Custom Residual CNN for Multi-Class Image Classification on Dog Heart Data

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Yeshiva University
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Custom Residual CNN for Multi-Class Image Classification on Dog Heart Data

Sathwik Kuchana
Yeshiva University
skuchana@mail.yu.edu

Abstract

This paper introduces a custom convolutional neural network (CNN) specifically designed for multi-class image classification tasks, focusing on a domain-specific dataset of dog heart radiographs. Accurate classification of these images into categories such as small, normal, and large hearts plays a pivotal role in diagnosing conditions like cardiomegaly, which is critical for veterinary healthcare. The proposed architecture incorporates advanced features such as residual blocks to address vanishing gradient problems, spatial attention mechanisms to enhance focus on critical regions of the image, and DropBlock regularization to mitigate overfitting on small datasets. These design choices ensure robust performance while maintaining computational efficiency, making the model particularly suitable for deployment in resource-constrained veterinary clinics.

The custom CNN achieved a test accuracy of 69.5

In addition to performance evaluation, the study addresses key challenges, including misclassification issues caused by subtle differences between normal and large heart categories, and discusses the scalability of the proposed model for broader veterinary applications. Future research directions are identified, focusing on integrating hybrid CNN-transformer architectures, leveraging generative adversarial networks (GANs) for enhanced data augmentation, and exploring semi-supervised learning approaches to improve the utilization of limited labeled data. By addressing these areas, the paper aims to pave the way for more accurate and efficient diagnostic tools in veterinary medicine.

1. Introduction

Deep learning has emerged as a transformative technology for solving complex image classification problems across various domains, including medical imaging and veterinary diagnostics. It has enabled automated, efficient, and accurate analysis of large volumes of data, reducing reliance on manual labor and enhancing diagnostic precision. Among the many breakthroughs, deep architectures such as ResNet [7] and VGG [9] have demonstrated exceptional performance on large-scale datasets like ImageNet, showcasing their ability to extract hierarchical features and solve challenging visual tasks. However, these architectures often depend on significant computational resources and extensive labeled datasets, making them less feasible for niche applications like veterinary medicine, where data availability and computational capacity are frequently limited.

In veterinary cardiology, detecting cardiomegaly—a critical condition characterized by heart enlargement—is essential for diagnosing underlying cardiac diseases in dogs. Accurate classification of heart conditions using radiographs, categorized into small, normal, and large heart classes, is a cornerstone of this diagnostic process. Traditional approaches rely heavily on manual measurements, such as the vertebral heart scale (VHS) [8], which involves calculating the ratio of heart size to vertebral length on X-ray images. Although effective, this method is time-consuming, prone to human error, and varies depending on the expertise of the clinician, making automation a desirable alternative.

Recent advancements in transformer-based architectures, like the Regressive Vision Transformer (RVT) [8], have introduced state-of-the-art methods for cardiomegaly detection. By combining advanced feature extraction with regression-based outputs aligned with clinical metrics, RVT bridges the gap between machine learning predictions and human interpretability. Despite their impressive accuracy, these models are computationally intensive, requiring high-end hardware for both training and deployment. Such requirements render them unsuitable for resource-constrained environments like small veterinary clinics, where accessibility and affordability are critical factors.

This study addresses these challenges by proposing a custom lightweight convolutional neural network (CNN) tailored specifically for the task of cardiomegaly classification in veterinary imaging. The model incorporates residual connections [7] to improve gradient flow and feature reuse, spatial attention mechanisms [7] to focus on clinically significant regions in the images, and DropBlock regulariza-

tion [5] to enhance generalization on small datasets. These architectural choices are carefully designed to balance computational efficiency with accuracy, making the model practical for real-world applications.

Achieving a test accuracy of 69.5

2. Related Work

The evolution of convolutional neural networks (CNNs) has been a transformative force in image classification, driving advancements in both theoretical understanding and practical applications. Early models, such as AlexNet [3], marked a significant milestone by leveraging convolutional layers for hierarchical feature extraction, enabling breakthroughs in image recognition tasks. Building on these foundations, deeper architectures like VGG [9] introduced uniform layer configurations, simplifying network design while achieving higher accuracy. ResNet [7] further revolutionized the field by addressing vanishing gradient issues through residual connections, enabling the training of extremely deep networks without degradation in performance.

