeat classification model to increase arrhythmia detection accuracy.

The one-size-fits-all methodology used by traditional ECG classification algorithms frequently ignores the individual variability in heartbeat rhythms. Our proposed approach uses deep neural networks to customize and adjust the model according to the distinct features of each person's ECG data by changing the model's parameters and considering patient-specific characteristics. These factors increase the sensitivity and specificity of arrhythmia detection. This methodology is a two-step process. First, training a generic ECG heartbeat classification model on a large dataset captured the general normal and pathological heartbeat patterns. Second, the model's weights and biases can be adjusted for better performance by personalizing them with patient-specific ECG data and transfer learning. We assessed the efficacy of our methodology using a heterogeneous dataset with a range of arrhythmia types to guarantee the stability of the model in diverse patient populations. Ultimately, compared with generic models, the results show a notable improvement in the accuracy and specificity of arrhythmia detection. The customized method shows how deep learning models may be tailored to specific individuals, opening the door to more efficient and patient-focused diagnostic instruments for cardiovascular health. Taji et al. [16] presented a novel Deep Belief Network (DBN)--based method for reducing false alarms in atrial fibrillation diagnosis. DBNs are a class of artificial neural networks that are particularly useful for identifying complex relationships and patterns in large, complicated datasets. We aim to reduce false alarms and increase the accuracy of AF detection using DBNs' deep learning capabilities of DBNs. The suggested technique incorporates normal sinus rhythm and AF situations using a significant electrocardiogram (ECG) signal dataset. DBN was trained to recognize minute distinctions between atrial fibrillation and normal rhythms and automatically extract pertinent data. Furthermore, the network integrates temporal dependencies within ECG data, improving its capacity to differentiate between short-lived anomalies and prolonged episodes of atrial fibrillation. Extensive experiments are conducted using real-world ECG datasets to evaluate the performance of the proposed system. The results demonstrated a significant reduction in false alarm rates compared to traditional AF detection methods. The DA's unique process for identifying and categorizing cardiac murmurs using DNNs in combination with neuromorphic auditory sensors was presented by Dominguez-Morales et al. [17].

Neuromorphic auditory sensors provide a biologically inspired signal-processing framework that simulates the human hearing system. These sensors record cardiac murmurs' temporal and frequency properties and provide a wealth of data for classification tasks. In this study, we take advantage of the benefits of neuromorphic auditory sensors to improve cardiac murmur representation for DNN analysis. The outcomes demonstrate how successfully the suggested DNN-based system can identify and categorize cardiac murmurs. Our technique outperforms existing methods, especially when it comes to managing murmur fluctuations in a variety of patient demographics. The outcomes show how well the suggested DL strategy recognizes the S1 and S2 heart sounds. The model achieved high sensitivity and specificity, demonstrating its potential as a valuable diagnostic tool. Du et al. [19] focused on creating and applying a deep regression segmentation method designed explicitly for cardiac biventricle MR images. Pixel-by-pixel classification is a standard method used in traditional picture segmentation techniques that may help handle cardiac structures' intrinsic complexity and diversity. By contrast, deep regression segmentation uses neural networks to anticipate continuous output values, making it possible to define borders and finer anatomical details more accurately. The deep learning architecture used in the suggested framework was created, particularly for the complex characteristics of cardiac bi-ventricle MR images. The model's robust performance across various patient demographics and imaging situations was ensured by its training on a broad dataset that included many annotated cardiac magnetic resonance images. Transfer learning approaches use pre-trained models on relevant medical imaging tasks to overcome the difficulties caused by the need for annotated data. The fine-tuning process adapts the network to the specifics of cardiac ventricle segmentation, enhancing its generalization capabilities and overall performance.

To solve these issues and increase the precision of cardiac image augmentation and segmentation, Oktay et al. [20] suggested a novel method called ACNNS. ACNNS improves the robustness and accuracy of cardiac image-processing tasks by combining anatomical limitations with the capacity of neural networks. A wide range of cardiac imaging datasets were used to train the model, allowing it to capture differences in architecture and disease. Anatomical priorities are incorporated into the architecture to guarantee that the network predictions match the expected heart structures. ACNNS uses a combination of CNNs and attention techniques to suppress artifacts and noise while selectively enhancing pertinent anatomical characteristics for cardiac image enhancement. As a result, the key features of the cardiac pictures were more clearly seen, and the image quality was improved. To separate the left ventricle (LV) from ultrasound data, Carneiro et al. [21] presented a novel approach that blends deep learning architectures with derivative-based search approaches. Precise LV segmentation is essential for identifying and tracking numerous cardiovascular disorders. The intrinsic difficulties ultrasound images present, such as noise, artifacts, and anatomical variability, are generally resisted by traditional segmentation techniques. The proposed approach uses deep learning (DL) to recognize and adjust intricate patterns in the ultrasound data automatically. We utilized the CNN architecture and trained it in various annotated ultrasound picture datasets. The potential of deep learning algorithms in identifying cardiovascular illnesses from mammograms, a commonly used medical imaging modality, was investigated by Wang et al. [22]. Our proposed technique uses CNNs to analyze mammography images and find minute markers linked to cardiovascular problems. A large dataset includes mammograms from various patient groups, including healthy controls and patients with established cardiovascular diseases. Expert radiologists carefully annotated the dataset to guarantee precise ground truth labels. The deep learning model was trained on this dataset using transfer learning approaches to utilize pre-existing knowledge from large-scale image datasets. These findings show how well the proposed deep learning model accurately and sensitively identifies cardiovascular disease from mammograms. This model successfully identified known cardiovascular abnormalities and exhibited the potential to discover subtle patterns that may elude traditional diagnostic methods.

