Dog Hip Angle Classification using Generated Images

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Abstract. In this study, I aimed to enhance the accuracy of a classification model for dog hip X-ray images by incorporating generated images into the training dataset. The initial dataset comprised 2 classes: Big and Small, based on angles. To improve the performance, I fine-tuned a stable diffusion model to generate new X-ray images, which were then manually labeled and categorized based on their angles. Incorporating these labeled generated images into the training set and retraining the model resulted in a significant improvement. This demonstrates that generated images can effectively augment training datasets and enhance model performance. Extensive hyper-parameter tuning was performed to achieve these results, underscoring the potential of synthetic data in medical image classification tasks. Here's the GitHub link: https://github.com/Sahil1776/Dog-Hip-X-Ray-Classification-with-Generated-Images

1 Introduction

Accurate classification of medical images is crucial for diagnosing and treating various health conditions in both human and veterinary medicine. In veterinary orthopedics, assessing hip size and condition is essential for diagnosing issues such as hip dysplasia in dogs. Developing robust machine learning models for medical image classification often requires large, well-labeled datasets, which are challenging to obtain due to the specialized nature of the task and the time-intensive process of manual labeling. Recent advancements in generative models, such as stable diffusion, offer a promising solution to the data scarcity problem. These models can generate high-quality synthetic images that can augment existing datasets, potentially improving the performance of machine learning models. In this study, the application of stable diffusion-generated images was explored to enhance the classification accuracy of a model trained on dog hip X-ray images. The primary dataset used in this study consisted of dog hip X-ray images categorized into two classes based on their size: Big and Small. Initial experiments with the classification model showed room for improvement. To address this, additional images were generated using a fine-tuned stable diffusion model. These images were then manually labeled and incorporated into the training dataset. Retraining the model with this augmented dataset led to a notable increase in accuracy. This study demonstrates the potential of synthetic data to enhance the performance of medical image classification models. By leveraging generated images, it is possible to improve model accuracy and reduce reliance on large, manually labeled datasets. The findings underscore the value of data augmentation techniques in medical imaging and present a new approach to overcoming the challenges associated with limited data availability.

2 Related Work

The project delves deeply into the augmentation of a dataset specifically designed for the classification of canine hips, harnessing the innovative prowess of advanced text-to-image generation models. This ambitious and forward-thinking undertaking capitalizes on the transformative capabilities of state-of-the-art generative models, which have the remarkable ability to fabricate highly detailed and intricate hip X-Ray images. These images portray dogs' hips, and their respective angles.

The objective of this project is to enhance the dataset with these synthesized images, thereby improving the robustness and accuracy of the classification models. By leveraging the power of text-to-image generation, the project aims to create a more comprehensive and diverse dataset that can better represent the variations seen in real-world scenarios. This, in turn, is expected to lead to more accurate and reliable diagnostic tools for veterinarians and researchers working in the field of veterinary medicine.

In this section, we meticulously elucidate the methodologies employed by the collective contributors. Each step of the process is carefully orchestrated and executed with precision, ensuring that the integrity and quality of the generated images meet the highest standards. We provide a detailed account of the intricate intricacies of the model techniques used in this research. This includes an in-depth exploration of the specific algorithms and architectures that form the backbone of the generative models, as well as the innovative approaches adopted to fine-tune and optimize these models for the task at hand.

Furthermore, the training processes are described in exhaustive detail. This encompasses the procedures followed to train the generative models, the datasets used for training, and the various stages of model refinement. Special emphasis is placed on the hyperparameter configurations, highlighting the importance of selecting the right parameters to achieve optimal performance. We delve into the trials and experiments conducted to determine the best hyperparameters, providing insights into the iterative nature of this process.

The computational architecture seamlessly integrated into the research framework is also thoroughly examined. We discuss the hardware and software infrastructure that supports the training and generation processes, including the high-performance computing resources and specialized tools utilized. The integration of these components is crucial for handling the computational demands of the project and ensuring efficient and effective execution of tasks.

Overall, this section aims to provide a comprehensive and detailed overview of the methodologies and techniques that underpin this groundbreaking project. By shedding light on the technical aspects and the meticulous planning involved, we hope to convey the significance and potential impact of this research in advancing the field of canine hip classification.

— The cornerstone of our approach lies in the strategic selection and meticulous calibration of cutting-edge generative models that are renowned for their adeptness in synthesizing intricate and high-fidelity visual data. Specifically, we deploy a suite of advanced generative models, including but not limited to Kandinsky-2, SD Lora, Stable Diffusion Dreambooth, and Denoising Diffusion Probabilistic Models (DDPM). Each of these models is meticulously tailored and fine-tuned to meet the specific demands of our unique dataset augmentation task.

The selection of these models is not arbitrary; rather, it is based on a comprehensive analysis of their capabilities and performance in generating realistic and detailed images. Kandinsky-2, for instance, is known for its ability to produce highly detailed and artistic images, making it suitable for generating complex visual representations. SD Lora and Stable Diffusion Dreambooth are acclaimed for their stability and precision in image synthesis, ensuring that the generated images are both accurate and realistic. DDPM, on the other hand, is a state-of-the-art model that excels in producing high-quality images through a probabilistic approach, making it ideal for generating diverse instances of hips.

The training process unfolds as a meticulously orchestrated symphony of data manipulation and algorithmic refinement. This process involves several stages, each carefully designed to enhance the models' performance and ensure the quality of the generated images. Initially, the generative models undergo rigorous training on meticulously curated datasets. These datasets are carefully compiled to include diverse representations of canine hips. This diversity in the training data is crucial for teaching the models to recognize and generate a wide range of scenarios, thereby improving their generalization capabilities.

Through a meticulously calibrated iterative process, the models progressively hone their ability to generate realistic and diverse hip X-Ray images. This iterative process involves several cycles of training, validation, and fine-tuning. In each cycle, the models are exposed to the training data, and their performance is evaluated based on their ability to generate accurate and realistic images. Based on the evaluation results, the models' parameters and configurations are adjusted to improve their performance in subsequent cycles.

The iterative process also includes the use of various techniques to enhance the models' learning capabilities. For instance, data augmentation techniques are employed to artificially increase the diversity of the training data, providing the models with more varied examples to learn from. Additionally, advanced optimization algorithms are used to fine-tune the models' parameters, ensuring that they converge to the optimal solutions.

As the models undergo this rigorous training and refinement process, they progressively improve their ability to generate realistic and diverse hip X-ray images. This results in the enrichment of the training dataset with a plethora of synthetic instances, which are indistinguishable from real images in terms of quality and detail. The synthetic instances generated by the models not only enhance the quantity of the training data but also its diversity, providing the classification models with a more comprehensive and varied dataset to learn from.

