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DESIGN AND ANALYSIS OF CNN BASED HEART BLOCKAGE DETECTION

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Abstract : This project represents a significant leap forward in cardiovascular disease diagnosis and management by aiming to enhance the prediction of blockage detection in angiograms. At its core, the project seeks to leverage the power of deep learning (DL) techniques and Convolutional Neural Networks to substantially improve the accuracy of angiogram analysis, with a specific focus on identifying blockages. This ambitious endeavor involves training the algorithms on meticulously annotated angiogram datasets, enabling them to discern intricate patterns indicative of blockages. Furthermore, the project will employ cutting-edge techniques such as feature extraction and deep learning methodologies to further refine the blockage identification process. By enhancing the accuracy of blockage detection in angiograms, this project has the potential to revolutionize cardiovascular care, leading to more precise diagnoses and more effective treatment strategies, ultimately improving patient outcomes.

***Keywords* – Angiograms, Deep learning**

I. INTRODUCTION

Cardiovascular diseases (CVDs) remain a leading cause of morbidity and mortality worldwide, underscoring the critical need for accurate diagnostic tools and effective treatment strategies. Among the diagnostic modalities utilized in CVD management, angiography plays a pivotal role in visualizing coronary artery blockages, guiding therapeutic interventions, and optimizing patient outcomes. However, the manual interpretation of angiogram images is labor-intensive, subjective, and prone to variability, highlighting the imperative for automated and precise blockage detection methodologies. In response to this pressing healthcare challenge, our project endeavors to harness the transformative potential of advanced deep learning techniques to revolutionize angiogram analysis and enhance the precision of blockage detection. By training sophisticated convolutional neural network (CNN) models on annotated datasets, we aim to empower machine learning algorithms to discern subtle patterns and intricacies within angiogram images, surpassing human capabilities in diagnostic accuracy and efficiency. At the intersection of medical knowledge and technological innovation, our initiative seeks to seamlessly integrate cutting-edge machine learning methods, specifically deep learning, into the realm of medical imaging. Through meticulous training and refinement, our CNN-based approach promises to unveil complex features and relationships within angiogram images, facilitating more informed clinical decision-making and optimizing cardiovascular disease management. Rooted in the fusion of medicine and deep learning, our project aspires to redefine the landscape of blockage detection in angiograms, elevating diagnostic precision and efficiency through the strategic application of state-of-the-art machine learning techniques. By leveraging the inherent capabilities of deep learning to extract intricate features from vast datasets, we aim to provide medical professionals with a powerful tool for precise and efficient blockage detection, ultimately enhancing patient care and outcomes in cardiovascular disease management. This study represents a paradigm shift in cardiovascular diagnostics, leveraging the transformative potential of deep learning to address a crucial healthcare problem. By seamlessly integrating advanced machine learning methods into medical imaging, we strive to propel the field of cardiovascular medicine forward, paving the way for enhanced diagnostic accuracy, optimized treatment strategies, and improved patient outcomes in the management of cardiovascular diseases.

II. LITERATURE REVIEW

Cootes, Tim F., and Christopher J. Taylor (2001)[1] demonstrated the Implementation of the algorithm in a multi-resolution framework. This involves first searching for the object in a coarse image, then refining the location in a series of finer resolution images. Image structures can be represented using statistical models of shape and appearance.
Hartig, Sean M. (2013)[2] outline the basic aspects of image analysis, including software installation, data import, image processing functions, and analytical tools that can be used to extract information from microscopy data using ImageJ34.

Patil, Pavan Digambar, and Girish A. Kulkarni.(2014)[3] The paper involves denoising and histogram equalization. Hessian matrix and Frangi 2D filter extract the vessel structure from input image. Erosion is done by deriving the shrinking image from extracted image. Length of blockage in angiography vessel is measured. The proposed algorithm extracts the blood vessels from the given angiogram image from which we can analyze the blockages. Also, from these images we can measure the length of blockage in vessels.

Pal, Kuntal Kumar, and K. S. Sudeep.(2016)[4] explains the Importance of preprocessing techniques for image classification using CNN. It uses the CIFAR10 dataset and three variations of CNNs to demonstrate the effectiveness of different preprocessing techniques. It provides valuable insights into how different preprocessing techniques can impact the performance of CNNs in image classification tasks.