Using HRV as a metric, Lacuesta et al. [23] developed a system that integrates physiological, geographic, and well-being indicators to determine the optimal location for a user's level of wellness. A recommendation engine is put in place that provides location suggestions based on the interests and wellness profile of the user. The engine should consider recreational possibilities, community involvement, air quality, healthcare quality, HRV, and climate. Hammad et al. [24] presents a unique multitier deep learning model for arrhythmia detection to improve sensitivity and specificity in recognizing various arrhythmic patterns. The proposed model is divided into several tiers, each focused on capturing unique ECG signal characteristics. The first tier uses CNN to extract fundamental morphological traits and lay the groundwork for later levels. The second tier uses an RNN to extract ECG data's temporal and dynamic patterns. To further improve the model's ability to identify tiny anomalies, the third tier uses attention mechanisms to focus on salient regions preferentially. An automated method for detecting myocardial infarction using harmonic phase distribution patterns obtained from ECG data was presented by Sadhukhan et al. [25]. The procedure is multistep, beginning with the collection of ECG signals from individuals who may have heart problems. The ECG data were subjected to Fourier analysis to obtain harmonic components following preprocessing and noise reduction. These constituents then produce harmonic phase distribution patterns that depict underlying heart activity.

The outcomes show how well the harmonic phase distribution patterns differentiate between cases of myocardial infarction and normal cardiac tissue. The automatic identification system has the potential to be used in real-time clinical applications and displays encouraging accuracy. Global sequence features were extracted from cardiac activity by Li et al. [26]. Global sequence features offer a comprehensive data picture by referring to patterns or attributes throughout the heartbeat sequence. A BiLSTM neural network with attention processes is used in this study. An RNN called BiLSTM can record dependencies both forward and backward. By assisting the model in concentrating on segments of the input sequence, attention mechanisms improve the model's capacity to identify pertinent patterns. Ultimately, this research attempts to shed light on the reasons for the neural network's classification of heartbeats. A hybrid model that combines the benefits of CNN and BiLSTM was proposed by Xu et al. [27] to improve the precision and effectiveness of ECG rhythm classification. Scientists have created models that combine CNN and BiLSTM. This combination is probably intended to leverage the complementary strengths of BiLSTM (temporal dependencies) and CNN (spatial characteristics) in ECG data. The ultimate objective of this integrated model is to categorize various ECG rhythms. Accurate classification is essential for diagnosis and therapy planning because different rhythms suggest different heart diseases.

PRE-TRAINED 3D CONVOLUTIONAL NEURAL NETWORKS (3D-CNN) FOR HEART VEIN BLOCKAGE DETECTION

Heart vein obstruction, commonly referred to as coronary artery disease (CAD), is a common and potentially fatal disorder that arises from the narrowing or blocking of the blood veins supplying the heart muscle. Early and precise blockage diagnosis is essential for prompt intervention and successful treatment. Advanced medical imaging has made sophisticated computer-aided diagnostic systems and incredibly three-dimensional (3D) imaging modalities possible. CNN has shown impressive results in image processing tasks; 3D-CNN brings this power to volumetric data, such as three-dimensional medical scans. For functions such as cardiac vein blockage identification, where spatial linkages and contextual information in the third dimension are critical for precise diagnosis, the use of 3D-CNNs is beneficial. The pre-trained models were trained on a large dataset for a specific purpose in the context of DL. These models can be improved or utilized as feature extractors for similar tasks. These models can drastically reduce the quantity of data and processing power required for training while still capturing hierarchical information from the data. A pre-trained 3D-CNN model can detect cardiac vein blockage and analyze volumetric medical images, including computed tomography angiography (CTA) scans. With the help of a varied dataset that includes annotated instances of blocked and normal vasculature, the model was trained to acquire the discriminative features necessary for precise classification.

B. *The following layers were used in the 3D-CNN model.*

1. Input Layer

- Input dimensions: Volumetric data representing the heart veins.
- Shape: Depth, height, Width, Channels.

2. Convolutional Layers

- Apply 3D convolutional operations to capture spatial features.
- Convolution operation:

$$Y[i,j,k] = \sum_{a=0}^{A-1}\sum_{b=0}^{B-1}\sum_{c=0}^{C-1} X[i+a, j+b, k+c] \cdot W[a,b,c] + b \qquad (1)$$

- Activation function (e.g., ReLU): A(x)=max(0, x).

3. Pooling Layers:

- It is used to reduce the spatial dimensions.

4. Flattening Layer:

- The output was flattened for fully connected layers.

5. Fully Connected (dense) layer

- Dense layer operation:

$$Y = A(W \cdot X + b) \qquad (2)$$

- Apply activation function (e.g., ReLU)

6. Output Layer:

- Output layer for binary classification (blockage or no blockage).
- Sigmoid activation function: $\sigma(x) = \frac{1}{1+e^{-x}}$

7. Loss Function:

The suitable loss function for binary classification used in this context is binary cross-entropy.

$$\text{Binary Cross} - \text{Entropy Loss} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(p_i) + (1-y_i)\log(1-p_i)] \qquad (3)$$

Where N - total samplesy_i is the actual label, and p_i is the predicted probability.