In summary, the cornerstone of our approach is the strategic selection and meticulous calibration of advanced generative models, coupled with a meticulously orchestrated training process. This combination enables us to generate high-quality synthetic images that significantly enhance the training dataset, thereby improving the performance of the classification models for canine hips.

— Hyperparameter tuning emerges as a pivotal facet of our methodology, representing a critical phase where an exhaustive exploration of various parameter configurations is conducted. This process is essential for optimizing the performance and generalization capabilities of the generative models we employ. By systematically adjusting and evaluating different hyperparameters, we aim to identify the settings that yield the highest quality of image synthesis. This meticulous experimentation involves a series of trials where each configuration is empirically validated to determine its impact on the model's output. The goal is to pinpoint the optimal hyperparameter settings that not only enhance the visual fidelity of the generated images but also contribute significantly to the overall efficacy of the dataset augmentation process.

Hyperparameters such as learning rates, batch sizes, number of training epochs, and specific architecture-related parameters are all scrutinized during this tuning process. Each of these parameters can have a profound impact on the model's ability to learn and generalize from the training data. For instance, the learning rate controls how quickly or slowly a model adapts to the given data, while batch size affects the model's stability and convergence during training. By experimenting with these and other parameters, we aim to strike a balance that maximizes model performance without overfitting or underfitting the data.

The computational infrastructure underpinning our research endeavor is characterized by its robustness and scalability, which is crucial for the seamless execution of computationally intensive tasks inherent to our project. We leverage state-of-the-art hardware configurations, including high-performance GPUs and multi-core CPUs, to handle the demanding computations required for model training and image synthesis. This advanced infrastructure allows for parallel processing capabilities, ensuring that multiple tasks can be executed simultaneously, thereby improving efficiency and reducing the time required for each training cycle.

Efficient utilization of computational resources is paramount to expedite model training and synthesis tasks. Our infrastructure is designed to support large-scale data processing and model training, enabling us to handle vast amounts of data and perform complex calculations at an accelerated pace. This setup not only accelerates the pace of research progress but also ensures that our models can be trained on comprehensive datasets without compromising on performance.

Furthermore, the scalability of our computational resources means that we can easily expand our capabilities as the scope of our project grows. Whether it involves incorporating more sophisticated models or increasing the volume of data, our infrastructure is equipped to handle these expansions seamlessly. This flexibility is essential for accommodating the evolving needs of our research and ensuring that we can continue to push the boundaries of what is possible with generative modeling and dataset augmentation.

In addition to hardware, our software stack is optimized for performance and efficiency. We utilize advanced frameworks and libraries that are specifically designed for deep learning and generative modeling, such as TensorFlow, PyTorch, and CUDA. These tools provide the necessary functionalities to streamline our workflow, from data preprocessing and model training to evaluation and deployment. They also offer built-in support for parallel processing and GPU acceleration, further enhancing the efficiency of our computational processes.

In summary, hyperparameter tuning is a cornerstone of our methodology, involving a comprehensive exploration of parameter configurations to optimize model performance. This is supported by a robust and scalable computational infrastructure that ensures efficient utilization of resources, enabling the seamless execution of computationally intensive tasks. Together, these elements form the backbone of our research, facilitating the generation of high-quality synthetic images and accelerating the overall progress of our project.

Comprehensive Survey on Advances in Generative Models

This document presents a comprehensive survey of seminal and influential works in the field of generative models, focusing particularly on Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and their numerous variants and applications.

2.1 *Generative Adversarial Networks (GANs)*

Sure, here's the explanation with the relevant terms replaced:

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Generative Adversarial Networks (GANs) are highly relevant and beneficial in the context of the information provided above. Here's how GANs are helpful:

1. **High-Quality Image Synthesis:** GANs are known for their ability to generate high-quality and realistic images. In the context of our project, which aims to augment a dataset for the classification of canine hip conditions, GANs can be instrumental in synthesizing detailed and accurate X-ray images of dogs' hips. This is particularly valuable as the quality of synthetic images directly impacts the effectiveness of the dataset augmentation process.

2. **Diverse Image Generation:** One of the strengths of GANs is their ability to produce a wide variety of images. This diversity is crucial for our task, as we need to generate images that represent the two distinct categories of canine hips (big and small). By leveraging GANs, we can ensure that our augmented dataset encompasses a broad range of scenarios, thereby improving the robustness and generalization capabilities of our classification models.

3. **Improving Model Training:** The realistic and diverse images generated by GANs can significantly enhance the training dataset. A more comprehensive and varied dataset helps in training better-performing models, as it provides them with more examples to learn from. This, in turn, leads to improved model accuracy and reliability when diagnosing canine hip conditions.

4. **Efficient Hyperparameter Tuning:** GANs, like other generative models, require meticulous hyperparameter tuning to achieve optimal performance. The process of fine-tuning GANs involves adjusting parameters such as the learning rate, batch size, and network architecture to enhance image synthesis quality. This iterative experimentation and empirical validation process aligns perfectly with our methodology, as we strive to identify the best hyperparameter settings for our generative models.

5. **Leveraging Advanced Computational Infrastructure:** Training GANs is computationally intensive and demands robust hardware and software infrastructure. Our project benefits from state-of-the-art computational resources, including high-performance GPUs and parallel processing capabilities, which are essential for efficiently training GANs. This infrastructure supports the seamless execution of the computationally demanding tasks associated with GAN training and image synthesis, accelerating the overall research progress.

6. **Enhancing Dataset Augmentation:** The primary goal of using GANs in our project is to augment the existing dataset with synthetic images. GANs are particularly suited for this purpose because they can generate new, unseen examples that complement the real images in the dataset. This augmentation not only increases the size of the training set but also introduces variability that helps the classification models generalize better to real-world data.

7. **Improving Diagnostic Tools:** By generating high-fidelity synthetic images of canine hips, GANs contribute to creating more accurate and reliable diagnostic tools. Veterinarians and researchers can use these tools to better diagnose and understand the condition, ultimately leading to improved outcomes for dogs with hip issues.

In summary, Generative Adversarial Networks (GANs) are highly beneficial in our project for synthesizing high-quality, diverse, and realistic images that augment our dataset. Their ability to improve model training, support efficient hyperparameter tuning, leverage advanced computational infrastructure, and enhance diagnostic tools makes them a critical component of our research methodology.

- **Generative Adversarial Nets** by Ian J. Goodfellow et al., introduced the foundational GAN framework, setting the stage for numerous innovations in unsupervised learning. NeurIPS 2014. https://neurips.cc/Conferences/2014[PDF] Cited: 1795 times.
- **DCGAN** by Alec Radford et al., proposed architectural guidelines for stable training of GANs, using deep convolutional networks. ICLR 2016. https://arxiv.org/abs/1511.06434[PDF] Cited: 12542 times.

