Title:Transformers for Dark Matter Morphology with Strong Gravitational Lensing

Introduction

Personal Details

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About Me / Biographical Information

I am Thanveer Ahamed, a B.Sc.(Hons.) in Information Technology graduate from the prestigious University of Moratuwa, Sri Lanka. I completed my degree from September 2017 to May 2022, securing an exceptional CGPA of 3.73/4.2, which ranked me among the top 5% of my cohort. Furthermore, I earned First Class Honours and the distinction of being included in the Dean's List for Semesters 3, 4, 7, and 8.

I have a strong background in machine learning and artificial intelligence. I have experience working with various AI/ML platforms and IDEs such as Anaconda, Google Colab, Kaggle, and Amazon SageMaker, as well as proficiency in using AI/ML libraries and frameworks such as Numpy, Pandas, Tensorflow, Scikit-learn, Matplotlib, OpenCV, Flask, and Fast API.

My expertise in machine learning is demonstrated through my final year research project on an AI-based Movie Content Rating System. This project involved using deep learning techniques in computer vision and audio processing to detect and rate violence, nudity, substance use, and profanity content in movies. I played a crucial role in designing and developing this project's violence content detection and rating module. I also introduced binary violent video data sets and two multi-class violent video data sets with six violent classes.

In addition to my research project experience, I participated in the ADL AI SUMMIT Hackathon 2021 and was part of the 1st Runners Up team. Axiata Digital Labs, associated with AWS, Snowflake, and Dell, organized this hackathon.

I have extensive experience developing computer vision models using deep learning techniques, specifically for STD detection and monkeypox risk assessment. Utilizing the Inception-ResNet-v2 model for transfer learning, I achieved 91% accuracy in detecting male STDs and 95% accuracy in classifying monkeypox cases. In addition, I employed the SIDU and Grad-CAM algorithms for model explainability.

To create accessible tools, I deployed the STD detection server using Flask API on Elastic Beanstalk and the monkeypox screening tool on an AWS EC2 instance. This enabled users to receive personalized risk assessments based on their input. Additionally, I established a CI/CD pipeline with GitHub using AWS CodePipeline. My experience has refined my model development, explainability, and deployment skills.

Overall, my ML and AI background is extensive and includes practical experience working on real-world projects that involve deep learning techniques. In addition, my proficiency in various AI/ML platforms and libraries makes me a valuable asset to any organization looking to leverage machine learning for their business needs.

Synopsis

This project aims to develop an innovative unsupervised machine learning approach using hybrid transformers to detect and analyze dark matter substructures in strong gravitational lensing images. By leveraging the power of hybrid transformers, and combining the strengths of convolutional neural networks and transformer architectures, the proposed model will effectively identify and classify dark matter substructures without needing labeled data. This cutting-edge research will enhance our understanding of dark matter properties and contribute to unraveling the mysteries of the universe.

Benefits to Community

The Unsupervised Decoding of Dark Matter Substructures using Hybrid Transformers in Strong Gravitational Lensing with Machine Learning for Science offers numerous benefits to the scientific community. Thanks to its unsupervised nature, it enables a deeper understanding of dark matter properties while reducing manual annotation efforts. The robust and versatile hybrid transformer architecture adapts to various dark matter substructures and handles noise and uncertainties in astronomical data. Enhanced collaboration opportunities arise from the shared methodology, which is scalable for upcoming surveys, and the open-source contribution inspires further research. The approach's broad applicability extends to other scientific domains where labeled data is scarce, highlighting the potential of machine learning in advancing scientific discovery and inspiring the next generation of interdisciplinary researchers.

Project

Abstract

The Unsupervised Decoding of Dark Matter Substructures using Hybrid Transformers in Strong Gravitational Lensing project aims to develop a novel machine-learning approach for identifying and analyzing dark matter substructures in astronomical data. Leveraging the power of hybrid transformer architectures, the project seeks to create an unsupervised model capable of detecting dark matter substructures in lensing images with increased accuracy and efficiency. By combining the strengths of convolutional neural networks and transformers, the proposed hybrid model will offer improved performance in handling complex, high-dimensional data. This project will also involve implementing domain adaptation techniques to bridge the gap between simulated and real-world data, maximizing the model's applicability and effectiveness. The successful completion of this project has the potential to advance our understanding of dark matter's distribution and properties, providing critical insights into the nature and evolution of the universe.

Objectives

The objectives of the Unsupervised Decoding of Dark Matter Substructures using Hybrid Transformers in Strong Gravitational Lensing project are as follows:

- Develop a novel unsupervised hybrid transformer architecture for detecting and analyzing dark matter substructures in strong gravitational lensing images.

- Implement unsupervised learning techniques to train the model for identifying and decoding dark matter substructures without reliance on pre-labeled data.

- Generate diverse simulated data for training and validation, and apply domain adaptation methods for real-world data.

- Rigorously evaluate the proposed model's performance and interpretability, comparing it to existing state-of-the-art methods.