8. Training:

- The network is optimized using an optimizer (e.g., Adam) to minimize loss.

$$\theta_{t+1} = \theta_t - \eta \cdot \nabla_\theta J(\theta) \quad (4)$$

- where θ is a parameter, η is the learning rate, and J(θ) is the loss.

C. Segmentation-based Threshold Approach

Segmentation-based thresholding techniques are used in image processing to distinguish objects or regions of interest from the background by assigning a threshold value. Otsu's well-liked segmentation method finds an ideal threshold by maximizing the variation between foreground and background pixel classes.

The following steps were used for Otsu's method:

1. Compute Histogram:

First, the grayscale image histogram is calculated, showing the pixel intensities' distribution.

$$P(i) = \frac{n_i}{N} \quad (5)$$

Where

P(i) → probability of occurrence of intensity i.

n_i: total pixels with intensity i

N: Total pixels of the input image.

2. Compute Cumulative Distribution

Compute the cumulative distributionw_i and cumulative meanμ_i.

$$w_i = \sum_{j=0}^{i} P(j) \quad (6)$$

$$\mu_i = \sum_{j=0}^{i} j \cdot P(j) \quad (7)$$

3. Compute Global Mean

$$\mu = \sum_{i=0}^{L-1} i \cdot P(i) \quad (8)$$

4. Compute Between-Class Variance

$$\sigma_B^2 = w_i \cdot (1 - w_i) \cdot (\mu_i - \mu)^2 \quad (9)$$

5. Find the Optimal Threshold T

$$T = \mathrm{argmax}_t\left(\sigma_B^2(t)\right) \quad (10)$$

D. *Feature Extraction Technique*

They play a crucial role in shape analysis, and several shape descriptors are based on mathematical equations. Some extraction-based shape descriptors and their corresponding equations are as follows.

In this section, features are extracted using shape descriptors.

1. Area (A):

$$A = \int_x \int_y dxdy \quad (11)$$

2. Perimeter (P)

$$P = \int_0^{2\pi} \sqrt{(\frac{dx}{d\theta})^2 + (\frac{dy}{d\theta})^2 \, d\theta} \quad (12)$$

3. Compactness ©:

$$\text{Compactness} = \frac{P^2}{4\pi A} \quad (13)$$

4. Circularity:

$$\text{Circularity} = \frac{4\pi A}{P^2} \quad (14)$$

E. Vessel Tracking Algorithm (VTA)

Detecting heart vein blockages involves medical imaging and analysis rather than a straightforward algorithm such as a vessel tracking algorithm (VTA). However, a basic algorithmic structure can be considered if you are interested in a simplified representation of how one might approach vessel tracking in medical imaging, particularly for detecting blockages. This section contains the following steps: vesselness filtering, vessel segmentation methods such as threshold and region growing, and a vessel-tracking algorithm to track the blockages using a Kalman filter in the given images.

Vesselness Filtering: Frangi filtering removes noise from the input images in this step.

$$R(x, \sigma) = \frac{\mathrm{Det}\big(C(\sigma)\big)}{\mathrm{Tr}\big(C(\sigma)\big)} \quad (15)$$

Where $C(\sigma)$ is the Hessian matrix at scale σ

Thresholding:

$$\text{Binary Image}(x) = \begin{cases} 1 & \text{if } I(x) > \mathit{Threshold} \\ 0 & \text{otherwise} \end{cases} \quad (16)$$

Region Growing:

$$\text{RegionGrowing}(x_i) = \begin{cases} 1 & \text{if } |\text{Intensity}(x_i) - \text{MeanIntensity}(\text{Region})| < \mathit{Tolerance} \\ 0 & \text{otherwise} \end{cases} \quad (17)$$

Kalman Filter:

$$X_{k+1} = AX_k + BU_k + W_k \quad (18)$$

Where X_k is the state vector is, A is the state transition matrix, B is the control-input matrix, U_k is the control vector, and W_k is the process noise.

MULTI-LAYERED MODEL APPROACH (MLMA) FOR HEART VEIN BLOCKAGE DETECTION USING GATED RECURRENT UNIT (GRU) AND DENOISING AUTOENCODERS (DAES)

Detecting heart vein blockages is a critical task in the medical field, and using a multilayered model approach can enhance detection accuracy. Combining GRU and DAE in a multilayered architecture is an interesting approach that leverages the strengths of both RNN and Auto-Encoders for feature extraction and sequence modeling. Cardiovascular disease remains a leading cause of mortality worldwide, necessitating advanced and accurate diagnostic tools for early detection and intervention. Among these conditions, heart vein blockage significantly threatens cardiac health, emphasizing the need for innovative and precise detection methods. In this context, the integration of ML techniques has shown promise for improving the accuracy and efficiency of diagnostic procedures.

This study proposes a multi-layered model approach that combines GRU and DAE for the early detection of heart vein blockages. An RNN type called GRU is very good at identifying sequential dependencies in time-series data, making it a valuable tool for studying physiological signals. However, DAEs are proficient in feature extraction and denoising, enhancing the robustness of the model against noisy input data. The motivation behind this research stems from the need to enhance the diagnostic accuracy of heart-vein blockages, enabling timely medical interventions and improving patient outcomes. Traditional diagnostic methods often rely on subjective interpretation and lack the sensitivity required for early detection. By leveraging the capabilities of GRU and DAEs, this study aimed to provide a more sophisticated and reliable tool for identifying subtle patterns indicating heart vein blockages. One type of RNN architecture called the Gated Recurrent Unit (GRU), was created to solve some problems with conventional RNNs, such as the vanishing gradient problem. The GRU and the Long Short-Term Memory (LSTM) networks have a similar architecture, although the GRU gating mechanism is more straightforward. The central concept is to employ gating units to regulate the data flow across the network, making it better to identify long-term relationships in sequences.

