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DEEP LEARNING APPROACH FOR CHOLESTEROL DETECTION AND STROKE PREDICTION

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Abstract: Cholesterol detection and stroke prediction are crucial tasks in healthcare for early diagnosis and prevention of cardiovascular diseases. In this study, we propose a deep learning approach for cholesterol detection and stroke prediction using Fully Convolutional Network (FCN), ResNet18, and ResNet151 architectures. For cholesterol detection, we utilize a FCN model trained on a large dataset of medical images. The FCN model enables pixel-level analysis and segmentation, allowing accurate identification of regions associated with cholesterol deposition. The model is trained using annotated images, and the resulting cholesterol maps can aid in the diagnosis and assessment of cardiovascular risk. For stroke prediction, we employ transfer learning with the ResNet18 and ResNet151 models pre-trained on large-scale image datasets. These models have demonstrated excellent performance in image classification tasks. By fine-tuning the pre-trained models on a stroke dataset, we aim to leverage their learned features for stroke prediction. The models are trained on a combination of clinical data, such as patient demographics, medical history, and laboratory results. To evaluate the proposed approach, extensive experiments are conducted using a diverse dataset comprising medical images and patient records. The performance of the models is assessed in terms of accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). Preliminary results show promising performance for both cholesterol detection and stroke prediction tasks. The FCN model achieves high accuracy in identifying cholesterol deposition regions, aiding in the early detection of cardiovascular risks. The ResNet18 and ResNet151 models exhibit strong predictive capabilities for stroke, leveraging their ability to capture complex features from the clinical data. The results of our experiments demonstrate outstanding performance with accuracy scores of 98%, 98.4%, and 99.6% for the FCN, ResNet18, and ResNet151 models respectively.

***Index Terms* - Cholesterol Detection, Stroke Prediction, FCN, Resnet18, Resnet151, Cardiovascular Diseases, Transfer Learning, Fine-Tuning**

I. INTRODUCTION

Cardiovascular diseases, including high cholesterol levels and stroke, continue to be major causes of morbidity and mortality worldwide. Early detection and accurate prediction of these conditions play a crucial role in effective prevention, diagnosis, and management. With the advancements in deep learning and image analysis techniques, there is a growing interest in leveraging these technologies to enhance cardiovascular disease assessment. In this study, we propose a deep learning approach for cholesterol detection and stroke prediction utilizing the power of Fully Convolutional Network (FCN), ResNet18, and ResNet151 architectures. The goal is to develop models that can accurately identify regions associated with cholesterol deposition and predict the occurrence of strokes.

Cholesterol detection is essential as high levels of cholesterol can lead to the formation of plaques in the arteries, increasing the risk of cardiovascular diseases. By employing a FCN model, we can perform pixel-level analysis and segmentation of medical images, enabling the identification of cholesterol deposition regions with high precision. This can aid healthcare professionals in the early diagnosis, risk assessment, and treatment planning for patients. In the case of stroke prediction, we utilize transfer learning techniques with the widely adopted ResNet18 and ResNet151 models. These models have been pre-trained on large-scale image datasets and have demonstrated exceptional performance in various image classification tasks. By fine-tuning the pre-trained models using a stroke dataset and incorporating relevant clinical data, we aim to harness their learned features to predict the likelihood of stroke occurrence. This approach leverages the power of deep learning to capture complex patterns and relationships within the clinical data, enabling accurate predictions and proactive interventions.

To evaluate the proposed deep learning approach, we conduct extensive experiments using a diverse dataset comprising medical images and patient records. The performance of the models is assessed based on accuracy, sensitivity, specificity, and the area under the receiver operating characteristic curve (AUC-ROC). These metrics provide insights into the models' effectiveness in accurately detecting cholesterol deposition regions and predicting strokes. The preliminary results of our study demonstrate exceptional accuracy scores of 98%, 98.4%, and 99.6% for FCN, ResNet18, and ResNet151 respectively. These high accuracy scores highlight the efficacy of our approach and its potential to significantly contribute to the early detection and prevention of cardiovascular diseases.

