Google Summer of Code

Updating the DeepLense Pipeline

Project Proposal for GSOC23

ML4SCI

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About Me

- Name: Usama Ahmed Kawashty
- Education: Senior Computer Engineering and AI student
- Contact Information: 0ssamaak0@gmail.com
- Time Zone: GMT+3
- GitHub: [0ssamaak0]
- LinkedIn: [Usama Ahmed]
- Curriculum Vitae: [Link]

Abstract

Dark matter is a mysterious and elusive substance that pervades the cosmos. To unravel its secrets, we can examine how it clumps together in smaller structures within larger halos of dark matter. One powerful tool to do this is strong gravitational lensing, the bending of light by massive objects such as galaxies and galaxy clusters.

In this project, we aim to use deep learning methods to apply Classification, Regression and Anomaly Detection simulated images of strong lensing by different dark matter models, such as WIMP particle dark matter, warm dark matter (WDM), self-interacting dark matter (SIDM), and dark matter condensates and superfluids with vortex substructure.

Our main objective is to update the previous results of DeepLense with our new dark matter simulations and assess the performance of deep learning in discriminating between different dark matter scenarios.

This project will contribute to our understanding of the substructure of dark matter and its implications for fundamental physics.

Proposal main():

The success of our project depends on the choice of appropriate deep learning methods that can effectively analyze the simulated images of strong lensing by different dark matter models.

However, we also face some challenges in terms of time and resource constraints, which limit the complexity and scalability of the models we can use. Therefore, we will try to select the most suitable SOTA models that are lightweight and efficient yet achieve the desired results in terms of accuracy and robustness.

1.Classification and Regression Tasks

Since the difference between classification and regression is small in terms of feature extraction, and the differences are only in terms of the loss function and the last layer, hence the architectures may be common in both tasks.

a) Efficient Net

EfficientNet[1] is a family of convolutional neural network models that achieve SOTA accuracy and efficiency on various image classification tasks.

The key idea behind EfficientNet is to use a compound scaling method that uniformly scales the network depth, width, and resolution with a fixed ratio, instead of scaling only one dimension at a time.

This method is based on the observation that carefully balancing these three dimensions can lead to better performance.

EfficientNet also uses neural architecture search to design a new baseline network that is optimized for this scaling method.

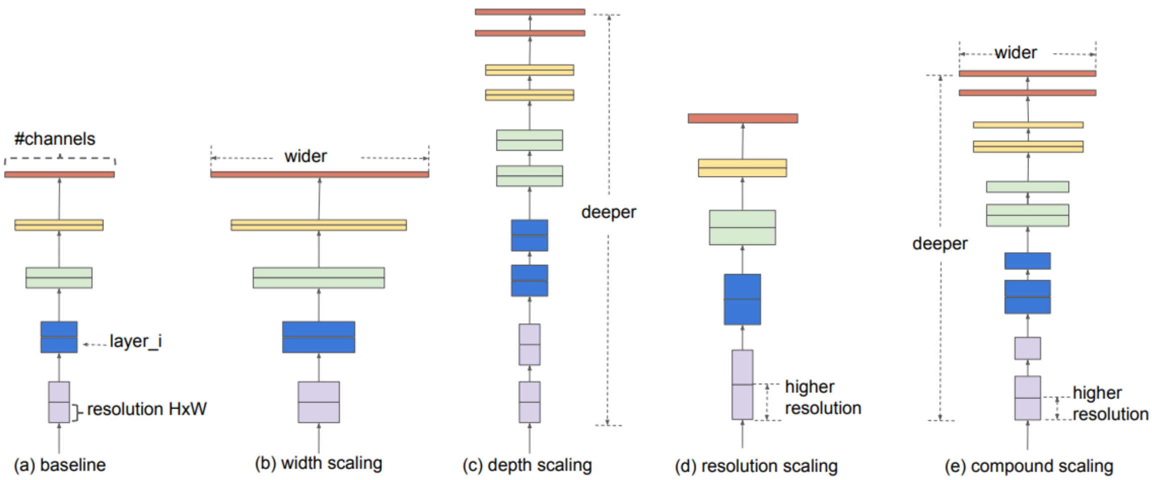

Figure 1: Model Scaling

b) ViT

ViT[2] stands for Vision Transformer, a model that applies the Transformer architecture to image recognition tasks.

ViT splits an image into patches and feeds them to a standard Transformer encoder, which outputs a representation that can be used for classification or other tasks.

ViT performs well when pre-trained on large datasets and fine-tuned on smaller ones, achieving SOTA results on several benchmarks.

ViT has less image-specific inductive bias than convolutional neural networks (CNNs), but benefits from the scalability and efficiency of Transformers.