The following equations and steps were used for GRU:

1. **Update gate (z_t):**

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \qquad (19)$$

2. **Reset gate (r_t)**

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \qquad (20)$$

3. **Candidate Hidden State ($\hat{h}_t$):**

$$\hat{h}_t = \tanh\left(W_h \cdot \left[r_t \odot h_{t-1}, x_t\right]\right) \qquad (21)$$

4. **New Hidden State** (h_t):

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \hat{h}_t \qquad (22)$$

W_z, W_r and W_h reweight matrices for the update gate, reset gate, and candidate hidden states, respectively.

where σ denotes the sigmoid activation function.

Tanh is the hyperbolic tangent activation function.

The update gate determines the amount of the previous concealed state to be retained (z_t), while the amount to be forgotten is determined by the reset gate (r_t). The new hidden state ($\hat{h}_t$) is a weighted mixture of the old and candidate hidden states governed by the update gate. The candidate's hidden state (h_t) is a new candidate value for the hidden state.

F. *Denoising Autoencoders (DAEs)*

Machine learning (ML) techniques have demonstrated the potential to improve the precision and effectiveness of cardiovascular disease detection in recent years. DAE, a particular kind of ANN intended for feature learning and data reconstruction, is one such method that is gaining popularity. To increase the sensitivity and specificity of diagnostic techniques, this study focused on using DAE in the context of cardiac vein blockage identification. Atherosclerotic plaque buildup is a common cause of heart vein blockage, which can result in serious health issues, such as myocardial infarction and stroke. The early diagnosis of these blockages is essential for implementing preventive measures, and the risk of unfavorable cardiovascular events is minimized. Creating accurate, affordable, and noninvasive diagnostic instruments is problematic. The use of the DAE is motivated by its capacity to introduce a denoising process and learn robust representations of incoming data. The network can recover clean signals from faulty inputs through autoencoder training, capturing essential features while removing noise and unnecessary data. Owing to its inherent denoising ability, the DAE is a good option for improving the precision of cardiac vein blockage diagnosis.

The variables of the DAE are as follows.

- X as the input data (noisy angiograms in this case).
- Z is an encoded representation (latent space).
- where, X is the reconstructed output.

1. Encoder Function: The input data (X with additional noise) are fed into the encoder, which converts it to a lower-dimensional representation (Z).

$$Z = f_{encoder}(X + noise) \qquad (23)$$

2. Decoder Function: The decoder reconstructs the clean version of the input from the encoded representation (Z).

$$\widehat{X} = f_{decoder}(Z) \qquad (24)$$

3. Denoising Autoencoder Objective Function: The objective is to minimize the reconstruction error across all input samples. ℓ is a loss function (e.g., mean squared error or binary cross-entropy) measuring the difference between the input (X_i) and the reconstructed output $(\widehat{X}_i)$ for each sample.

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N} \ell(X_i, \widehat{X}_i) \qquad (25)$$

A dataset of noisy angiograms was used to train the Denoising Autoencoder for heart-vein blockage identification. The encoded representation (Z) that was learned may then be applied to downstream tasks such as classification or anomaly detection. Early Identification of Cardiac Abnormalities Using Ensemble Algorithms and Vein Blockage. Figure 1 shows a sample heart angiogram image of the veins in the heart.