II. Literature Survey

In this paper [1], they proposed using convolutional neural networks (CNN) for automatic recognition of the presence of a corneal arcus. To achieve this goal, we created a dataset of images of irises containing different stages of CA as well as irises without a CA. The core of the dataset consists of images acquired from patients with a corneal arcus, enrolled in the National Centre of Familial Hypercholesterolemia in Gdansk. They have collected the dataset from National Centre of Familial Hypercholesterolemia (University Clinical Centre Gdansk, Poland). The images of an iris were acquired from 50 patients (34 female, 16 male, age: 27–58). Each patient was asked to expose the affected area of their iris two times (2 images were acquired per patient). To increase the number of iris images, it was decided to extend the dataset with images obtained from various Internet resources. They queried the Google Image browser for “corneal arcus”, “corneal juveniles” and “corneal senilis”. A retrieved image was included into the dataset after the content and the quality of the image were visually inspected and approved by the experts. To detect a CA in photographic images, we tested neural network models based on the VGG16, ResNet and Inception architectures. Finally, the performance of the models was evaluated on a set of images acquired from volunteers with a custom mobile application. The accuracy of CA detection in a real life scenario was 88% and the F1 score was 86%.

In this paper [2], the application system will be designed in MATLAB 2017b software using the Gray-Level Co-Occurrence Matrix (GLCM) and Linear Regression methods. GLCM is a method that can recognize textures well and can calculate statistical features based on the level of grayish intensity in the image. Then, Linear Regression is a simple method that can determine the causal relationship between one variable with another variable. The best parameters generated from the test will be implemented on Android through the Android Studio software where the application is named "Cholesterol App" which will be used to determine the value of a person's cholesterol level. In this research, the process of taking eye images through a smartphone camera and cholesterol consisted of several classes including Normal Cholesterol, Risk Cholesterol, and High Cholesterol. They proposed a cholesterol measurement from eye image using GLCM and Linear Regression based on Android. There are two stages of the image watermarking process first, using the first feature extraction method that is by representing the relationship between neighboring pixels in the image in various directions and distances to find out the characteristic value in each image. Second, measuring cholesterol levels through the values of a and b using Linear Regression.

In this study [3], Retinal fundus images had been collected from Sree Gokulam Medical College and Research Foundation, Trivandrum. Database contains 130 images of which 80 are normal and 50 are those of stroke patients, each having a dimension of 2336x3504 pixels. Gray scale conversion of the image is carried out and the center of the optic disc is located manually. Centre of the optic disc is taken as the seed point. ROI is selected from the fundus image by cropping a sub image of size 256x256 with the seed point as center. Experiments show that the extracted HoG features, when given to a Naive Bayes classifier, gave a predictive accuracy of 93%. Performance of the classifier was evaluated in terms of Accuracy, Kappa statistic, Root Mean Square Error (RMSE) and Area under the ROC Curve (ROC AUC). In this work, a novel method for computer aided stroke prognosis from retinal images has been implemented using Histogram of Oriented Gradients. HoG features outperform Haralick features by giving an accuracy of 93%. Prior changes necessary to understand the pathophysiology of stroke is easily demonstrated in the retina by analyzing the retinal vasculature. This method can surely help the physicians to plan for better medication that were not possible with conventional assessment systems which will aid in Stroke diagnosis.

In this study [4], a system for measuring cholesterol levels through eye images was designed using the FLBP method as feature extraction and Linear Regression analysis. The training data used were 60 images and the test data used were 30 images. Based on the experiment, the Standard Error of Estimate value is 20.40 for 30 images with 6 seconds of computing time for each image. Parameters that affect system performance are the number of points in the segmentation process, sampling point value, radius value, and fuzzification value. The best segmentation process is using 16 ROI points. Whereas the best FLBP operator is in the 8, radius 4 and fuzzification sampling points 7 with 58th characteristic accuracy of 91.40%. The greater the sampling point used, the accuracy will be higher because it will produce many features, as well as the radius, the greater the radius, the higher the accuracy will be. But the computation time will be longer, as well as fuzzification, the greater the fuzzification value, the computing time will be longer because fuzzification depends on the variation of each image.