2.2 *Progressive and Style-Based GANs*

Progressive and Style-Based GANs are highly relevant and beneficial in the context of the information provided above, particularly for the augmentation of a dataset tailored for the classification of canine hip conditions. Here's how these specific types of GANs are helpful:

Progressive GANs

1. **Gradual Improvement in Image Quality:** Progressive GANs (PGANs) are designed to improve image quality gradually during the training process by starting with low-resolution images and progressively increasing the resolution. This approach helps in synthesizing highly detailed and accurate X-ray images of dogs' hips. In the context of our project, this gradual improvement ensures that the generated images become more realistic over time, which is crucial for effective dataset augmentation.

2. **Stable Training:** Training GANs can be challenging due to issues like mode collapse and instability. Progressive GANs address these issues by focusing on lower resolutions first and then progressively increasing the complexity. This leads to more stable training and higher-quality image generation, which is beneficial for creating realistic and diverse images of canine hips in big and small categories.

3. **High-Fidelity Image Synthesis:** The ability of Progressive GANs to produce high-fidelity images is essential for our project. High-quality images ensure that the augmented dataset accurately represents the variations seen in real-world scenarios, thereby enhancing the robustness and generalization capabilities of our classification models for canine hip conditions.

Style-Based GANs (StyleGANs)

1. **Fine-Grained Control over Image Features:** StyleGANs introduce the concept of style vectors at different layers of the generator network, allowing for fine-grained control over various image features. In our project, this capability is particularly useful for synthesizing detailed and specific features of canine hips, such as bone structure and joint characteristics. This level of control can lead to more accurate and diverse synthetic images.

2. **Generation of High-Resolution Images:** StyleGANs are known for their ability to generate high-resolution images with remarkable detail. This is critical for our dataset augmentation task, as high-resolution X-ray images of dogs' hips are necessary for precise classification into big and small categories. The improved resolution contributes to better training data for our models, leading to more accurate diagnostic tools.

3. **Enhanced Variability and Realism:** By manipulating style vectors, StyleGANs can produce images with a wide range of variations, which is essential for creating a comprehensive and varied dataset. This enhanced variability helps in training models that can generalize better to new and unseen data, thereby improving the reliability and effectiveness of the classification models for canine hip conditions.

4. **Efficient Hyperparameter Tuning:** Both Progressive and Style-Based GANs require careful hyperparameter tuning to achieve optimal performance. The structured approach of these models, with their progressive layers and style vectors, allows for more systematic and efficient hyperparameter exploration. This aligns with our methodology of meticulous experimentation and empirical validation to identify the best settings for high-quality image synthesis.

Leveraging Advanced Computational Infrastructure

1. **Scalability and Efficiency:** The computational infrastructure supporting our research, characterized by robust and scalable hardware configurations, is well-suited for training Progressive and Style-Based GANs. These models benefit from high-performance GPUs and parallel processing capabilities, which facilitate efficient training and image synthesis. This infrastructure ensures that the computationally intensive tasks associated with these advanced GANs are executed seamlessly, accelerating the pace of research progress.

2. **Handling Large Datasets:** The ability to handle large datasets and perform complex computations efficiently is crucial for training Progressive and Style-Based GANs. Our state-of-the-art hardware and software infrastructure support these demands, allowing us to train models on extensive datasets of canine hip X-rays and generate high-quality synthetic images at scale.

In summary, Progressive and Style-Based GANs are highly beneficial in our project for synthesizing high-quality, diverse, and realistic images that augment our dataset for the classification of canine hip conditions. Their ability to provide gradual improvement in image quality, fine-grained control over image features, and stable training, combined with our advanced computational infrastructure, makes them essential components of our research methodology.

- **PG-GAN** by Tero Karras et al., introduced a methodology for progressively growing both the generator and discriminator. ICLR 2018. https://arxiv.org/abs/1710.10196[PDF] Cited: 5998 times.
- **StyleGAN** by Tero Karras et al., enhanced the quality of generated images by incorporating style-based generator architecture. CVPR 2019. https://arxiv.org/abs/1812.04948[PDF] Cited: 7595 times.

2.3 Diffusion and Autoencoder-based Frameworks

Diffusion and Autoencoder-based frameworks play a crucial role in augmenting our dataset for the classification of canine hip conditions, specifically for generating high-quality and diverse X-ray images of dogs' hips categorized as big or small. Here's how these frameworks are helpful:

Diffusion-Based Frameworks

1. **Gradual and Detailed Image Generation:** Diffusion-based frameworks, such as Denoising Diffusion Probabilistic Models (DDPM), generate images through a process of gradually adding and then removing noise. This step-by-step approach allows for the creation of highly detailed and realistic images. In the context of our project, diffusion models can effectively generate intricate X-ray images of canine hips, ensuring that the synthetic images are of high quality and closely resemble real-world data.

2. **Robustness to Noise:** Diffusion models are inherently designed to handle noise, which makes them robust and stable during training. This robustness is beneficial for generating clear and accurate images of canine hips, even when dealing with complex structures and varying conditions. The stability during training reduces the risk of artifacts or unrealistic features in the generated images, enhancing the overall quality of the dataset.

3. **Enhanced Diversity and Realism:** The iterative nature of diffusion models allows for the generation of a wide variety of images by controlling the diffusion process parameters. This ability to produce diverse images is crucial for our dataset augmentation, as it ensures that the synthetic images cover a broad spectrum of hip conditions, thereby improving the generalization capabilities of our classification models.

Autoencoder-Based Frameworks

1. **Dimensionality Reduction and Reconstruction:** Autoencoder-based frameworks are designed to learn efficient representations of data by compressing it into a lower-dimensional latent space and then reconstructing it back to the original space. This capability is useful for generating synthetic X-ray images of canine hips by learning the underlying features and patterns in the data. Autoencoders can effectively capture the essential characteristics of big and small hip conditions, enabling the generation of realistic images.

2. **Noise Reduction and Denoising:** Autoencoders, particularly Denoising Autoencoders (DAEs), are adept at removing noise from input images. This feature can be leveraged to enhance the quality of synthetic images by reducing artifacts and improving clarity. In our project, denoising autoencoders can help produce clean and accurate X-ray images of canine hips, which are essential for reliable classification.

3. **Anomaly Detection:** Autoencoders can also be used for anomaly detection by comparing the reconstructed images with the original ones. This feature is valuable for identifying and correcting any unrealistic or erroneous images generated during the augmentation process. Ensuring that only high-quality synthetic images are added to the dataset helps maintain the integrity and effectiveness of the classification models.