Figure 1: Sample heart angiography image

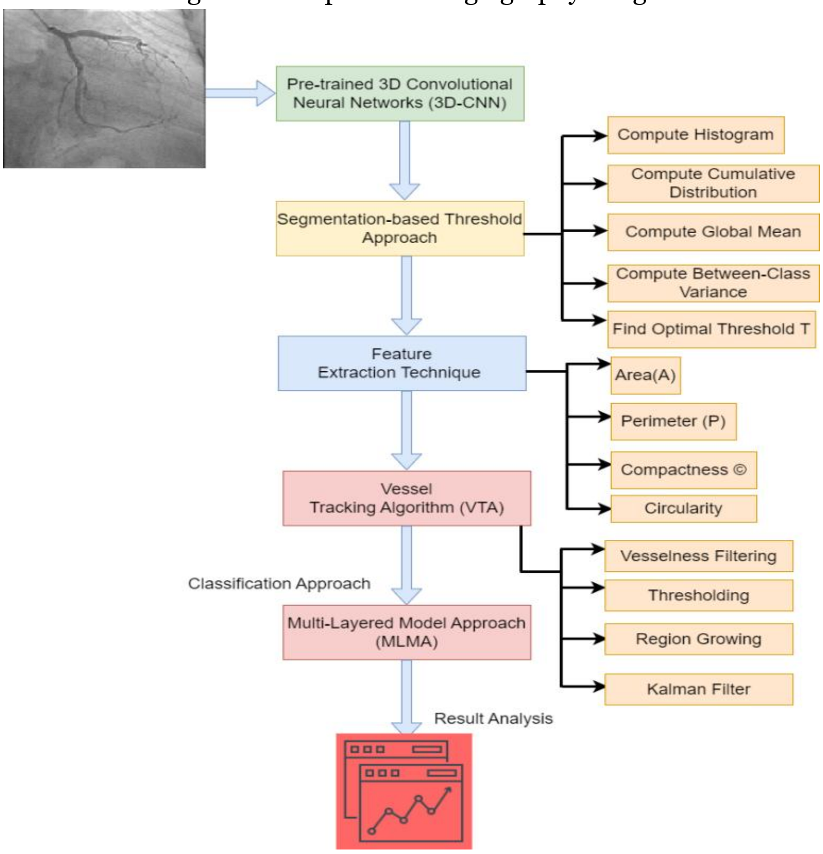

Figure 2: Overall System Architecture

G. Dataset Description and Performance Metrics

The dataset comes from the XCA images collected in [31]. This consists of two types of image segmentation. The first dataset shows the partitioning of a heart into 25 distinct areas according to the SYNTAX Score. It consists of 1500 coronary vascular tree images and accompanying annotations. The second category contained 1500 images annotated with atherosclerotic plaque-containing regions. Scientists can now actively contribute to advancing an automated risk assessment system for patients with CAD thanks to the meticulous annotations made by medical specialists on this dataset. This dataset is the most extensive, publicly accessible, and expert-labeled set of XCA pictures. These two segments were used to identify abnormal vein blockages. Table 1 shows the two types of datasets used to detect vein blockages.

Table 1: Two types of X-ray Angiography images

Dataset Type	Training	Testing
Coronary Artery Segments	1000	500
Stenotic Plaques	1000	500
Total	1500	1500

H. Training and Testing Loss

In this section, the training and testing contain the loss and accuracy. Mini batches of training data were sent over the network. The difference in accuracy between the expected and actual results is calculated. The error is repropagated, and the network's weights are updated with the selected optimizer. This process continued for a few epochs until the model converged. Training loss gauges the performance of the 3D-CNN model on the training dataset. It is computed using the discrepancy between the actual target and anticipated training set values. Reducing this loss is the main objective of training. In this work, an optimization technique such as Adam is usually used to modify the model's parameters to attain the desired performance. The suggested pre-trained model achieved a lower testing loss after training, indicating less overfitting. However, the overfitting issue was resolved when the optimization algorithm was applied. The testing loss calculates the model's performance on a different dataset that is not exposed during training. Figure 3 shows the training and testing losses of the Coronary Artery Segments. Figure 4 shows the analysis of training and testing loss for Stenotic Plaques. The study was conducted for 20 epochs. In Figure 3, the testing loss obtained the value of 0.079%, which is low compared with the training loss, which is acquired at 0.101. The low testing loss indicates the strength of the training model, which performed better on the given coronary artery segment dataset. In Figure 4, the testing loss is higher than the training loss. If the testing loss is high, it is considered that the model does not perform better on stenotic plaque data.

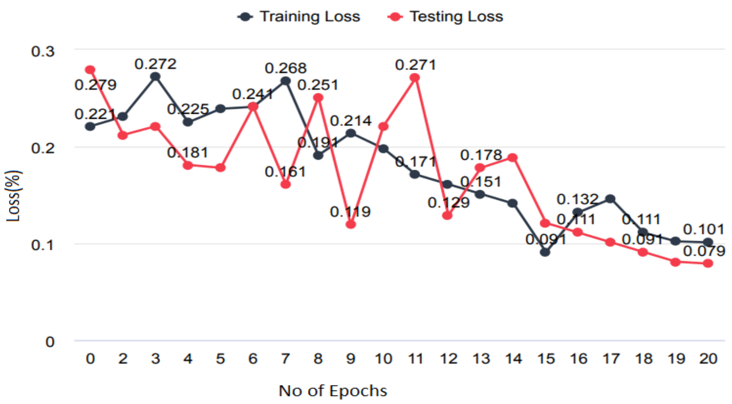

Figure 3: Training and Testing Loss for Coronary Artery Segments

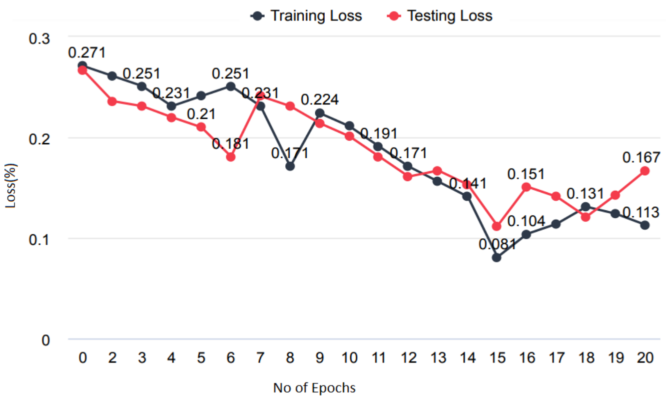

Figure 4: Training and Testing Loss for Stenotic Plaques

I. Training and Testing Accuracy

The primary goal of training accuracy was to measure the model's accuracy on the training data. This compares the model predictions with the actual labels found in the training dataset. The proposed method achieves high training accuracy, indicating that the model has effectively learned from the training set. Accuracy testing was conducted using a separate dataset not used for the training. The proposed method demonstrates the same accuracy for testing and training.

