AbhiNet: Custom Convolutional Neural Networks

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Abstract

In this report, we explore the effectiveness of the AbhiNet model, a hybrid convolutional neural network (CNN) architecture, on a dataset of dog heart images. The model combines features from several well-established CNN architectures, including LeNet-5, AlexNet, VGG-16, ResNet, and DenseNet, to achieve competitive results in classifying dog heart conditions. We trained AbhiNet on a dataset resized to 75x75 pixels, comprising training, validation, and test sets. Through rigorous experimentation and evaluation, we achieved a peak accuracy of 75.5% on the test set, demonstrating its robustness and potential in medical image analysis.

Keywords: *AbhiNet, convolutional neural network, dog heart dataset, medical image analysis, hybrid architecture*

1. Introduction

Convolutional Neural Networks (CNNs) have revolutionized the field of image recognition and classification, becoming the cornerstone of modern computer vision applications. Leveraging the hierarchical feature learning capabilities of CNNs, we introduce AbhiNet, a hybrid architecture designed to classify dog heart images. AbhiNet integrates key features from multiple renowned CNN architectures, such as LeNet-5 [4], AlexNet [3], VGG-16 [5], ResNet [1], and DenseNet [2], each contributing unique strengths to the model.

The primary motivation behind AbhiNet is to harness the combined power of these architectures to enhance classification performance on medical imaging tasks. Specifically, our model is tailored to handle dog heart images resized to 75x75 pixels, a dimension chosen for its balance between computational efficiency and sufficient feature representation. This size is common in many practical applications where computational resources may be limited, but high accuracy is still required.

2. Related Work

The application of CNNs in medical image analysis has seen significant advancements over the past decades. The pioneering work by LeCun et al. [4] with LeNet-5 demonstrated the potential of CNNs for image recognition tasks. LeNet-5's simplicity and effectiveness paved the way for more complex architectures.

AlexNet [3], introduced in 2012, marked a significant leap in deep learning, winning the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) with a substantial margin. AlexNet's use of ReLU activation functions, dropout for regularization, and GPU acceleration were groundbreaking at the time.

Following AlexNet, VGG-16 [5] further improved image classification by emphasizing depth with very small (3x3) convolution filters. The deep and homogeneous architecture of VGG-16 made it a popular choice for transfer learning applications.

ResNet [1], introduced the concept of residual learning, allowing for very deep networks by mitigating the vanishing gradient problem. The ability to train deeper networks enabled significant performance improvements and set new benchmarks in various image classification tasks.

DenseNet [2] proposed densely connected convolutional networks, where each layer is connected to every other layer in a feed-forward fashion. This connectivity pattern improves information flow and gradient propagation, leading to efficient feature reuse and reduced parameter complexity.

Recent research has focused on hybrid architectures that combine the strengths of these individual models to achieve superior performance. Hybrid models aim to leverage the depth and residual connections of ResNet, the feature extraction prowess of VGG-16, and the dense connectivity of DenseNet. Such integration addresses specific challenges in medical image analysis, such as overfitting and the need for robust feature extraction.

AbhiNet is a novel contribution to this line of research. By integrating elements from LeNet-5, AlexNet, VGG-16, ResNet, and DenseNet, our model aims to provide a balanced approach to feature extraction, depth, and connectivity. The competitive performance of AbhiNet on the dog heart dataset underscores its potential for broader applications in medical imaging, where precision and reliability are critical.

3. Model Architecture

The AbhiNet model consists of several layers, including convolutional layers, batch normalization, ReLU activation, max pooling, dropout, residual blocks, adaptive average pooling, and fully connected layers. Below, we detail each component of the architecture and its mathematical formulation.

3.1. Convolutional Layer

The first layer is a convolutional layer with 64 filters, a kernel size of 3×3, stride of 2, and padding of 1. The output of a convolutional layer is given by:

$$H_{out} = \left\lfloor \frac{H_{in} - \text{Kernel\_Size} + 2 \times \text{Padding}}{\text{Stride}} \right\rfloor + 1$$

For an input of size $3 \times 75 \times 75$:

$$H_{out} = \left\lfloor \frac{75 - 3 + 2 \times 1}{2} \right\rfloor + 1 = 38$$

Thus, the output shape is $64 \times 38 \times 38$.

3.2. Batch Normalization, ReLU, MaxPooling, and Dropout

After the convolution, batch normalization, ReLU activation, max pooling, and dropout are applied. The batch normalization and ReLU are defined as:

$$y = \max(0, \frac{x - \mu}{\sqrt{\sigma^2 + \epsilon}} \cdot \gamma + \beta)$$

Max pooling is applied with a kernel size of 3×3, stride of 2, and padding of 1:

$$H_{out} = \left\lfloor \frac{38 - 3 + 2 \times 1}{2} \right\rfloor + 1 = 19$$

Thus, the output shape after max pooling is $64 \times 19 \times 19$. Dropout is applied with a probability of 0.5.