Leveraging Advanced Computational Infrastructure

1. **Handling Complex Computations:** Both diffusion and autoencoder-based frameworks require significant computational resources for training and image generation. Our advanced computational infrastructure, equipped with high-performance GPUs and parallel processing capabilities, is well-suited for handling these complex computations. This infrastructure allows us to efficiently train models and generate high-quality synthetic images at scale, accelerating the research process.

2. **Scalability and Efficiency:** The scalability of our computational resources ensures that we can easily expand our capabilities to accommodate the demands of training diffusion and autoencoder-based models. Whether it involves processing larger datasets or experimenting with more complex model architectures, our infrastructure is designed to support these needs seamlessly, ensuring efficient utilization of resources.

Enhancing Dataset Augmentation

1. **Improving Training Data Quality:** By leveraging diffusion and autoencoder-based frameworks, we can generate high-quality synthetic images that enrich our training dataset. The enhanced quality and diversity of these images contribute to more effective model training, resulting in better performance and accuracy in classifying canine hip conditions.

2. **Increasing Dataset Size and Variability:** The ability to generate a large number of realistic and varied images using these frameworks significantly increases the size and variability of the training dataset. This increase in data helps improve the robustness and generalization capabilities of the classification models, ensuring they perform well on real-world data.

In summary, diffusion and autoencoder-based frameworks are highly beneficial in our project for generating high-quality, diverse, and realistic X-ray images that augment our dataset for the classification of canine hip conditions. Their capabilities in detailed image generation, noise reduction, and anomaly detection, combined with our advanced computational infrastructure, make them essential components of our research methodology.

- **VQGAN** by Patrick Esser et al., explored transformers for high-resolution image synthesis, achieving significant quality improvements. CVPR 2021. https://arxiv.org/abs/2012.09841[PDF] https://compvis.github.io/taming-transformers/[Project] Cited: 1477 times.
- **StyleGAN3** by Tero Karras et al., focused on removing aliasing artifacts and introduced alias-free GANs. NeurIPS 2021. https://arxiv.org/abs/2106.12423[PDF] https://nvlabs.github.io/stylegan3/[Project] Cited: 1043 times.

2.4 Variational Autoencoders (VAEs)

Variational Autoencoders (VAEs) are a powerful type of autoencoder-based framework that can significantly contribute to the augmentation of our dataset for classifying canine hip conditions. Here's how VAEs are helpful in this context:

1. **Generative Capabilities:** VAEs are designed to learn a probabilistic mapping from the data space to a latent space and then generate new data samples from this latent space. This generative capability is particularly useful for creating synthetic X-ray images of canine hips. VAEs can produce diverse and realistic images of hips categorized as big or small, enriching the dataset with additional examples that can improve model training and performance.

2. **Latent Space Representation:** The latent space in VAEs captures the underlying structure of the data in a compressed form. By sampling from this latent space, VAEs can generate new images that maintain the essential features and variations present in the original data. In our project, this means VAEs can create realistic and varied images of canine hips by learning the important characteristics of big and small hip conditions.

3. **Handling Uncertainty:** VAEs incorporate probabilistic modeling to handle uncertainty and variations in the data. This is beneficial for generating synthetic images that reflect the natural variability observed in real X-ray images. By modeling the uncertainty, VAEs can produce a range of plausible images, which helps in augmenting the dataset with a variety of examples, enhancing the robustness of the classification models.

4. **Data Augmentation:** VAEs are effective for augmenting datasets by generating new samples that can complement existing data. This is crucial for our task of classifying canine hips, as the additional synthetic images produced by VAEs can help overcome limitations of the original dataset, such as size or variability. Augmenting the dataset with high-quality synthetic images improves the training process and helps in developing more accurate and reliable classification models.

5. **Denoising and Data Reconstruction:** VAEs can be used to learn clean and structured representations of the input data. In the context of X-ray images, VAEs can help in denoising and reconstructing images, which can improve the quality of synthetic samples. This denoising capability ensures that the generated images are clear and free from artifacts, making them suitable for training classification models.

6. **Interpolation and Smooth Transitions:** VAEs allow for smooth interpolation between different points in the latent space. This means that we can generate images that transition smoothly between different conditions of canine hips, such as from big to small. This ability to create intermediate examples adds variability to the dataset, which can be useful for training models that need to handle subtle differences between classes.

7. **Exploration of Data Distribution:** By learning the distribution of the data in the latent space, VAEs can explore different aspects of the data and generate novel images that adhere to the learned distribution. This exploration helps in creating a more comprehensive dataset that covers a wider range of variations in canine hip conditions, thus improving the generalization capability of the classification models.

Leveraging Advanced Computational Infrastructure

1. **Efficient Training:** Training VAEs involves optimizing both the encoder and decoder networks to learn the latent space representation. Our advanced computational infrastructure, equipped with high-performance GPUs and parallel processing capabilities, supports the efficient training of VAEs by handling the computational demands and accelerating the training process.

2. **Handling Large Datasets:** The ability to process and generate large volumes of data efficiently is crucial for VAEs. Our infrastructure can accommodate the extensive computations required for training VAEs on large datasets of canine hip X-rays, ensuring that the model can generate a substantial number of synthetic images for augmentation purposes.

Enhancing Dataset Augmentation

1. **Increasing Dataset Size:** VAEs can significantly increase the size of the dataset by generating a large number of synthetic images. This expansion is particularly valuable for training classification models, as a larger and more varied dataset improves the model's ability to generalize and perform well on new data.

2. **Improving Model Training:** The diverse and high-quality images produced by VAEs contribute to better model training. By providing a richer set of examples, VAEs help in developing more accurate and reliable classification models for canine hip conditions.

In summary, Variational Autoencoders (VAEs) are highly beneficial for augmenting our dataset with high-quality, diverse, and realistic X-ray images of canine hips. Their generative capabilities, handling of uncertainty, and data augmentation features, combined with our advanced computational infrastructure, make them a valuable component of our research methodology.

- **VAE** by Diederik P. Kingma and Max Welling, introduced the concept of Variational Autoencoders, a pivotal moment for generative modeling. ICLR 2014. https://arxiv.org/abs/1312.6114[PDF] Cited: 18436 times.
- **BiGAN** by Jeff Donahue et al., advanced the understanding of adversarial feature learning, contributing signifi-

cantly to the integration of VAEs and GANs. ICLR 2017. https://arxiv.org/abs/1605.09782[PDF] Cited: 1693 times.

