Iris Diagnosis Using VGG16 and ResNet50 Algorithms

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Abstract: Early detection of kidney disease is essential for preventing severe complications and improving patient outcomes. Traditional diagnostic approaches, such as blood and urine tests, are invasive and time-consuming. This study explores a non-invasive iris-based diagnostic approach utilizing deep learning models to classify individuals as normal or abnormal based on kidney disease markers present in the iris. We implemented VGG16, ResNet50 CNN for feature extraction and classification. The models were trained on a dataset comprising iris images from healthy individuals and patients diagnosed with kidney disease. Image preprocessing techniques, including normalization and contrast enhancement, were applied to improve feature visibility. Among the architectures, Separable CNN outperformed others, achieving the highest classification accuracy for predicting abnormal and normal conditions.
Keywords: iris diagnosis, CNN, ResNet, VGG16

Introduction

In recent years, image processing and machine learning have been increasingly employed to tackle real-life issues, particularly medical image analysis and surveillance [1], [2], and [3]. Over the previous two decades, alternative medicine and early diagnosis have been the primary objectives in the health-care system is designed to deliver great health treatment while simultaneously avoiding many difficulties [4]. Iridology, or iris diagnosis, is a widely used method for assessing patient health. The human eye's iris is crucial for monitoring health and identifying potential organ problems [5].
Figure 1 illustrates the distinct locations correlated with various human organs [6]. A mark pattern or spot may appear in result of any weakness or damage of the organ [7]. These iris-patterns can help us to identify the corresponding/affected organ [8]. Figure 2 shows the seven zones in the iris around the pupil [8], [9]. In case of unhealthy stomach, the changes may appear near the pupil in the iris. On the other hand, unhealthy kidneys may be detected through the changes at the bottom edge of iris.
In the human urinary system, kidneys play an important role to eliminate the waste products from human body. Any renal condition may result in diabetes, hypertension, urological complications, acute renal dysfunction, and cardiovascular disorders, which are significant deadly concerns. Any renal condition may result in diabetes, hypertension, urological complications, acute renal dysfunction, and cardiovascular disorders, which are significant deadly concerns [10].

Related work

Convolutional Neural Networks (CNNs) have emerged as the dominant deep learning architecture for image analysis tasks due to their ability to automatically learn hierarchical feature representations from raw pixel data. Their success in various image-related applications, including image classification, object detection, and segmentation, has made them a natural choice for iris image analysis. [4] [5] [6] In the context of iris diagnosis, CNNs are used to extract relevant features from iris images, which can then be used to classify different ophthalmic conditions.

Several variants of CNNs have been employed, each with its own strengths and limitations.

ResNet, for instance, addresses the vanishing gradient problem in deep networks through the use of skip connections, allowing for the training of significantly deeper networks with improved accuracy. [4] InceptionResNet combines the Inception module, which uses parallel convolutional layers with different kernel sizes to capture multi-scale features, with the ResNet architecture to further enhance performance. [5] Efficient Net focuses on scaling up network depth, width, and resolution in a balanced manner, achieving state-of-the-art accuracy while maintaining computational efficiency. [7] U-Net, on the other hand, is specifically designed for image segmentation tasks, effectively capturing both local and global context in the image to produce accurate segmentation masks. [8] The choice of CNN architecture depends on the specific application, dataset size, computational resources, and desired performance characteristics. Data augmentation techniques, such as image rotation, flipping, and scaling, are often employed to increase the size and diversity of the training dataset, mitigating overfitting and improving model generalization. [4] [8] [7] These techniques play a vital role in enhancing the robustness and accuracy of CNN models for iris image analysis.

Method, Experiments

The research on **Kidney Disease Detection through Iris Recognition** using deep learning architectures like **VGG16, ResNet50 CNN** highlights the potential of iris biometrics in early diagnosis. By applying preprocessing, feature extraction, and classification steps, the approach effectively differentiates between healthy and diseased cases, offering a non-invasive method for kidney disease identification.

Figure 1 shows the architecture of the proposed methodology.