Nasr-Esfahani, Ebrahim, et al. (2016)[5] CNN is used for detecting vessel regions in angiograms. This paper presents a novel approach to improve the diagnosis of Coronary artery disease (CAD) by enhancing the quality of Xray angiograms. The use of deep learning shows promising results in medical imaging and diagnosis.

Sameh, Salma, Mostafa Abdel Azim, and Ashraf AbdelRaouf. (2017)[6] the proposed approach focuses on enhancing and removing the noises from the Angiographic scan images and therefore detect the Coronary Arteries. The application proved to be an effective and accurate approach that can minimize examination time. It enhances, detects and facilitates the diagnosis of the coronary scans.

Anwar, Syed Muhammad, et al.(2018)[7] involves Convolutional neural network, Computer aided diagnosis, Segmentation, Classification, Medical image analysis techniques, used for CNN based medical analysis of images. A review of deep learning techniques and its application in medical image analysis is shown. For larger datasets, availability of more compute power and better DL architectures is paving the way for a higher performance. This would improve computer aided diagnosis and detection systems.

Ramamoorthy, M., N. Ayyanathan, and M. Padma Usha. (2018)[8] the proposed algorithm is tested on real image with blockages. Blockages are detected based on the diameter profile and long blockages remain underestimated.

Dan Han, Jiayi Liu, Zhonghua Sun, Yu Chi Yi He, Zhenghan Yang (2020). (2020)[9] elaborates on Deep Learning (Convolutional neural networks). The author suggests that deep learning analysis can be a promising tool for the diagnosis and management of coronary artery disease. The use of deep learning algorithms based on Convolutional Neural Networks (CNNs) can accurately identify and classify coronary artery stenosis, outperforming traditional methods.

Qiao, Hong Yan, et al. (2020)[10] throws light on ML based fractional flow reserve derived from computed tomography. A study in this paper indicated ML-based FFR had superior prognostic value with the potential to improve efficiency of ICA.

Molenaar, Mitchel A., et al (2022)[11] demonstrates Machine Learning (Random forrest), Deep Learning (CNN). ML models have the potential to improve the efficiency of coronary angiography imaging analysis, but further research is needed to validate these findings and optimize its performance. The review highlights the exciting potential of artificial intelligence for improving the diagnosis and treatment of ischemic heart disease.

III. RESEARCH METHODOLOGY

The Convolutional Neural Network (CNN) serves as the cornerstone of our automated blockage detection system. With its ability to learn intricate features from angiogram images, the CNN empowers accurate identification of heart blockages. Through successive convolutional layers, it extracts hierarchical representations, while activation functions like ReLU introduce non-linearity for complex feature learning. Max-pooling layers enhance computational efficiency by down-sampling feature maps, and fully connected layers integrate features for classification. The CNN's training process involves optimizing parameters using annotated datasets, ensuring precise blockage detection in clinical settings. we explore the effectiveness of three prominent CNN architectures: ResNet (Residual Network)AlexNet, and DenseNet tailored for angiogram analysis and blockage detection.

The ResNet architecture is chosen for its ability to address the vanishing gradient problem in very deep networks. ResNet introduces residual blocks, allowing the network to learn residual mappings instead of directly fitting the desired underlying mapping. This facilitates the training of deeper networks, essential for capturing intricate features in angiogram images. By leveraging residual connections, ResNet enables efficient feature extraction and enhances the model's ability to discriminate between normal vasculature and regions with blockages. AlexNet is another CNN architecture considered for its pioneering role in image classification tasks. Despite being relatively simpler compared to newer architectures, AlexNet's design consists of multiple convolutional layers followed by max-pooling layers, facilitating hierarchical feature extraction. The utilization of ReLU activation functions and dropout regularization in AlexNet helps prevent overfitting and enhances generalization, making it suitable for our angiogram analysis task. DenseNet is a deep learning architecture characterized by densely connected blocks, where each layer receives feature maps from all preceding layers. This dense connectivity pattern promotes feature reuse, enhances gradient flow, and reduces the number of parameters compared to traditional convolutional neural networks (CNNs). DenseNet has demonstrated strong performance in image classification tasks, achieving state-of-the-art results on various benchmarks, making it a popular choice for deep learning researchers and practitioners.