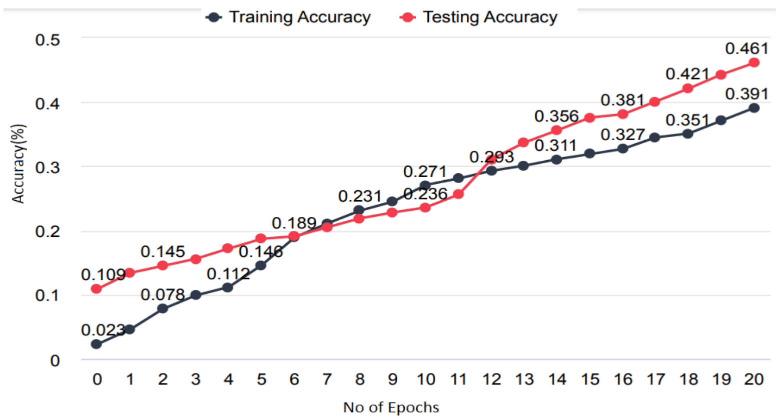

Figure 5: Training and Testing Accuracy for Coronary Artery Segments

Figure 5 shows the training and testing accuracy performance for the coronary artery segment dataset with values of 0.39% for training and 0.46% for testing, which is high. Training data may have provided a model with insufficient knowledge. There could be several causes, including inadequate training data and model complexity. Figure 6 shows the performance of the training and testing accuracy for the Stenotic Plaques dataset with a value of 0.456% for training and 0.458% for testing, which is slightly high.

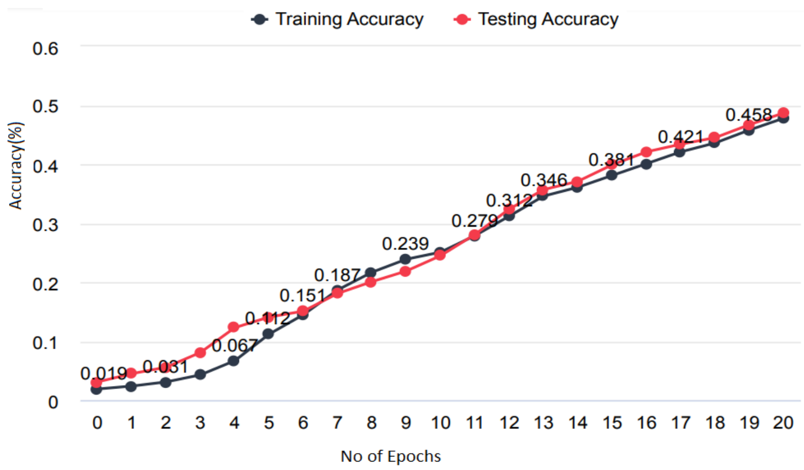

Figure 6: Training and Testing Loss Stenotic Plaques

Figure 7 shows the confusion matrix for analyzing the results. It shows the analysis's results based on the actual and predicted values.

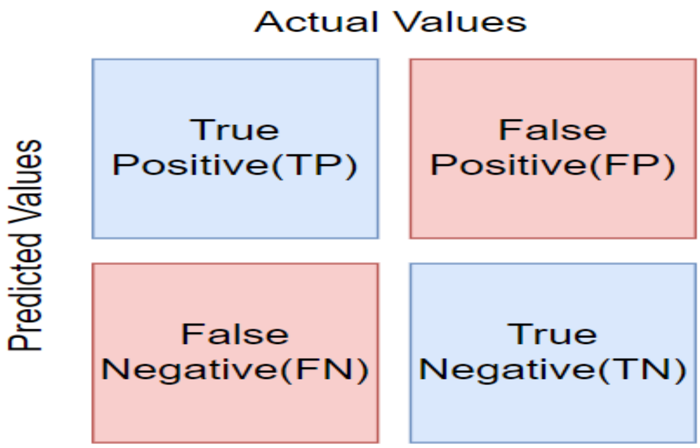

Figure 7: Attributes of Confusion Matrix

RESULTS AND DISCUSSIONS

The results in this section demonstrate the advantages of the proposed approach. Python programming language was used to develop the model. Based on the attributes of the confusion matrix count values, the following metrics were used to measure the algorithm performance:

$$\text{Accuracy(ACC)} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \quad (26)$$

$$\text{Precision(Pre)} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (27)$$

$$\text{Sensitivity (Sn)} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (28)$$

$$\text{Specificity (Sp)} = \frac{\text{TN}}{\text{TN} + \text{FP}} \quad (29)$$

$$\text{F1} - \text{Score} = 2 * \frac{(\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})} \quad (30)$$