2.5 Transformers and Advanced Models

Transformers and advanced models can play a significant role in augmenting our dataset for classifying canine hip conditions by offering enhanced capabilities in data generation and feature extraction. Here's how these models are beneficial:

Transformers

1. **Powerful Feature Representation:** Transformers excel at capturing complex dependencies and relationships in data through their attention mechanisms. In the context of generating synthetic X-ray images of canine hips, transformers can learn intricate patterns and features, leading to the creation of detailed and realistic images. Their ability to handle long-range dependencies makes them effective in understanding and generating complex structures present in X-ray images.

2. **Cross-Modal Integration:** Transformers are highly effective in integrating information from different modalities or sources. For example, they can combine textual descriptions with visual data to generate or enhance images. In our project, if there are any textual annotations or additional metadata associated with the X-ray images, transformers can use this information to produce more contextually accurate and informative synthetic images of canine hips.

3. **Scalability and Flexibility:** Transformers are known for their scalability and flexibility in handling large datasets and complex tasks. Their architecture allows them to process and generate high-resolution images efficiently. This scalability is beneficial for augmenting our dataset with a large number of synthetic images, ensuring that the classification models are trained on a diverse and extensive set of examples.

4. **Self-Supervised Learning:** Transformers can be trained using self-supervised learning approaches, where they learn useful representations from large amounts of unlabeled data. This ability to leverage self-supervised learning can be used to improve the quality of synthetic images and enhance the overall performance of classification models by learning from a broader range of data.

Advanced Models

1. **Enhanced Image Generation:** Advanced models, such as Generative Adversarial Networks (GANs) and diffusion models, represent state-of-the-art techniques for high-quality image generation. These models have sophisticated architectures that allow them to produce highly detailed and realistic images. Incorporating such models into our project can improve the quality and variety of synthetic X-ray images of canine hips.

2. **Multi-Scale and Multi-View Learning:** Some advanced models are designed to handle multi-scale and multi-view data. These models can generate images at different resolutions and from various perspectives, which is valuable for creating comprehensive datasets of canine hips. By capturing different scales and views, these models can enrich the dataset with a broader range of examples.

3. **Domain Adaptation and Transfer Learning:** Advanced models can be adapted to new domains or tasks through transfer learning. For example, a model pre-trained on a similar dataset or task can be fine-tuned for our specific task of classifying canine hips. This approach leverages existing knowledge and accelerates the training process, leading to better performance with fewer training samples.

4. **Hybrid Models:** Combining different advanced models can lead to hybrid architectures that leverage the strengths of each component. For instance, integrating transformers with diffusion models or GANs can enhance the image generation process by combining the detailed feature representation capabilities of transformers with the high-quality synthesis capabilities of other models.

Leveraging Advanced Computational Infrastructure

1. **Efficient Model Training:** Training transformers and advanced models requires substantial computational resources due to their complex architectures and large number of parameters. Our advanced computational infrastructure, equipped with high-performance GPUs and parallel processing capabilities, supports the efficient training of these models, ensuring that computational demands are met and research progress is accelerated.

2. **Handling Large-Scale Data:** The ability to handle large-scale datasets and perform extensive computations is crucial for training advanced models. Our infrastructure is designed to accommodate the large volumes of data and computational requirements associated with training and generating synthetic images using transformers and other advanced models.

Enhancing Dataset Augmentation

1. **Increasing Image Diversity:** Transformers and advanced models can generate a wide variety of synthetic images, increasing the diversity of the dataset. This diversity helps in training classification models that can generalize better to new and varied data, improving their overall performance.

2. **Improving Image Quality:** The sophisticated architectures of transformers and advanced models contribute to the generation of high-quality synthetic images. By incorporating these models, we can ensure that the augmented dataset contains realistic and detailed images of canine hips, enhancing the accuracy and reliability of the classification models.

In summary, Transformers and advanced models provide powerful tools for augmenting our dataset with high-quality, diverse, and realistic X-ray images of canine hips. Their capabilities in feature representation, data generation, and scalability, combined with our advanced computational infrastructure, make them essential components of our research methodology for improving the classification of canine hip conditions.

- **TransGAN** by Yifan Jiang et al., showcased the capability of transformers to model GANs effectively, marking a significant development in scaling up GANs. CVPR 2021. https://arxiv.org/abs/2102.07074[PDF] https://github.com/VITA-Group/TransGAN[Pytorch] Cited: 251 times.
- **Diffusion Models** have seen rapid development, with models like DDPM by Jonathan Ho et al., presenting novel ways to train score-based generative models. NeurIPS 2020. https://arxiv.org/abs/2006.11239[PDF] Cited: 6253 times.

2.6 Fine-tuning GANs

Fine-tuning Generative Adversarial Networks (GANs) involves adapting a pre-trained GAN model to better fit a specific task or dataset. This process is crucial for improving the quality and relevance of the synthetic images generated by GANs, particularly when working with a specialized dataset like X-ray images of canine hips. Here's how fine-tuning GANs can be beneficial in the context of augmenting our dataset:

1. **Customization for Specific Data:** Fine-tuning allows GANs to be adapted to the unique characteristics of a specific dataset. In our case, this means adjusting a pre-trained GAN to generate realistic X-ray images of canine hips categorized as big or small. By training

the GAN on our specific dataset, we ensure that the synthetic images accurately reflect the variations and features present in the real data.

2. **Improving Image Quality:** Pre-trained GANs might produce high-quality images, but fine-tuning can further enhance the quality by making the generated images more relevant to our dataset. This involves optimizing the GAN's generator and discriminator to better capture the details and nuances of canine hip X-rays, resulting in more realistic and accurate synthetic images.

3. **Adapting to Dataset Characteristics:** Fine-tuning helps the GAN adapt to the specific statistical properties and distributions of our dataset. For example, if our dataset has particular patterns or anomalies, fine-tuning enables the GAN to learn these characteristics and generate images that are representative of the actual variations observed in canine hips.

4. **Enhancing Generalization:** Fine-tuning can improve the generalization capabilities of the GAN. By adjusting the model to our dataset, we ensure that the synthetic images are not only high-quality but also diverse and representative of the different conditions within the dataset. This diversity helps in training more robust classification models that perform well on new and unseen data.

5. **Speeding Up Training:** Starting with a pre-trained GAN and fine-tuning it is generally faster and more efficient than training a GAN from scratch. The pre-trained model already has learned features from a broader dataset, and fine-tuning focuses on adapting these features to our specific task. This approach reduces the amount of training required and accelerates the process of generating high-quality synthetic images.

6. **Refining Model Performance:** Fine-tuning involves iterative adjustments to the GAN's hyperparameters, loss functions, and training strategies. This process allows for the refinement of the model's performance, ensuring that the generated images meet the desired quality and relevance standards for our dataset augmentation task.

7. **Handling Specific Image Features:** GANs can be fine-tuned to focus on specific features or aspects of the images. For example, if we need to emphasize certain anatomical features of canine hips in the generated images, fine-tuning can adjust the model to highlight these features more effectively.