Technical Details

The Unsupervised Decoding of Dark Matter Substructures using Hybrid Transformers in Strong Gravitational Lensing project will be a comprehensive study combining cutting-edge machine learning techniques and astronomical data analysis. Here are the technical components of the project:

1. Data collection and preprocessing:

   The project will involve collecting and preprocessing a large dataset of simulated strong gravitational lensing images, including dark matter substructures. This dataset will be used for training and evaluating the hybrid transformer model.

2. Hybrid transformer architecture:

   The core component of the project will be the development of a hybrid transformer model that combines the strengths of convolutional neural networks (CNNs) and transformer architectures. This hybrid approach will allow the model to efficiently process and analyze high-dimensional lensing images, capturing both local and global spatial information.i hope to utilize hybrid models like Convolutional Vision Transformer,Compact Convolutional Transformers ,Swin Transformer or combination of those models.

3. Unsupervised learning:

   The hybrid transformer will utilize unsupervised learning techniques for training, enabling it to recognize dark matter substructures in lensing images without needing labeled examples. This approach allows the model to adapt to unfamiliar and previously unseen substructure types, providing broader applicability and scalability. One such technique, contrastive learning, distinguishes between similar and dissimilar data points by optimizing a contrastive loss function. In this project, contrastive learning can be applied to learn significant representations of lensing images by comparing positive (similar) and negative (dissimilar) data pairs.

4. Domain adaptation:

   To ensure the model's effectiveness in analyzing real-world data, domain adaptation techniques will be implemented to bridge the gap between the simulated training data and real observational data. This will involve fine-tuning the model on a smaller dataset of real lensing images, allowing it to generalize effectively to unseen data.

5. Model evaluation:

The performance of the hybrid transformer model will be rigorously evaluated using metrics such as accuracy, precision, recall, and F1 score. These evaluations will help determine the model's effectiveness in identifying dark matter substructures and inform potential improvements or modifications.

Milestones and Timeline

Milestone 1: Project Setup and Literature Review (Weeks 1-2)

- Conduct a thorough literature review on hybrid transformers, strong gravitational lensing, and dark matter substructures.
- Set up project repository, environment, and tools required for development.
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Milestone 2: Data Collection and Preprocessing (Weeks 3-4)

- Generate diverse simulated lensing images with dark matter substructures for training and validation.
- Preprocess and organize the data to make it suitable for training hybrid transformers.
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Milestone 3: Develop Hybrid Transformer Architecture (Weeks 5-7)

- Design and implement a novel hybrid transformer architecture tailored to unsupervised analysis of dark matter substructures in lensing images.
- Train the model on simulated data and evaluate its performance.
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Milestone 4: Domain Adaptation and Model Evaluation (Weeks 8-10)

- Apply domain adaptation techniques to improve the model's performance on real-world astronomical data.
- Perform extensive evaluation and comparison of the hybrid transformer model against existing methods in the field.

Milestone 5: Documentation, Tutorials, and Code Refinement (Weeks 11-12)

- Develop comprehensive documentation, user guides, and tutorials to facilitate model adoption.
- Refine and optimize the code for better performance and user experience.
- Prepare a final project report, summarizing the achievements, challenges, and future directions.

Milestone 6: Project Wrap-up and Dissemination (Week 13)

- Present the project outcomes and findings to the wider community.
- Submit the final project report and codebase to the organization and mentors.
- Explore opportunities for publishing the results in relevant conferences or journals.

Deliverables

Deliverable 1: Comprehensive Literature Review (Milestone 1)

- A well-documented literature review that covers hybrid transformers, strong gravitational lensing, and dark matter substructures and their intersection.
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Deliverable 2: Processed Dataset (Milestone 2)

- A dataset of diverse simulated lensing images with dark matter substructures, preprocessed and organized for training and validation.
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Deliverable 3: Hybrid Transformer Architecture and Model (Milestone 3)

- A novel hybrid transformer architecture designed for unsupervised analysis of dark matter substructures in lensing images.
- A trained and evaluated hybrid transformer model based on the developed architecture.

Deliverable 4: Domain Adaptation Results and Model Evaluation (Milestone 4)

- Implementation and results of domain adaptation techniques applied to the hybrid transformer model.
- A detailed evaluation report comparing the performance of the hybrid transformer model with existing methods in the field.

Deliverable 5: Comprehensive Documentation, Tutorials, and Optimized Code (Milestone 5)

- Well-structured documentation, user guides, and tutorials to facilitate the adoption of the hybrid transformer model.
- Optimized and refined code, ensuring better performance and user experience.
- A final project report summarizing achievements, challenges, and future directions.

Deliverable 6: Project Presentation and Dissemination (Milestone 6)

- A public presentation of the project outcomes and findings.
- Submission of the final project report and codebase to the organization and mentors.
- A plan for publishing results in relevant conferences or journals, if applicable.