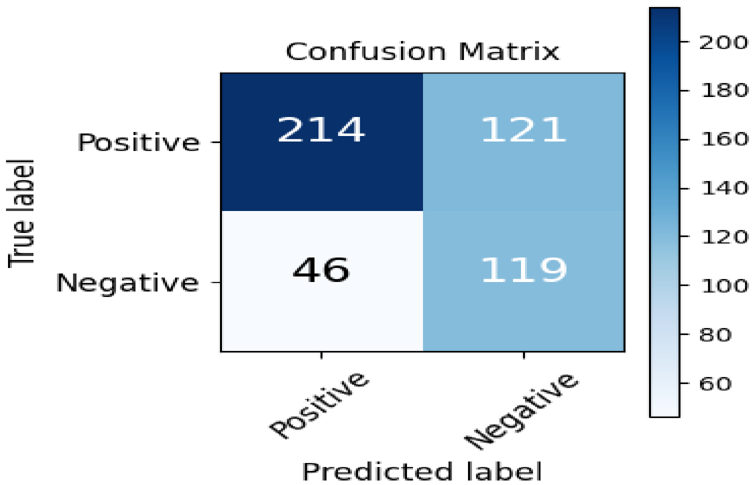

Figure 8: Count values obtained using confusion matrix for CNN model

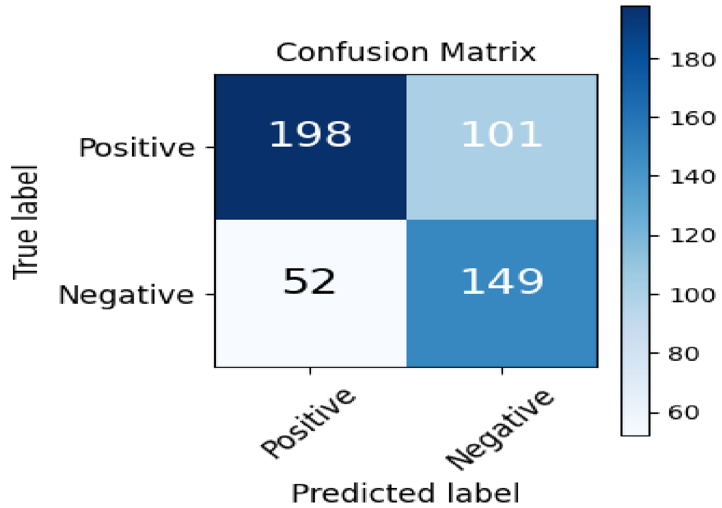

Figure 9: Count values obtained using confusion matrix for YOLOv8 [31] model

Figure 8 shows the count values obtained using the confusion matrix for the CNN model. TP acquired 214 values: FP-121, FN-46, and TN-119. The parameters were then measured using these values. Figure 9 shows the performance of count values from the confusion matrix for the YOLOv8 model. Figure 10 shows the performance of count values from the confusion matrix for the MLMA model. All these models were applied to the Coronary Artery Segment datasets.

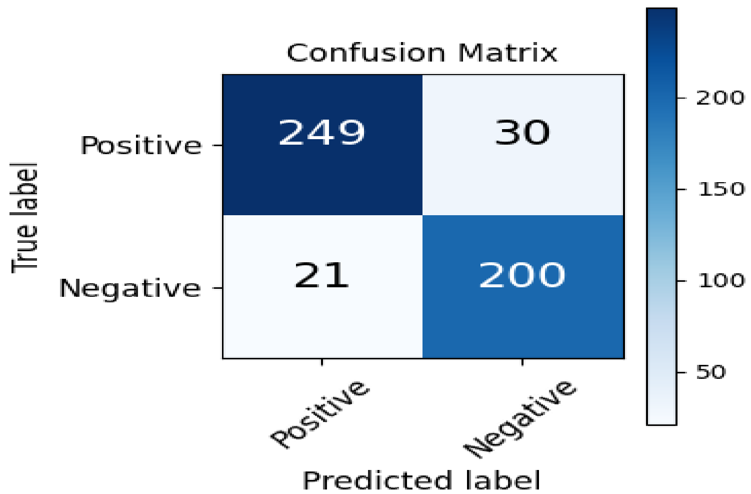

Figure 10: Count values obtained using confusion matrix of MLMA model

Table 2: List of Algorithms that perform classification based on given parameters using coronary artery segment datasets

Algorithms	Acc	Pre	Sn	Sp	F1-Score
CNN	0.66	0.63	0.82	0.49	0.71
YOLOv8[31]	0.69	0.66	0.79	0.59	0.72
MLMA	0.89	0.89	0.92	0.86	0.90

Table 1 lists the performance of various DL algorithms for classifying normal and abnormal images. The proposed approach showed high performance in terms of accuracy (0.89), precision (0.89), sensitivity (0.92), specificity (0.86), and F1-score (0.90).

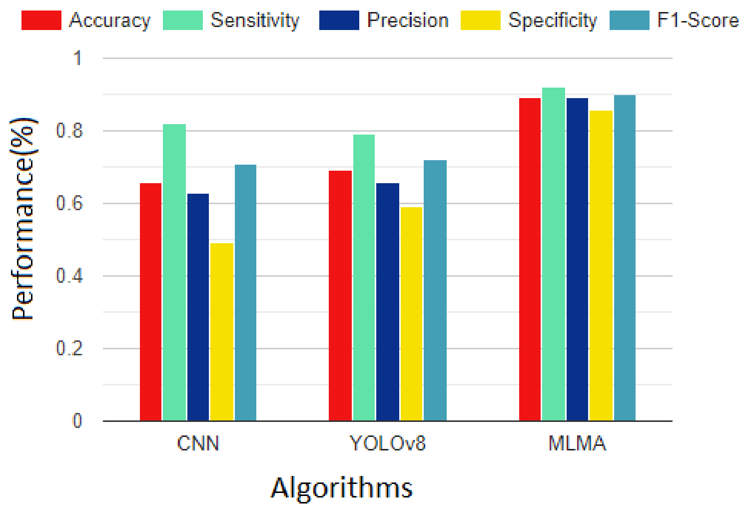

Figure 11: Represents the overall performance of the algorithms applied to the coronary artery segment datasets