By evaluating ResNet, AlexNet and DenseNet architectures, we aim to identify the most effective model for automated blockage detection in angiogram images. Through rigorous experimentation and performance evaluation, we seek to determine which architecture yields superior accuracy and robustness in identifying heart blockages, ultimately enhancing the diagnostic capabilities of our automated system.

The proposed CNN-based model is designed to analyze angiogram images for the detection of heart blockages. The model follows a convolutional neural network architecture, which has proven effective in various medical image analysis tasks.

3.1 Input Data Representation

Angiogram images serve as the primary input to the CNN-based model. These images are typically captured during invasive procedures and are represented as two-dimensional matrices of pixel values. Each pixel encodes the intensity of light at that point, providing visual information about the underlying blood vessels and potential blockages.

3.2 Convolutional Layers

The CNN architecture comprises multiple convolutional layers responsible for feature extraction. Convolutions are applied with learnable filters, also known as kernels, which systematically scan the input image to capture local patterns and structures relevant to heart blockage detection. Through successive convolutional layers, the model progressively learns hierarchical representations of the angiogram images, capturing both low-level features (e.g., edges, textures) and high-level patterns (e.g., vessel shapes, blockage formations).

3.3 Activation Functions

ReLU (Rectified Linear Unit) activation functions are commonly employed after each convolutional layer. ReLU introduces non-linearity into the model, allowing it to learn complex representations of the input data. By rectifying negative values and preserving positive ones, ReLU activation functions enable faster convergence during training and mitigate the vanishing gradient problem, facilitating more effective learning of intricate features relevant to heart blockage detection.

3.4 Pooling Layers

Max-pooling layers are strategically inserted after certain convolutional layers to down-sample the feature maps obtained from the preceding layers. Pooling helps reduce the spatial dimensions of the feature maps while retaining the most relevant information. By aggregating the maximum values within local regions, max-pooling enhances computational efficiency and reduces the risk of overfitting by promoting spatial invariance and preserving the dominant features of the input data.

3.5 Flattening and Fully Connected Layers

Following the convolutional and pooling layers, the feature maps are flattened into a one-dimensional vector to be processed by one or more fully connected layers. These fully connected layers serve as the classifier component of the CNN, integrating the extracted features and learning to distinguish between different classes, such as the presence or absence of heart blockages. Through iterative training, the fully connected layers refine their weights to optimize classification performance based on the learned representations from the earlier layers.

3.6 Output Layer

The final layer of the CNN typically consists of a softmax activation function, which generates probability distributions over the output classes. In the context of heart blockage detection, the model outputs the probability of blockage presence based on the input angiogram image. By interpreting the softmax probabilities, medical professionals can assess the likelihood of blockages and make informed clinical decisions regarding patient care and treatment strategies.

3.7 Training Process

During the training process, the CNN is fed with a dataset of angiogram images labeled with ground truth annotations indicating the presence or absence of heart blockages. The model iteratively learns to map input images to their corresponding labels by optimizing a chosen loss function, such as categorical cross-entropy. Backpropagation, coupled with gradient descent optimization techniques, is employed to update the model parameters iteratively, minimizing the loss and improving the model's predictive performance. Through repeated training iterations, the CNN learns to generalize from the training data to unseen angiogram images, enhancing its ability to accurately detect heart blockages in clinical settings.

IV. DATA AND SOURCE OF DATA

For this project, Angiograms (images) real-time data was collected from hospitals along with some data from Kaggle. The dataset contained 1554 images belonging to 6 classes. Angiogram images capture the intricate vascular structures of the cardiovascular system, exhibiting anatomical variability across different patients and imaging sessions. To augment the dataset and improve model generalization, various augmentation techniques may be applied, including rotation, scaling, flipping, and adding noise to the angiogram images.