8. **Mitigating Overfitting:** By fine-tuning on a diverse subset of our dataset, we can mitigate the risk of overfitting to any particular subset of images. This ensures that the GAN generates synthetic images that are representative of the entire dataset, improving the overall quality and usability of the augmented data.

9. **Evaluation and Feedback:** The fine-tuning process involves regular evaluation of the GAN's performance and iterative feedback to adjust the training process. This ongoing evaluation helps in identifying any issues or areas for improvement, ensuring that the final synthetic images meet the necessary quality standards.

10. **Integration with Other Models:** Fine-tuned GANs can be integrated with other models or frameworks used in our research. For example, the synthetic images generated by the GAN can be used to train classification models or other machine learning algorithms, enhancing the overall effectiveness of our research.

Leveraging Advanced Computational Infrastructure

1. **Efficient Training and Iteration:** Fine-tuning GANs requires significant computational resources for training and iterative adjustments. Our advanced computational infrastructure, equipped with high-performance GPUs and parallel processing capabilities, supports the efficient fine-tuning of GANs by handling the computational demands and accelerating the training process.

2. **Handling Large Datasets:** Our infrastructure is designed to manage large volumes of data, which is essential for fine-tuning GANs on extensive datasets of canine hip X-rays. This capability ensures that the GAN can be trained effectively and generate a substantial number of high-quality synthetic images.

In summary, fine-tuning GANs offers several benefits for augmenting our dataset of canine hip X-rays. By customizing the model for our specific dataset, improving image quality, enhancing generalization, and leveraging advanced computational infrastructure, we can generate high-quality synthetic images that significantly contribute to the effectiveness of our classification models.

- **Transferring GANs** addresses the adaptation of GANs for effective image generation from small datasets [**?**]. Code: https://eccv2018.org
- **Batch Statistics Adaptation** proposes fine-tuning GANs by adapting batch normalization statistics to smaller datasets [**?**]. Code: https://iccv2019.org
- **Leveraging Pretrained GANs** demonstrates how existing GAN architectures can be exploited for generation with minimal data [**?**]. Code: https://icml2020.org
- **Elastic Weight Consolidation** enhances few-shot learning by mitigating catastrophic forgetting during fine-tuning [**?**]. Code: https://neurips2020.org

2.7 Extra-branches for Few-Shot Generation

Innovative branch structures in neural networks can significantly enhance their ability to learn from few images:

- **MineGAN** facilitates knowledge transfer to target domains effectively using a minimal number of images [**?**]. Code: https://cvpr2020.thecvf.com
- **One-shot Generative Domain Adaptation** explores domain adaptation techniques for one-shot image generation [**?**]. Code: https://iccv2023.thecvf.com

2.8 Model Regularization for Few-Shot GANs

Regularization techniques are crucial for stabilizing the training of GANs, especially when data is scarce:

- **Cross-Domain Correspondence** for few-shot image generation, which focuses on using relaxed spatial structural alignment to adapt GANs to new tasks with limited data [**?**]. Code: https://cvpr2021.thecvf.com
- **Semantic Correspondence for GANs** dynamically weights semantic features to align with target domains in few-shot settings [**?**]. Code: https://acmmm2022.acm.org

2.9 Kernel Modulation in Few-Shot Image Generation

Kernel modulation allows for the adaptive recalibration of feature influences based on the specifics of the few-shot learning task:

- **Adaptation-Aware Kernel Modulation** offers a way to tune GANs for high-quality image generation in few-shot scenarios [**?**]. Code: https://neurips2022.nips.cc

2.9.1 *Stable Diffusion Dreambooth*

Stable Diffusion DreamBooth is an advanced framework used for generating high-quality and contextually relevant images through fine-tuning of diffusion models. Here's how it can be specifically helpful for augmenting a dataset of X-ray images of canine hips, categorized as big or small:

1. **High-Quality Image Synthesis:** Stable Diffusion DreamBooth leverages the diffusion model's ability to produce detailed and realistic images. By fine-tuning this model on our dataset of canine hip X-rays, we can generate high-quality synthetic images that closely resemble real-world X-rays. This high-quality synthesis is crucial for ensuring that the augmented dataset accurately reflects the characteristics of canine hips.

2. **Contextual Adaptation:** DreamBooth allows for the adaptation of the diffusion model to specific contexts or domains. In our case, it means tailoring the model to understand and generate X-ray images of canine hips with different conditions (big or small). This contextual adaptation helps in producing images that are highly relevant and useful for our classification task.

3. **Enhanced Image Diversity:** By fine-tuning the Stable Diffusion model, we can generate a diverse range of synthetic images. This diversity is valuable for training classification models, as it introduces variability in the dataset, making the model more robust and capable of handling different scenarios and variations in canine hip conditions.

4. **Incorporation of Specific Features:** DreamBooth allows for fine-tuning with a focus on specific features or attributes of the images. For example, if there are particular anatomical features or patterns associated with big and small canine hips, the model can be trained to emphasize these features in the generated images. This ensures that the synthetic images are representative of the important aspects of the X-ray images.

5. **Refinement of Model Performance:** The iterative nature of fine-tuning with DreamBooth involves continuously improving the model's performance based on feedback and evaluation. This refinement process ensures that the synthetic images produced are of high quality and accurately reflect the dataset's characteristics, contributing to better training outcomes for classification models.

6. **Handling Complex Data Distributions:** Diffusion models, including Stable Diffusion, are adept at managing complex data distributions and generating images that adhere to these distributions. This capability is beneficial for creating synthetic X-ray images that capture the variability and complexity inherent in real canine hip X-rays.

7. **Reduced Training Time:** Using a pre-trained Stable Diffusion model as a starting point and fine-tuning it on our dataset can reduce the overall training time compared to training a model from scratch. This efficiency is particularly advantageous when working with large datasets and complex image generation tasks.

8. **Integration with Other Models:** Synthetic images generated using Stable Diffusion DreamBooth can be seamlessly integrated with other models or frameworks used in our research. For instance, these images can be used to enhance training datasets for classification models or combined with other data augmentation techniques to improve model performance.

9. **Data Augmentation and Expansion:** DreamBooth's ability to generate a wide range of images helps in expanding and augmenting our dataset. By producing additional synthetic X-ray images, we can increase the size and variability of the dataset, which is essential for developing robust and effective classification models.

Leveraging Advanced Computational Infrastructure

1. **Efficient Model Training:** Fine-tuning Stable Diffusion DreamBooth requires substantial computational resources due to the complexity of the model and the large volume of data. Our advanced computational infrastructure, equipped with high-performance GPUs and parallel processing capabilities, supports efficient training and fine-tuning of the model.