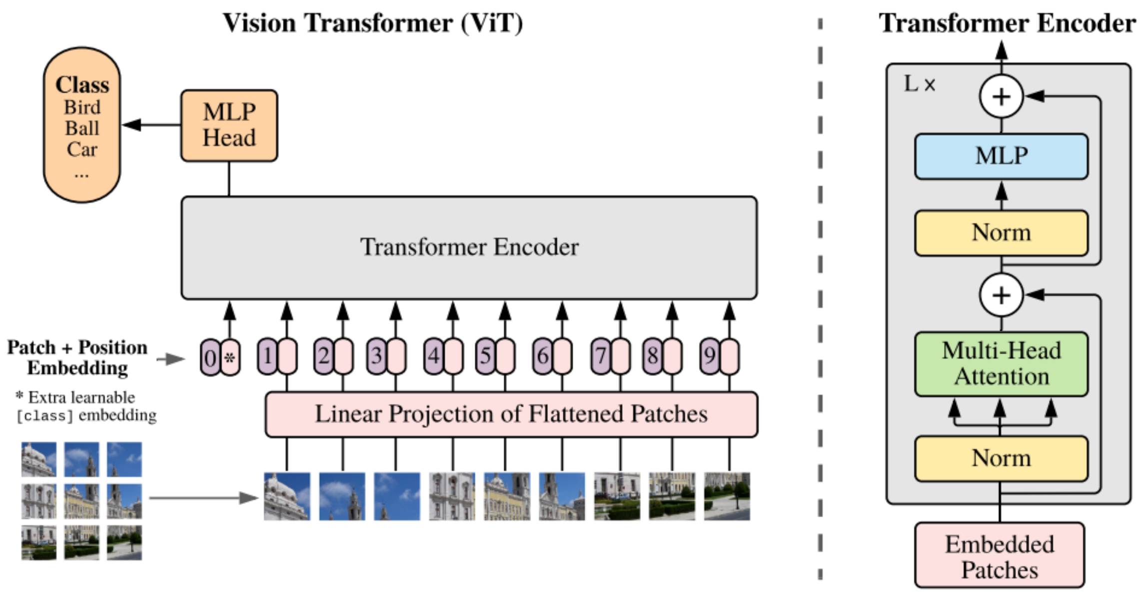

Figure 2: ViT Architecture

It's worth mentioning that recent research[3] paper explored the use of Vision Transformer (ViT) for estimating the parameters and uncertainties of strong gravitational lensing systems.

The paper showed that ViT outperformed ResNet, a classic convolutional neural network (CNN) model, for most of the lensing parameters, especially the mass-related ones such as the center of lens, the ellipticities, and the radial power-law slope.

The paper also showed that ViT captured the spatial features of the lensing images better than ResNet, as ViT can retain more spatial information and focus on different subjects in the images, such as the lensing galaxy, the quasar images, and the lensed background host galaxy.

The paper used a dataset of 31,200 simulated strong lensing images with eight target variables, generated by using realistic mass profiles, light distributions, and point spread functions.

The paper compared the performance of ViT and ResNet on a test set of 1,200 images and evaluated their predictions by using root mean square errors and percentage errors.

c) SWIN-T (it exceed Efficient Net)

Another variation is Swin Transformer[4], which constructs hierarchical feature maps by merging image patches in deeper layers and computes self-attention within local windows that are shifted between consecutive layers.

Swin Transformer achieves linear computational complexity with respect to image size and can serve as a general-purpose backbone for various vision tasks.

Regarding the Throughput, Swin Transformer outperforms previous vision Transformers and some SOTA convolutional networks on image classification, object detection, and semantic segmentation benchmarks.

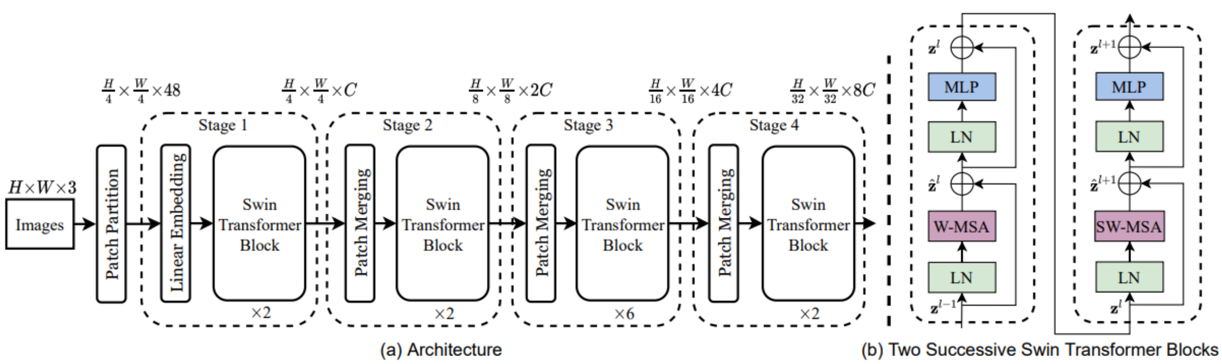

Figure 3: Swin Transformer Architecture

Anomaly Detection Task

Anomaly Detection Task is a binary classification problem that aims to identify unusual or unexpected patterns in a dataset, which deviate significantly from most of the data.