3.3. Residual Blocks

The residual blocks consist of two convolutional layers, each followed by batch normalization and ReLU activation. The residual connection is defined as:

$$y = \text{ReLU}(x + F(x))$$

$$F(x) = \text{Conv2}(\text{ReLU}(\text{BatchNorm}(\text{Conv1}(x))))$$

3.4. Adaptive Average Pooling

Adaptive average pooling reduces the spatial dimensions of each feature map to 1×1 by averaging:

$$y = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} x_{i,j}$$

For an input shape of $256 \times 5 \times 5$, the output shape is $256 \times 1 \times 1$.

3.5. Fully Connected Layers

The first fully connected layer maps the flattened vector of size 256 to a 128-dimensional vector:

$$y = \text{ReLU}(Wx + b)$$

where $W \in \mathbb{R}^{128 \times 256}$ and $b \in \mathbb{R}^{128}$.

The second fully connected layer maps the 128-dimensional vector to the number of classes:

$$y = Wx + b$$

where $W \in \mathbb{R}^{\text{num\_classes} \times 128}$ and $b \in \mathbb{R}^{\text{num\_classes}}$.

4. Mathematical Understanding

The mathematical understanding of the AbhiNet model involves several key operations:

4.1. Convolution

The convolution operation applies a filter to the input, producing an output feature map:

$$\text{Conv}(x) = \sum_{i=1}^{k} \sum_{j=1}^{k} w_{ij} \cdot x_{(i+s) \cdot (j+s)}$$

4.2. Batch Normalization

Batch normalization normalizes the input to a layer by re-centering and re-scaling:

$$\text{BN}(x) = \gamma \left(\frac{x - \mu}{\sqrt{\sigma^2 + \epsilon}} \right) + \beta$$

4.3. ReLU Activation

ReLU activation applies a non-linearity to the input:

$$\text{ReLU}(x) = \max(0, x)$$

4.4. Max Pooling

Max pooling reduces the spatial dimensions by taking the maximum value in each window:

$$y_{i,j} = \max_{m,n} x_{i+m, j+n}$$

4.5. Dropout

Dropout randomly sets a fraction of input units to zero during training:

$$y = x \cdot \text{Mask}$$

4.6. Residual Connection

Residual connections help to mitigate the vanishing gradient problem:

$$y = \text{ReLU}(x + F(x))$$

AbhiNet consists of several stages, each inspired by different CNN architectures. These stages include:

- **BasicBlock**: This class represents a basic block in the network. Each `BasicBlock` consists of two sets of Convolution $\rightarrow$ Batch Normalization $\rightarrow$ ReLU layers. If downsampling is required, a convolutional layer is applied to the input before adding it to the output of the block (residual connection).
- **AbhiNet**: This is the main CNN model class. It uses the `BasicBlock` defined above. The architecture is as follows:
  - A convolutional layer (`conv1`) with 64 output channels, a kernel size of 3, a stride of 2, padding of 1, and no bias.
  - A batch normalization layer (`bn1`).
  - A ReLU activation function (`relu`).
  - A max pooling layer (`maxpool`) with a kernel size of 3, a stride of 2, and padding of 1.
  - A dropout layer (`dropout`) with a dropout rate of 0.5.
  - Three layers (`layer1`, `layer2`, `layer3`) each made up of multiple `BasicBlock`s. The number of `BasicBlock`s in each layer is defined by the `layers` argument. The number of output channels for these layers are 64, 128, and 256 respectively. Stride of 2 is used in `layer2` and `layer3` for downsampling.
  - An adaptive average pooling layer (`avgpool`) that reduces the size of the output to 1x1.
  - A fully connected layer (`fc1`) with 128 output features.
  - A ReLU activation function.
  - A final fully connected layer (`fc2`) that outputs the class scores. The number of output features is equal to the number of classes.
- **AbhiNet17**: This function returns an instance of `AbhiNet` with a specific configuration of `BasicBlock`s. It uses 2 `BasicBlock`s in each of the three layers, hence the name `AbhiNet17`.

This architecture is a variant of the ResNet architecture, which is a popular architecture for image classification tasks due to its ability to train deep networks. The key idea in ResNet is the use of "shortcut connections" or "skip connections" that allow the gradient to be directly backpropagated to earlier layers.