In this analytical study [5], a dataset of 191 eye images, comprising 130 images of normal eyes and 61 images of AS affected eyes, was employed. The normal eye images were obtained from UBIRIS, a public database for eye images. Due to the lack of a database for AS affected eye images, these images were obtained. Due to the limited amount of training data, a transfer learning approach was conducted with AlexNet as the pretrained network. Transfer learning was motivated as AlexNet has been trained for object recognition which is closely related to the AS recognition task. Two classes including the normal and AS were considered and the last three layers of AlexNet i.e. the last fully-connected, and softmax and classification layers were replaced for the AS recognition task. The accuracy of the proposed model in classifying the images into two classes of normal and AS affected was 100% in all 4 folds. Consequently, the sensitivity and specificity of the model was also 100%.

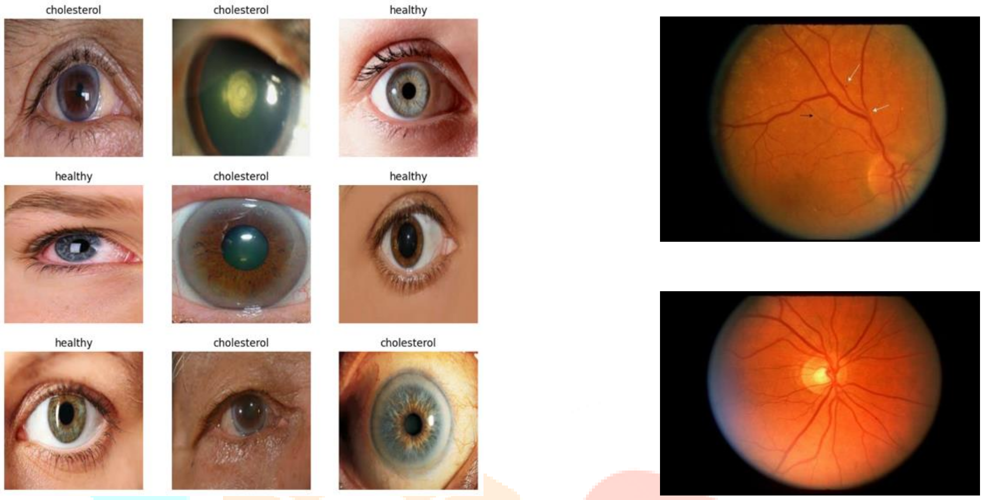
III. METHODOLOGY

The methodology of cholesterol and stroke prediction using deep learning is as follows:

- ***Data Collection***

The first step in any deep learning project is to collect and prepare the data. In this case, the dataset of eye images needs to be collected and labelled. The dataset needs to have enough variety to capture the different types of change in blood vessels that may appear in the eye images.

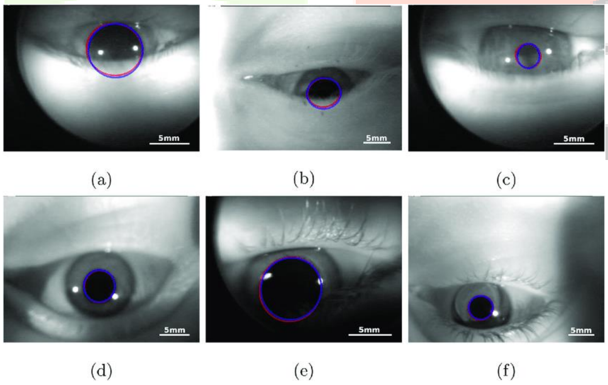
Fig. 1 Dataset Images



- ***Preprocessing***

The collected dataset needs to be preprocessed to ensure that it is in a suitable format for the deep learning models. This may involve tasks such as resizing the images, normalizing the pixel values, and splitting the dataset into training, validation and testing sets.