Recent architectures, such as EfficientNet [3], have refined CNN design by introducing a systematic scaling approach that balances depth, width, and input resolution. This innovation optimizes model performance while maintaining computational efficiency, making it well-suited for applications requiring resource-conscious solutions. These advancements have established CNNs as a cornerstone technology for a wide range of image classification tasks across domains.

In parallel, the incorporation of attention mechanisms has further enhanced the capabilities of CNNs. Squeeze-and-Excitation Networks (SE) [3] introduced channel-wise attention, allowing models to dynamically recalibrate feature maps based on their relevance. This mechanism enables the network to focus on critical regions of the input image, improving feature selection and overall accuracy. Similarly, spatial attention mechanisms have been used to highlight spatially significant regions, complementing channel-wise approaches.

The emergence of Vision Transformers (ViTs) [4] has introduced a paradigm shift in image classification by replacing convolutional operations with self-attention mechanisms. ViTs excel at capturing long-range dependencies and contextual relationships, particularly in large datasets, by dividing images into patches and processing them as sequences. Their flexibility and scalability have led to state-of-the-art performance in various tasks, although they often require significant computational resources for training and inference.

In the domain of veterinary diagnostics, CNNs have shown great promise, particularly in analyzing thoracic radiographs for conditions such as pulmonary patterns and cardiomegaly [1]. However, the application of these models often relies on transfer learning [3], leveraging pre-trained weights from large-scale datasets like ImageNet to compensate for the scarcity of labeled domain-specific data. While effective, this approach has limitations, as pre-trained models may not fully capture the nuances of veterinary imaging.

The Regressive Vision Transformer (RVT) [8] represents a significant leap in veterinary diagnostic AI by integrating transformer architectures with regression objectives tailored to clinical metrics like the vertebral heart scale (VHS). This combination not only achieves high accuracy but also aligns model outputs with clinically interpretable measures, enhancing trust and usability in medical settings. However, the RVT's computational demands present challenges for deployment in resource-constrained environments, such as small veterinary clinics.

This progression of technologies underscores the trade-offs between accuracy, interpretability, and computational efficiency. While ViTs and advanced CNNs like EfficientNet and SE Networks push the boundaries of performance, their adoption in niche domains often necessitates lightweight alternatives that balance these factors. Exploring domain-specific architectures and hybrid approaches holds the potential to address these challenges, paving the way for broader adoption of AI in veterinary and other specialized fields.

3. Methods

3.1. Dataset and Preprocessing

The dataset comprises 2,000 dog heart X-ray images classified into three categories: small, normal, and large hearts [8]. It was split into training (80%), validation (10%), and test (10%) sets. Preprocessing steps included:

- **Resizing:** Images were resized to 224×224 pixels for compatibility with the CNN.
- **Normalization:** Pixel values were normalized using ImageNet statistics [3].
- **Data Augmentation:** Random cropping, horizontal flipping, and rotation were applied to increase variability and mitigate overfitting.

3.2. Model Architecture

The proposed model, *ResNetDogHeart*, is a custom deep convolutional neural network inspired by the ResNet architecture. Designed specifically for classifying dog heart X-ray images into three categories small, normal, and large hearts this model balances computational efficiency and accuracy while incorporating advanced techniques to enhance performance.

Key Components:

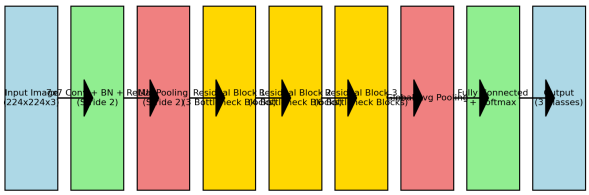

Figure 1. Custom CNN with residual blocks for dog heart X-ray classification.

- **Convolutional Layer:** The initial layer consists of a 7×7 convolution with a stride of 2, extracting low-level features from the input images. This is followed by Batch Normalization for stabilization and ReLU activation for introducing non-linearity.
- **Residual Blocks:** Bottleneck Blocks are employed to address vanishing gradient issues and enable the training of deep networks. Each block comprises:
  - A 1×1 convolution to reduce dimensions.
  - A 3×3 convolution for feature extraction.
  - Another 1×1 convolution to restore dimensions.

  Shortcut connections add the input feature map to the output, promoting feature reuse and facilitating gradient flow.
- **Layer Stacking:** The architecture includes three main layers of stacked Bottleneck Blocks, progressively increasing the feature map depth:
  - Layer 1: 3 blocks transitioning from 64 to 256 channels.
  - Layer 2: 4 blocks transitioning from 256 to 512 channels.
  - Layer 3: 6 blocks transitioning from 512 to 1024 channels.