5. Methods

5.1. AbhiNet Architecture

AbhiNet is a convolutional neural network (CNN) designed for image classification tasks. The architecture of AbhiNet is as follows:

- **Conv1**: A convolutional layer with 64 output channels, a kernel size of 3x3, a stride of 2x2, padding of 1, and no bias.
- **Batch Normalization 1 (bn1)**: A batch normalization layer for the 64 output channels from the previous layer.
- **ReLU**: An in-place ReLU activation function.
- **MaxPool**: A max pooling layer with a kernel size of 3, a stride of 2, padding of 1, dilation of 1, and no ceil mode.
- **Dropout**: A dropout layer with a dropout rate of 0.5.
- **Layer1, Layer2, Layer3**: Each of these is a sequential layer consisting of two basic blocks. Each basic block consists of two convolutional layers followed by batch normalization. The first convolutional layer in each basic block reduces the dimensionality, while the second one retains the dimensionality. If the dimensionality is reduced, a downsample layer is used to match the dimensions.
- **Adaptive Average Pooling (avgpool)**: An adaptive average pooling layer that reduces the spatial dimensions to 1x1.
- **Fully Connected Layers (fc1, fc2)**: Two fully connected layers that map the features to the final output classes. The first fully connected layer (fc1) reduces the dimensionality from 256 to 128, and the second one (fc2) further reduces it to the number of output classes, which is 3 in this case.

AbhiNet Architecture Description

AbhiNet is a convolutional neural network (CNN) designed specifically for image classification tasks. It leverages a hybrid architecture inspired by several well-known CNN models, including LeNet-5, AlexNet, VGG-16, ResNet, and DenseNet. This combination aims to capitalize on the strengths of these architectures to achieve robust performance in classifying images of dog hearts.

Components of AbhiNet

1. **Conv1:**
   - **Type:** Convolutional layer
   - **Parameters:**
     Output channels: 64
     Kernel size: 3×3
     Stride: 2×2
     Padding: 1
     Bias: None
   - **Purpose:** Initiates feature extraction from the input images. The stride of 2×2 reduces the spatial dimensions of the feature maps.
2. **Batch Normalization 1 (bn1):**
   - **Type:** Batch normalization layer
   - **Purpose:** Normalizes the output from Conv1, stabilizing and accelerating the training process by reducing internal covariate shift.
3. **ReLU:**
   - **Type:** Activation function
   - **Purpose:** Introduces non-linearity into the network, allowing it to learn complex patterns and relationships within the data.
4. **MaxPool:**
   - **Type:** Max pooling layer
   - **Parameters:**
     Kernel size: 3×3
     Stride: 2
     Padding: 1
     Dilation: 1
     Ceil mode: No
   - **Purpose:** Downsamples the feature maps, retaining the most significant information while reducing computational complexity and memory usage.
5. **Dropout:**
   - **Type:** Dropout layer
   - **Parameters:**
     Dropout rate: 0.5
   - **Purpose:** Regularizes the network by randomly dropping out (setting to zero) a fraction of input units during training, reducing overfitting.
6. **Layer1, Layer2, Layer3:**
   - **Type:** Sequential layers, each composed of BasicBlocks
   - **BasicBlock Structure:**
     – Consists of two convolutional layers followed by batch normalization.
     – The first convolutional layer may reduce the dimensionality (stride ¿ 1), while the second maintains it.
     – If dimensionality is reduced, a downsample layer adjusts dimensions to match.
   - **Purpose:** Hierarchically extracts and refines features from the input through multiple layers of convolutions and batch normalization, enhancing the model's ability to learn complex representations.
7. **Adaptive Average Pooling (avgpool):**
   - **Type:** Adaptive average pooling layer
   - **Parameters:**
     Output size: 1×1
   - **Purpose:** Aggregates spatial information by computing the average value of each feature map, regardless of its spatial dimensions, resulting in a fixed-size output regardless of input size.
8. **Fully Connected Layers (fc1, fc2):**
   - **Type:** Linear (fully connected) layers
   - **Parameters:**
     fc1: Reduces the dimensionality from 256 to 128
     fc2: Further reduces it to the number of output classes, which is 3 in this case (for dog heart conditions).
   - **Purpose:** Maps the extracted features from the convolutional layers to the final output classes, enabling the network to make predictions based on the learned representations.

6. Results

6.1. Training and Validation Results

The model was trained over 20 epochs. The training and validation losses for each epoch are shown in Table 1.

Epoch	Training Loss	Validation Loss
1	0.6296	0.6479
2	0.6103	0.6145
3	0.6012	0.6637
4	0.5751	0.6216
5	0.5536	0.6204
6	0.5382	0.6183
7	0.5094	0.6006
8	0.4935	0.6296
9	0.4880	0.5583
10	0.4661	0.5886
11	0.4687	0.6237
12	0.4687	0.5929
13	0.4601	0.5873
14	0.4269	0.6055
15	0.4323	0.6108
16	0.4340	0.6073
17	0.4402	0.6080
18	0.4293	0.6087
19	0.4281	0.6144
20	0.4261	0.6041

Table 1. Training and Validation Losses

6.2. Final Test Accuracy

The final test accuracy of the model is 71.75%.

7. Conclusion

In conclusion, the convolutional neural network achieved a final test accuracy of 71.75%.

References

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