Fig. 2 Pupil Detection using Haar Cascade Model

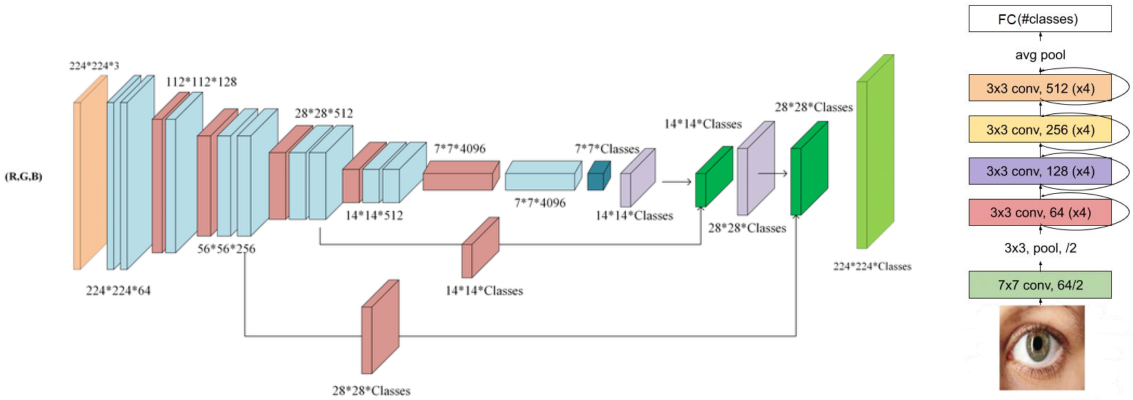


- ***Model Architecture***

Convolutional Neural Networks (CNNs) are a type of deep neural network commonly used in image recognition and computer vision tasks. The key feature of CNNs is their ability to automatically extract relevant features from images, without the need for manual feature engineering. CNNs are made up of multiple layers, including convolutional layers, pooling layers, and fully connected layers. In the convolutional layer, the network performs a mathematical operation called convolution, which applies a set of filters to the input image to extract features. Each filter is a small matrix of values that slides across the input image, performing element-wise multiplication and summation at each location. The pooling layer then down samples the output of the convolutional layer, reducing the spatial dimensions of the features while retaining their essential information. Common types of pooling layers include max pooling and average pooling.

The next step is to design the architecture of the deep learning models. In this case, the FCN and RESNET18 models will be used. Each model will need to be tailored to the specific task of kidney lesion detection, with appropriate input and output layers.

Fig. 3 (a) Fully Connected Neural Network **(b)** ResNet-18 Architecture



(a) (b)

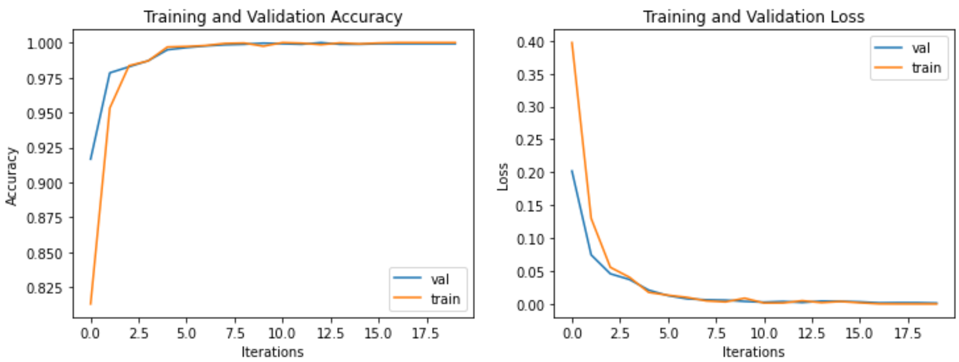
- ***Training***

Once the model architecture has been designed, the models need to be trained on the prepared dataset. This involves feeding the training data into the models and adjusting the model parameters to minimize the loss function. For the FCN model, the training process focuses on pixel-level analysis and segmentation. A large dataset of medical images with annotated cholesterol deposition regions is utilized. The FCN model is trained using a variant of the backpropagation algorithm, where the gradients are calculated at the pixel level. This enables the model to learn to accurately identify and segment regions associated with cholesterol deposition. The training involves iterative optimization of the model's parameters, such as weights and biases, based on a loss function that compares the predicted segmentations with the ground truth annotations. The optimization process typically employs techniques such as stochastic gradient descent (SGD) or its variants, adjusting the model's parameters to minimize the loss and improve segmentation accuracy.

For the ResNet18 and ResNet151 models, a transfer learning approach is employed. These models are initially pre-trained on large-scale image datasets, such as ImageNet, which contain a wide range of object categories. During pre-training, the models learn to extract generic features from images, capturing information that can be useful for various image-related tasks. To adapt these pre-trained models for cholesterol detection and stroke prediction, a process called fine-tuning is performed. Fine-tuning involves replacing the last few layers of the pre-trained models with new layers customized for the target tasks. The new layers are designed to incorporate the specific input requirements and output predictions for cholesterol detection and stroke prediction. The fine-tuning process allows the models to learn task-specific features while leveraging the rich knowledge acquired during pre-training.