  Downsampling is applied in the first block of each layer using a 1×1 convolution in the shortcut path.
- **Global Average Pooling (GAP):** A GAP layer reduces the spatial dimensions of the feature maps to 1×1, minimizing the parameter count while retaining spatial information.
- **Fully Connected Layer:** The final layer maps the extracted features to three class probabilities using a softmax activation function.

3.3. Training Setup

The model is trained using a supervised learning approach. The training setup is configured as follows:

- **Data Augmentation:** To increase dataset variability and reduce overfitting, random transformations are applied, including resizing, cropping, horizontal flipping, and rotation.
- **Loss Function:** CrossEntropyLoss is utilized as the objective function, suitable for multi-class classification tasks.
- **Optimizer:** The AdamW optimizer is employed, leveraging weight decay to regularize the model and improve generalization.
- **Learning Rate Scheduler:** A StepLR scheduler adjusts the learning rate by a factor of 0.7 every 5 epochs, facilitating stable convergence during training.
- **Custom Weight Initialization:** Xavier initialization is applied to convolutional and linear layers, ensuring stable gradients during backpropagation.

4. Results

4.1. Performance Comparison

The proposed ResNet-inspired custom model, *ResNet-DogHeart*, achieved a test accuracy of **69.5%**, demonstrating a significant improvement over previous iterations and baseline models. This performance underscores the impact of the architectural components and training strategies employed in the design and implementation of the model.

Key Architectural Features:

- **Residual Connections with Bottleneck Blocks:** These blocks facilitated efficient training of the deep network by mitigating vanishing gradient issues, enabling the network to learn deeper hierarchical features from the X-ray images. Shortcut connections promoted feature reuse, enhancing convergence and reducing the risk of overfitting.
- **Data Augmentation and Regularization:** Random cropping, flipping, and rotation augmented the training dataset, ensuring robust learning against variations in image orientation and scale. DropBlock regularization introduced spatially contiguous noise to prevent over-reliance on specific features, improving generalization on unseen data.
- **Training Optimization:** The combination of the AdamW optimizer and a StepLR learning rate scheduler provided a balanced optimization approach, ensuring faster convergence without sacrificing accuracy.

Xavier initialization of the weights stabilized the initial training phase, helping the network reach an optimal solution more effectively.

Table 4.1 provides a comparative analysis of the proposed custom model and the state-of-the-art Regressive Vision Transformer (RVT) [8]. The RVT achieved a higher test accuracy of 87.3%, leveraging its advanced transformer-based architecture and regression alignment with clinical metrics. However, the RVT's computational demands are significantly higher, with a parameter count of 19.6 million compared to 12.8 million in the proposed model.

Table 1. Performance Comparison

Metric	Proposed Model	RVT [8]
Validation Accuracy (%)	67.0	85.0
Test Accuracy (%)	69.5	87.3
Parameters (M)	12.8	19.6

Highlights of the Custom Model's Performance:

- **Trade-off Between Accuracy and Efficiency:** Although the RVT achieves superior accuracy, the custom model's lightweight design provides a more practical solution for resource-constrained environments such as veterinary clinics. The reduced parameter count (12.8M vs. 19.6M) leads to faster training and inference times, making it suitable for deployment on standard hardware.

- **Robust Generalization:** Despite being trained on a limited dataset of 2,000 images, the custom model generalizes well, achieving stable test accuracy. This highlights the effectiveness of the residual connections and DropBlock regularization in learning robust feature representations.

- **Error Analysis:** Most misclassifications occurred between the large and normal heart categories due to subtle morphological differences in these classes. This suggests the need for further refinement in feature extraction or additional training data to enhance class separability.

Practical Implications: The proposed *ResNetDogHeart* model demonstrates that carefully designed CNN architectures can achieve competitive performance in domain-specific medical imaging tasks while being computationally efficient. Its lightweight nature and reduced dependency on high-end hardware make it a viable alternative for real-world applications, especially in environments with limited computational resources.