V. PROCESS FLOW

1. Start
2. Data Collection / Data Preprocessing
    a. Collection of Angiogram Dataset
    b. Annotation of Angiogram Images with Ground Truth Labels (Blockage Presence/Absence)
    c. Preprocessing of Angiogram Images:
        - Image Resizing
        - Contrast Enhancement
        - Noise Reduction
        - Normalization

3. CNN Model Training
   a. Training Data Preparation:
      - Splitting Dataset into Training, Validation, and Testing Sets
      - Data Augmentation (Rotation, Scaling, Flipping)
   b. Selection of CNN Architecture (ResNet, AlexNet, DenseNet)
   c. Training CNN Model:
      - Convolutional Layer Feature Extraction
      - Activation Function (ReLU) Application
      - Max-Pooling Layer Integration
      - Fully Connected Layer Training
      - Backpropagation and Gradient Descent Optimization
4. Evaluation of Trained CNN Model a. Testing Data Preparation:
   a. Preprocessing of Test Angiogram Images
   b. Model Evaluation Metrics:
      - Accuracy
      - Precision
      - Recall
      - F1-Score
5. Display Result in User Interface
6. End.

VI. RESULT AND DISCUSSION

The CNN model using ResNet achieved an accuracy of 82%, AlexNet achieved an accuracy of 73% and DenseNet achieved an accuracy of 94%.
In addition to developing the CNN-based model for heart blockage detection using angiogram images, a user-friendly interface has been created to facilitate seamless interaction with the developed system. The user interface serves as a crucial component to enable healthcare professionals to utilize the model effectively in clinical settings. The following outlines the integration of the model with the user interface:
1) Input Handling: The user interface is designed to accept angiogram images as input from the user. This can be achieved through various input methods, such as uploading digital angiogram images or directly interfacing with imaging devices to capture real-time angiograms.
2) Preprocessing and Model Inference: Upon receiving the input angiogram image, the user interface preprocesses the image as necessary to ensure compatibility with the input requirements of the CNN-based model. This may involve resizing, normalization, or other preprocessing steps to prepare the image for analysis. Subsequently, the preprocessed image is passed through the trained CNN model for inference. The model analyzes the image and generates a prediction regarding the presence or absence of heart blockages.
3) Output Display: The output of the model, indicating the likelihood of heart blockage presence, is displayed on the user interface in a clear and intuitive manner. This may include visual indicators such as text-based notifications, graphical representations, or color-coded annotations to convey the prediction outcome effectively.

VII. CONCLUSION

In this study, we developed a comprehensive system for automated blockage detection in angiogram images, leveraging advanced Convolutional Neural Network (CNN) architectures. Through a systematic workflow encompassing data preprocessing, model training, and performance evaluation, we demonstrated the efficacy of our approach in automating and optimizing blockage detection in cardiovascular diagnostics.
Our findings underscore the significance of utilizing state-of-the-art deep learning techniques in medical image analysis, particularly in the context of cardiovascular health. By harnessing the power of CNNs, we achieved remarkable accuracy and efficiency in detecting blockages in angiogram images, thereby facilitating timely intervention and patient care.
DenseNet exhibited the most accuracy with 94%. ResNet and AlextNet achieved accuracy slightly lesser, 82% and 73% respectively.
The selection and customization of ResNet, AlexNet and DenseNet architectures, coupled with transfer learning techniques, enabled us to leverage pre-trained weights and accelerate model convergence, even with limited angiogram datasets. Furthermore, ensemble learning approaches demonstrated the potential for further enhancing the robustness and accuracy of blockage detection through the fusion of complementary predictions from multiple CNN models.
Our study contributes to the ongoing efforts in advancing computer-aided diagnosis systems for cardiovascular diseases, offering a reliable and scalable solution for automating blockage detection in angiogram images. The developed system holds promise for integration into clinical workflows, where it can augment the capabilities of healthcare professionals and improve patient outcomes through early and accurate diagnosis.

VIII. FUTURE WORK

Future research directions may include the exploration of additional CNN architectures, the integration of multi-modal imaging data, and the deployment of the developed system in real-world clinical settings. By addressing these avenues, we aim to further enhance the efficacy, accessibility, and impact of automated blockage detection systems in cardiovascular diagnostics, ultimately contributing to improved patient care and outcomes.

The deployment of our automated blockage detection system in real-world clinical settings represents a crucial step towards its practical utility and impact on patient care. Collaborations with healthcare institutions and clinicians for pilot testing and validation in clinical workflows are essential for assessing the system's performance, usability, and integration feasibility.

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