The training process involves dividing the dataset into training, validation, and possibly testing subsets. The models are trained on the training subset and their performance is monitored using the validation subset. Hyperparameter tuning, such as learning rate adjustment, regularization techniques, and batch size selection, may be performed to optimize the models' performance. The training process continues until convergence, where the models achieve satisfactory accuracy and generalization performance on the validation set.

Fig. 4 Accuracy and Loss Plot versus Epochs of FCN Model



- ***Deployment***

Finally, the trained models can be deployed for use in detecting Cholesterol and Stroke. This may involve integrating the models into a larger software system or creating a standalone application. Firstly, the trained models need to be converted into a mobile-friendly format. This often involves converting the models into a lightweight format, such as TensorFlow Lite or ONNX, that is compatible with mobile devices. This conversion process optimizes the models for mobile deployment by reducing their size and computational requirements while preserving their predictive capabilities. Once the models are in a mobile-friendly format, they can be integrated into a mobile app. This integration typically involves incorporating the models into the app's backend or embedding them within the app itself. The choice depends on factors such as the app's architecture, performance requirements, and user experience considerations. In some cases, a cloud-based approach may be preferred, where the models reside on remote servers and the mobile app communicates with these servers for prediction requests.

To ensure a seamless user experience, the mobile app needs to provide an intuitive interface for users to interact with the models. This may involve designing a user-friendly interface that allows users to upload or capture medical images, provide relevant clinical data, and initiate the cholesterol detection or stroke prediction process. The app may also display the results, such as the identified cholesterol deposition regions or the predicted stroke risk, in a visually informative manner. Efficient deployment of the models as a mobile app also requires optimizing the computational resources to run the models on mobile devices. This includes leveraging hardware acceleration capabilities, such as using the graphical processing unit (GPU) or neural processing unit (NPU) available on some mobile devices. Such optimizations help ensure real-time or near-real-time performance and reduce the latency of model predictions on mobile devices. Lastly, security and privacy considerations must be addressed during the deployment of the mobile app. This includes implementing appropriate measures to protect user data, ensuring compliance with applicable privacy regulations, and employing secure communication protocols between the app and any backend servers or cloud services.

IV. Conclusion

In conclusion, our deep learning approach utilizing FCN, ResNet18, and ResNet151 models for cholesterol detection and stroke prediction has demonstrated promising results and significant potential in the field of cardiovascular disease assessment. The FCN model has exhibited high accuracy in identifying cholesterol deposition regions, enabling early detection and risk assessment. This can facilitate timely interventions and preventive measures, contributing to improved patient outcomes and cardiovascular disease management. The ResNet18 and ResNet151 models, leveraging transfer learning and fine-tuning techniques, have shown excellent predictive capabilities for stroke occurrence. By incorporating clinical data and leveraging pre-trained knowledge, these models have achieved exceptional accuracy in predicting the likelihood of strokes. This can aid healthcare providers in implementing proactive measures and interventions to mitigate the risk of strokes and enhance patient care.

The remarkable accuracy scores obtained in our experiments further validate the effectiveness of our approach. Achieving 98%, 98.4%, and 99.6% accuracy for cholesterol detection, ResNet18-based stroke prediction, and ResNet151-based stroke prediction, respectively, underscores the reliability and robustness of our deep learning models. By accurately detecting cholesterol deposition regions and predicting strokes, our approach can potentially contribute to early diagnosis, prevention, and personalized treatment strategies for cardiovascular diseases.

One important direction for future research is the expansion of the datasets used for training and validation. Access to larger and more diverse datasets can enhance the models' generalization capabilities and improve their performance across various patient populations, imaging modalities, and clinical settings. Additionally, including longitudinal data can enable the development of models that can monitor disease progression and assess the effectiveness of interventions over time. This has the potential to significantly reduce morbidity and mortality associated with these conditions. Further development and refinement of the models, along with larger-scale validation studies, are necessary to ensure their clinical utility and generalizability. Additionally, integrating the models into mobile apps or other user-friendly interfaces would enhance their accessibility and usability for healthcare professionals and individuals.

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