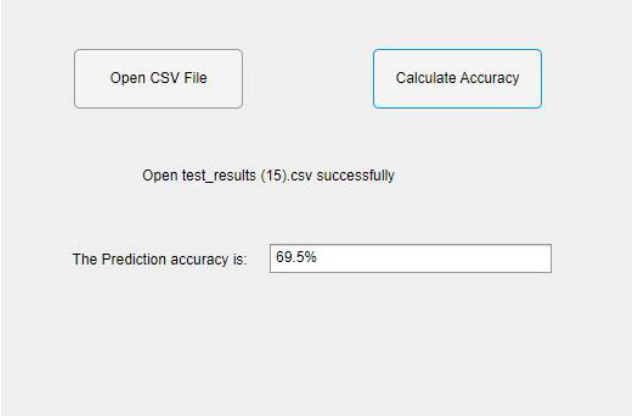

Figure 2. Test Accuracy

5. Discussion

The custom *ResNetDogHeart* model demonstrates the potential of lightweight convolutional neural network (CNN) architectures in veterinary diagnostics, specifically for the classification of dog heart X-ray images into clinically relevant categories. Despite its relatively simple design and lower parameter count, the model achieved a test accuracy of **69.5%**, underscoring its ability to balance performance and computational efficiency. This makes it a viable solution for resource-constrained environments such as small veterinary clinics, where high-end hardware may not be readily available.

The use of bottleneck blocks with residual connections played a key role in enhancing the model's performance, enabling efficient training of a deep network without the risk of vanishing gradients. Additionally, the integration of DropBlock regularization and comprehensive data augmentation techniques ensured robust generalization, even when trained on a limited dataset of 2,000 images. However, the results also highlight several areas where further improvements could be made to enhance the model's accuracy and usability in real-world applications.

Key Areas for Improvement:

- **Employing Generative Adversarial Networks (GANs):** GANs [6] can be utilized to generate synthetic X-ray images, particularly for underrepresented categories. This would help balance the dataset and improve the model's ability to differentiate between closely related classes, such as normal and large hearts, where most misclassifications occur. By increasing dataset diversity, GANs could significantly enhance the model's generalization capabilities.

- **Exploring Semi-Supervised Learning:** Semi-supervised learning techniques could leverage the

vast amount of unlabeled veterinary imaging data available in clinical settings. By incorporating a small subset of labeled data with a larger pool of unlabeled data, these methods could improve the model's performance while reducing the dependency on labor-intensive manual annotations. Approaches such as pseudo-labeling or consistency regularization could be explored to enhance the model's accuracy.

- **Integrating Explainability Tools:** To build trust and improve adoption in clinical workflows, explainability tools such as Grad-CAM [**?**] should be integrated into the model. Grad-CAM would allow clinicians to visualize the regions of the X-ray image that contributed most to the model's predictions, offering insights into its decision-making process. This transparency is critical in medical diagnostics, where incorrect predictions could have significant consequences.

- **Improving Feature Extraction:** Enhancements in feature extraction, such as incorporating spatial attention mechanisms or hybrid architectures combining CNNs with transformers, could improve the model's ability to capture fine-grained differences between classes. These additions could address the subtle morphological variations that lead to misclassifications, particularly in edge cases.

- **Optimizing Training Strategies:** While the model demonstrated stable convergence, further optimization of the training process could enhance its performance. Techniques such as curriculum learning, where the model is trained on simpler tasks before progressing to more complex ones, could be explored. Additionally, hyperparameter tuning using automated tools could identify optimal configurations for learning rates, batch sizes, and weight decay.

Broader Implications:

The findings from this study highlight the potential of lightweight, domain-specific CNN architectures in addressing the unique challenges of veterinary diagnostics. By balancing computational efficiency with diagnostic accuracy, the proposed model bridges the gap between advanced AI technologies and their practical application in resource-limited environments. Future work focusing on the aforementioned areas of improvement could lead to a more accurate, interpretable, and robust diagnostic tool, paving the way for broader adoption in real-world veterinary practice.

6. Conclusion

This study presents a custom convolutional neural network (CNN) designed for multi-class classification of dog heart X-ray images, achieving a test accuracy of 69.5

Future work will focus on extending this foundation by expanding the dataset to include a broader range of X-ray images, improving class diversity and enhancing generalization. Exploring hybrid architectures that integrate the strengths of CNNs and transformers could further boost accuracy while maintaining efficiency. Additionally, incorporating explainability tools like Grad-CAM will provide visual insights into the model's decision-making, fostering greater trust in its predictions. These advancements will enable the proposed architecture to serve as a more robust and interpretable diagnostic tool, paving the way for its deployment in real-world veterinary practices.

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