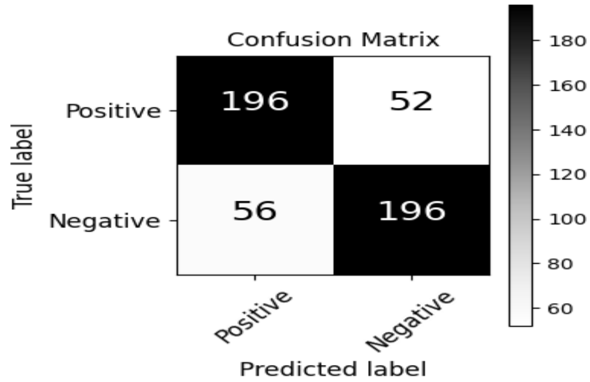

Figure 12: Count values obtained using confusion matrix for CNN model

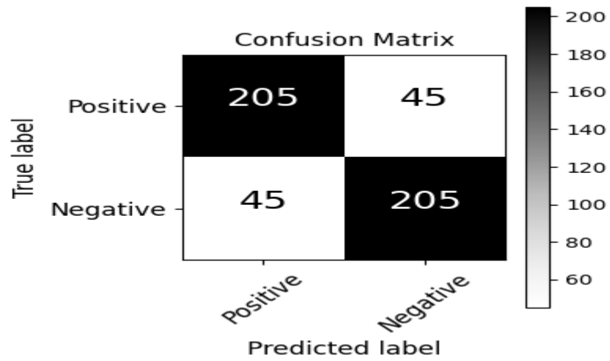

Figure 13: Count values obtained using confusion matrix for YOLOv8 model

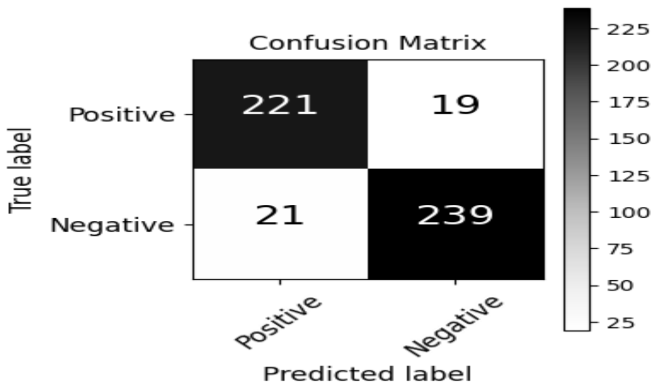

Figure 14: Count values obtained using confusion matrix for YOLOv8 model

Table 3: List of Algorithms that perform the classification based on given parameters of Stenotic Plaques

Algorithms	Acc	Pre	Sn	Sp	F1-Score
CNN	0.78	0.79	0.77	0.79	0.78
YOLOv8[31]	0.82	0.82	0.82	0.82	0.82
MLMA	0.92	0.92	0.91	0.92	0.91

Figures 12, 13, and 14 show the performance in terms of the count values from the confusion matrix. Table 2 lists the algorithms' overall performance based on the given parameters. Figure 15 shows a visualization of the algorithms applied to the Stenotic Plaques datasets.

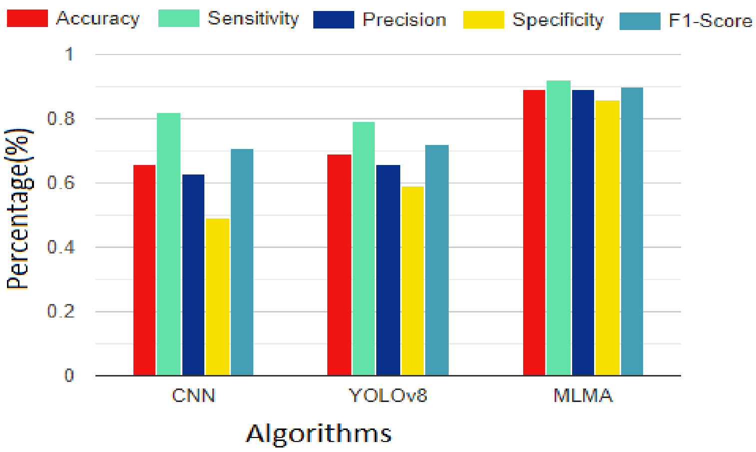

Figure 15: shows the overall performance of the algorithms applied to the Stenotic Plaques dataset

CONCLUSION

This paper describes a multilayered model approach (MLMA) that incorporates a Gated Recurrent Unit (GRU) and a Denoising Autoencoder (DAE). It is a powerful and versatile framework that combines the strengths of both architectures for various tasks, particularly sequence modeling and feature learning. One type of recurrent neural network (RNN) that works well in identifying sequential dependencies in data is the GRU. It can capture long-term dependencies while reducing the effects of the vanishing gradient problem owing to its gating method. This makes the GRU a good fit for jobs involving time-series data, natural language processing, and other sequential data. A Denoising Autoencoder (DAE) is adept at learning robust and meaningful representations of input data by reconstructing the original input from corrupted or noisy versions. This property makes the DAE valuable for unsupervised feature learning, enhancing the model's ability to extract relevant features from raw data. By integrating GRU and DAE into a multilayered model, the MLMA takes advantage of the complementary strengths of both architectures. The GRU captures sequential patterns and dependencies, whereas the DAE refines and enriches the learned features, resulting in a more comprehensive and expressive representation of the input data. Its effectiveness in capturing dependencies, learning robust features, and adaptability to diverse domains makes it a promising framework for advancing research and applications in machine learning. Researchers and practitioners are encouraged to explore and extend this approach to specific use cases, considering the nuances and requirements of their respective domains.

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