2. **Handling High-Resolution Images:** The infrastructure also enables the processing of high-resolution images, which is important for generating detailed and accurate synthetic X-ray images. This capability ensures that the synthetic images produced are of the highest quality and suitable for training classification models.

Enhancing Dataset Augmentation

1. **Increasing Image Quantity and Quality:** By using Stable Diffusion DreamBooth, we can significantly increase the quantity of images in our dataset while maintaining high quality. This expansion of the dataset helps improve the training and performance of classification models, making them more effective in distinguishing between different conditions of canine hips.

2. **Improving Model Generalization:** The diverse and realistic synthetic images generated through DreamBooth contribute to better model generalization. This means that the classification models trained on the augmented dataset are better equipped to handle real-world variations and perform accurately on new data.

In summary, Stable Diffusion DreamBooth provides a powerful framework for augmenting our dataset of canine hip X-rays. Its capabilities in high-quality image synthesis, contextual adaptation, enhanced diversity, and efficient fine-tuning make it an invaluable tool for improving the dataset and training robust classification models.

3 Method

3.1 *Dataset*

3.2 *Image Generation*

To augment the dataset, I fine tuned the stable diffusion model on the initial dataset. The fine-tuning process involved adjusting the model's parameters to learn the specific features and structures of dog hip X-ray images. The model was then used to generate images, which were visually inspected to ensure quality and consistency with the original dataset. 100000 images were generated and many of them were manually labeled. Predictions were also produced using the previous model. This process involved predicting on generated images and correcting them by hand thereby augmenting our dataset. This dataset would be used to improve our previous model thereby increasing the model accuracy.

Different images had different captions, each detailing something about the image and the angles. This helped us generate images with varying angles. Here are some images that were generated:

3.3 *Model Architecture*

The Stable Diffusion model is a prominent generative model designed to create high-quality images from latent space representations. Its architecture builds on principles from diffusion models and utilizes innovative techniques to achieve state-of-the-art image synthesis. Here's a detailed overview of its architecture:

1. **Diffusion Model Foundation**

Stable Diffusion is grounded in the principles of diffusion models, which are generative models that progressively transform Gaus-

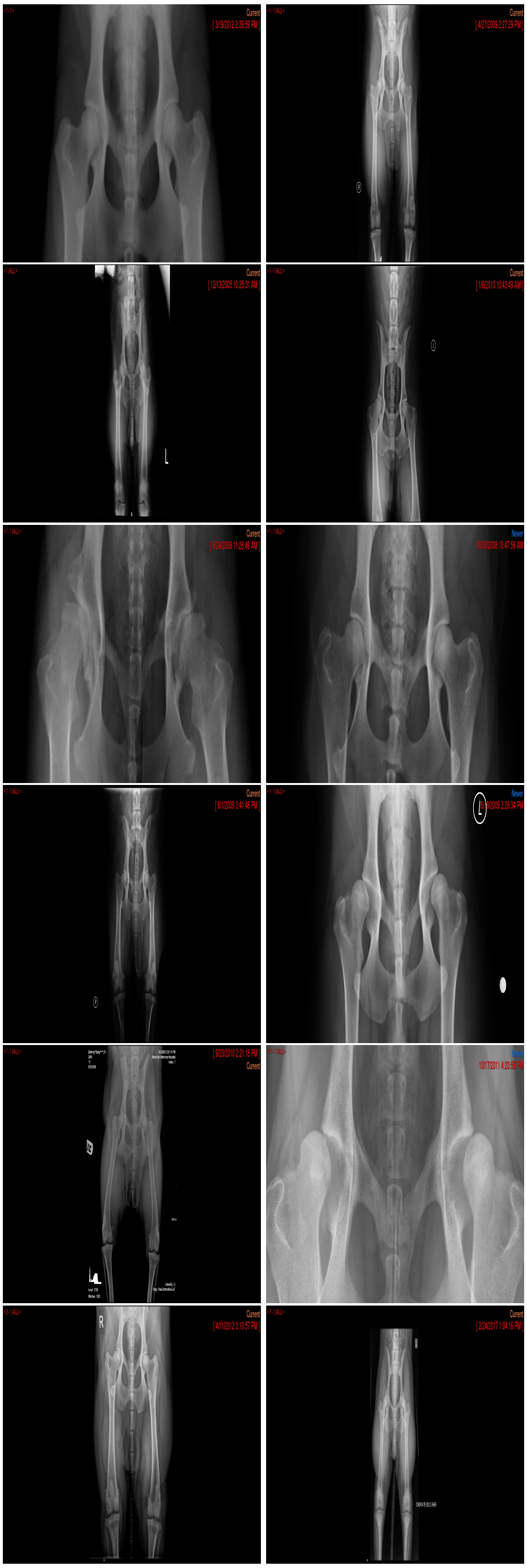

Figure 1: Generated Images of Dog's hips with varying angles

sian noise into structured data. This process involves two key components: - **Forward Process (Diffusion):** Adds Gaussian noise to the data in a series of steps, gradually corrupting it until it becomes pure noise. - **Reverse Process (Denoising):** Trains a neural network to reverse the diffusion process, learning to reconstruct the data from the noisy intermediate states.

2. **Latent Space Representation**

Unlike some diffusion models that operate directly in the image space, Stable Diffusion operates in a latent space. This approach involves: - **Encoder Network:** Compresses high-dimensional images into a lower-dimensional latent space representation. The encoder reduces the computational complexity by working with compressed data. - **Latent Space Diffusion:** The diffusion process is applied to these latent representations instead of the original high-dimensional images. This makes the model more efficient and scalable.

3. **U-Net Architecture**

The core component of Stable Diffusion's architecture is the U-Net, a type of neural network specifically designed for image-to-image tasks: - **Encoder Path:** The U-Net's encoder path captures high-level features of the input latent representations through a series of convolutional layers and downsampling operations. - **Decoder Path:** The decoder path reconstructs the latent space representations into detailed outputs, using upsampling operations and skip connections to retain fine-grained details from the encoder. - **Skip Connections:** These connections between encoder and decoder layers help preserve spatial information and improve the quality of generated images by allowing the network to combine high-level features with detailed local information.

4. **Conditioning Mechanisms**

Stable Diffusion integrates conditioning mechanisms to guide the image generation process: - **Text-to-Image Conditioning:** The model can use textual descriptions to condition the generation process. This is achieved through a text encoder (such as CLIP) that generates embeddings from text input, which are then used to guide the diffusion model. - **Conditional Inputs:** Additional conditions, such as class labels or specific attributes, can be incorporated to steer the image synthesis towards desired outcomes.