Block Diagram

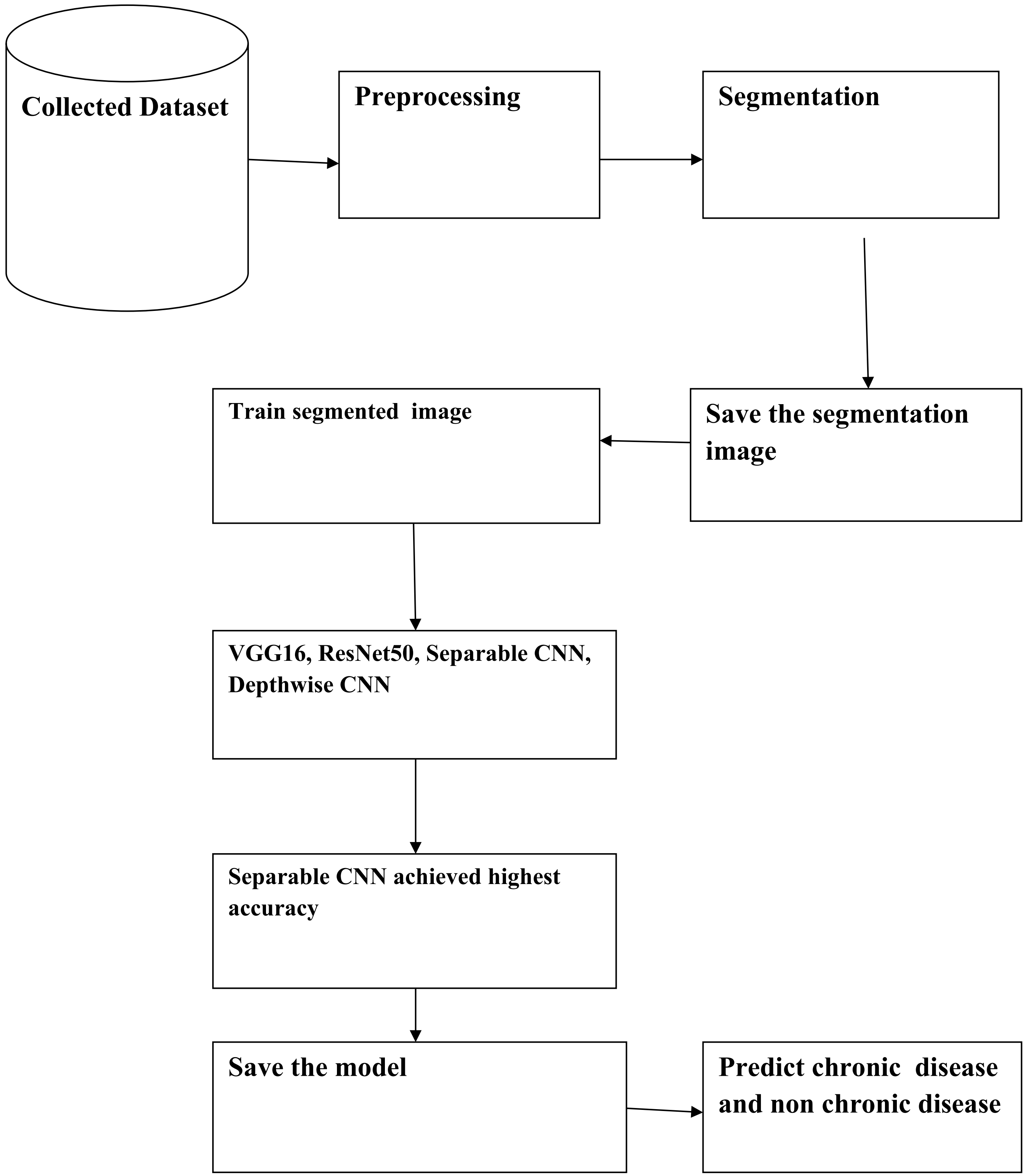

Figure1: Block diagram of the mode

1. VGG16

VGG16 is a deep convolutional neural network architecture proposed by the Visual Geometry Group (VGG) at Oxford. It has **16 weight layers**:

- **13 convolutional layers** for feature extraction.
- **3 fully connected layers** for decision-making.

Its main characteristics are:

- Uses **3×3 convolution filters** throughout the network.
- **ReLU activation** after each convolution to introduce non-linearity.
- **2×2 max pooling** to downsample features while preserving spatial patterns.
- Final **softmax layer** for classification.

Step-by-Step Execution in Kidney Disease Identification

Step 1: Input Image Preprocessing

- The iris image (captured for kidney disease analysis) is resized to **224×224 pixels**.
- Pixel values are normalized (scaled to [0,1] or [-1,1]) to improve numerical stability.

Step 2: Feature Extraction using Convolutional Layers

- **13 convolutional layers** learn spatial features such as edges, textures, and fine iris patterns.
- Small **3×3 kernels** allow detection of subtle variations critical in medical imaging.
- **ReLU activation** ensures the network can learn complex, non-linear relationships.

Step 3: Downsampling using Max Pooling

- **2×2 max pooling** reduces the resolution of the feature maps.
- This reduces computational cost while retaining important information.

Step 4: Fully Connected Layers & Classification

- Feature maps are **flattened** into a 1D vector.
- Passed through **3 fully connected layers** to combine features.
- A final **softmax layer** outputs the probability of two classes:
    - **Normal (Healthy Iris)**
    - **Abnormal (Kidney Disease Detected)**

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2. Separable CNN

Separable CNNs are an efficient variant of CNNs that reduce the **number of parameters** and **computational cost** without losing performance.
Instead of a standard convolution, they break it into two steps:

1. **Depthwise Convolution**
   - Each filter operates on a **single input channel** independently.
   - This reduces redundant computations.
2. **Pointwise Convolution (1×1 Convolution)**
   - Combines outputs of depthwise convolutions across channels.
   - Helps in learning cross-channel feature relationships.

This two-step process is often called **Depthwise Separable Convolution** (used in models like MobileNet).

Step-by-Step Execution in Kidney Disease Identification

Step 1: Input Image Preprocessing

- Iris image resized to **224×224 pixels** for consistency.
- Pixel values normalized to stabilize learning.

Step 2: Feature Extraction using Separable Convolutions

- **Depthwise Convolution** extracts spatial features from iris textures.
- **Pointwise Convolution (1×1)** aggregates these features across channels.
- **ReLU activation** introduces non-linearity for better feature learning.
- **Batch Normalization** helps stabilize and speed up training.

Step 3: Downsampling with Max Pooling

- **2×2 max pooling** reduces the size of the feature maps, keeping essential information intact.

Step 4: Fully Connected Layers & Classification

- Flattened features are passed into fully connected layers.
- A **softmax classifier** outputs probabilities for two categories:
  - **Normal (Healthy)**
  - **Abnormal (Kidney Disease Detected)**

Conclusions

The study on Identification of Kidney Disease Using Iris Recognition utilizing deep learning models such as VGG16, ResNet50, Separable CNN, Squeeze-DDConvNet, and Depthwise CNN demonstrates the feasibility of leveraging iris biometrics for early disease detection. Through preprocessing, feature extraction, and classification, the system efficiently distinguishes between normal and abnormal conditions, aiding in non-invasive kidney disease diagnosis

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