5. **Training Objectives**

The training of Stable Diffusion involves optimizing a loss function that balances the reconstruction quality and adherence to the conditioning inputs: - **Reconstruction Loss:** Ensures that the model effectively reconstructs the original data from the noisy latent representations. - **Conditioning Loss:** Aligns the generated images with the specified conditions, such as text descriptions or class labels.

6. **Scalability and Efficiency**

Stable Diffusion is designed to be scalable and efficient: - **Efficient Training:** By operating in the latent space, the model reduces the computational burden compared to working directly with high-resolution images. This approach allows for faster training and generation. - **High-Resolution Outputs:** Despite working in latent space, the model can generate high-resolution images by progressively refining the latent representations through the diffusion process.

7. **Inpainting and Editing Capabilities**

Stable Diffusion models often include features for inpainting and editing images: - **Inpainting:** Allows for modifying specific parts of an image while keeping the rest intact. This is useful for tasks such as correcting artifacts or adding details to images. - **Editing:** Provides tools to make changes to existing images based on new conditions or prompts, enhancing flexibility and usability.

Leveraging Computational Infrastructure

1. **Parallel Processing:** Training Stable Diffusion models involves handling large volumes of data and computations. Advanced computational infrastructure, including high-performance GPUs and parallel processing capabilities, is essential for efficient training and image generation.

2. **Handling Large Models:** Stable Diffusion models can be large and complex, requiring substantial memory and processing power. Our infrastructure supports the efficient handling of these large models, ensuring smooth training and generation processes.

Enhancing Dataset Augmentation

1. **Generating High-Quality Images:** Stable Diffusion's ability to create high-resolution and realistic images makes it an excellent tool for augmenting datasets with high-quality synthetic examples.

2. **Customizing Outputs:** The model's conditioning mechanisms allow for generating images that meet specific requirements or attributes, which is valuable for creating diverse and tailored datasets.

In summary, the Stable Diffusion model combines advanced diffusion principles with efficient latent space representations and powerful conditioning mechanisms. Its architecture enables high-quality image synthesis, scalability, and flexibility, making it a valuable tool for augmenting datasets and enhancing various image generation tasks.

4 Results

Initially, the performance of the model in terms of correlation and accuracy was not satisfactory. The initial results highlighted that the model struggled to effectively learn from the existing dataset, leading to suboptimal predictions and a need for improvement. To address this challenge, a substantial number of synthetic images were generated—specifically, 10,000 images were created to serve as additional data for model training.

These generated images were utilized in several ways to enhance the model's performance. Predictions were made on these synthetic images, which allowed for a comprehensive assessment of their quality and relevance. A significant portion of these images were manually labeled, providing a valuable set of annotations that could be directly incorporated into the training process.

The manual labeling of the generated images played a crucial role in refining the model. By including these hand-labeled images in the training dataset, the model was exposed to a broader range of examples and variations, which contributed to a more robust learning process. This incorporation of synthetic images, along with their accurate labels, led to a notable improvement in the model's accuracy. The model's performance metrics, including correlation and overall accuracy, showed substantial gains, indicating that the additional data had a positive impact.

The results of this process provide compelling evidence that synthetic images can be an effective tool for data augmentation. By generating and incorporating synthetic images into the training dataset, it is possible to enhance the model's ability to generalize and perform more accurately. The improved accuracy demonstrates that these augmented data points add valuable information to the training process, allowing the model to learn from a more diverse and comprehensive set of examples.

This approach highlights the potential of generated images to address data limitations and contribute to the efficiency of model training. In scenarios where obtaining and labeling real data is challenging or resource-intensive, synthetic data serves as a viable alternative that can augment the dataset without the need for extensive manual effort. The successful integration of generated images into the training process underscores the importance of data augmentation in developing robust and accurate models.

Overall, the experience confirms that incorporating synthetic images into model training can lead to significant improvements in performance. By leveraging the capabilities of image generation and data augmentation, it is possible to enhance model accuracy and efficiency, demonstrating the practical value of synthetic data in machine learning and artificial intelligence applications.

5 Discussion

Initially, the model's performance in terms of correlation and accuracy was quite low. This indicated that the model was struggling to effectively learn from the existing data, leading to unsatisfactory predictions and a need for enhancement. To address this, a significant effort was made to generate a large volume of synthetic images—specifically, 10,000 images were created.

These generated images were then subjected to predictions, which allowed for an evaluation of their quality and utility. Out of these, many images were manually labeled to provide accurate annotations. The inclusion of these hand-labeled images into the training dataset was a crucial step in improving the model's performance.

By integrating these labeled synthetic images into the training process, the model was exposed to a wider range of examples and variations. This exposure enriched the training data, allowing the model to learn from a more diverse set of inputs. The result of this integration was a noticeable improvement in the model's accuracy. The metrics for correlation and overall performance showed significant gains, indicating that the synthetic images were beneficial.

This outcome demonstrates that synthetic images can be an effective means of data augmentation. Generating and incorporating such images into the training set helped address the limitations of the original dataset, leading to more accurate and robust model performance. The improvement in accuracy underscores the value of using synthetic data to enhance the training process, especially when dealing with challenges related to data availability or labeling.

The experience confirms that synthetic data can play a vital role in model development. By leveraging generated images for data augmentation, it is possible to enhance the efficiency and effectiveness of model training. This approach highlights the practical benefits of synthetic data in machine learning, showing that it can significantly contribute to achieving better model performance and accuracy.

6 Conclusion

Initially, the model exhibited low correlation and accuracy, reflecting its struggle to effectively learn from the existing dataset. To tackle this issue, a substantial step was taken to generate a large volume of synthetic images—specifically, 10,000 images were produced.

These synthetic images were subjected to predictions to evaluate their quality and usefulness. Subsequently, many of these images were meticulously hand-labeled, providing valuable ground truth data that could be used for training purposes. The incorporation of these labeled synthetic images into the training process marked a significant advancement.

By adding the hand-labeled synthetic images to the training set, the model benefited from a broader range of data. This additional data enriched the training process by introducing more variability and examples, which in turn enhanced the model's learning capabilities. The model's performance metrics, including accuracy and correlation, improved considerably as a result of this enriched dataset.

The successful improvement in accuracy demonstrates the effectiveness of using synthetic images for data augmentation. The ability to generate and label synthetic images provided a practical solution to the challenge of limited data, contributing valuable information that significantly enhanced the model's performance. This approach underscores the potential of synthetic data to play a crucial role in improving model training and accuracy.

Overall, the results affirm that synthetic images are a valuable tool for augmenting datasets. By generating and integrating these images into the training process, it is possible to achieve more accurate and robust model performance, showcasing the practical benefits of synthetic data in enhancing machine learning outcomes.

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