The goal of anomaly detection is to flag such anomalies, which could represent errors, fraud, or other types of unusual events, for further investigation.

Anomaly detection is an important and challenging task in gravitational wave astronomy, where it can be used to detect signals from unknown sources or glitches in the detector.

a) Variational Autoencoders

Autoencoders are a type of neural network that can learn a compressed representation of input data. They consist of two parts: an encoder that maps the input to a latent space, and a decoder that reconstructs the input from the latent space.

Autoencoders can be used for anomaly detection by training them on normal data and measuring the reconstruction error on new data. The assumption is that normal data can be reconstructed well by the autoencoder, while anomalous data will have a high reconstruction error.

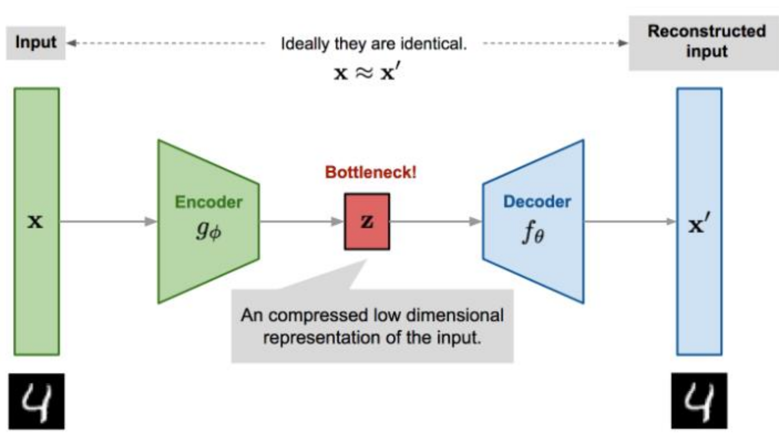

Figure 4: Autoencoders[5]

b) Variational Autoencoders

one improvement to Autoencoders are Variational autoencoders (VAEs)[6] which are a type of autoencoder that can learn a probabilistic representation of input data.

Unlike regular autoencoders that map the input to a fixed latent vector, VAEs map the input to a distribution over the latent space.

VAEs also impose a prior distribution on the latent space, usually a standard normal distribution, that regularizes the learning process and encourages the latent space to have a meaningful structure.

c) Adversarial Autoencoders

Adversarial autoencoders (AAEs)[7] are another type of autoencoder that can also learn a probabilistic representation of input data.

Like VAEs, they map the input to a distribution over the latent space and impose a prior distribution on the latent space. However, instead of using a variational inference technique to match the posterior and prior distributions, they use a generative adversarial network (GAN) to do so.

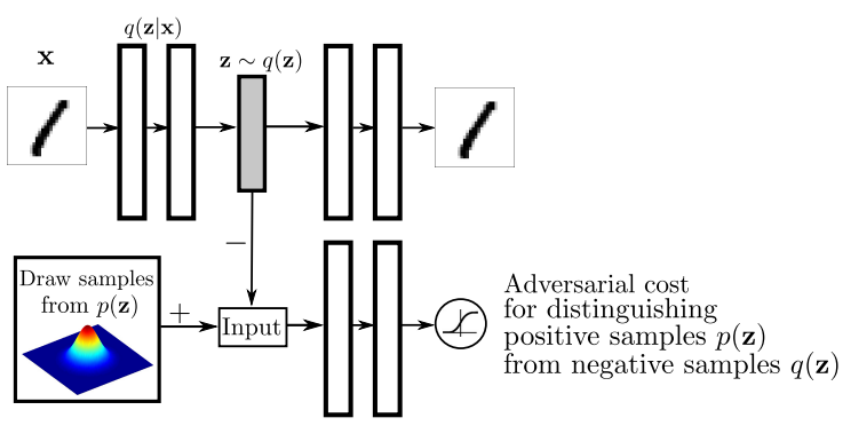

Figure 5: Architecture of an adversarial autoencoder

Project Timeline

From	To	Task
May 4	May 28	Community Bonding Period
May 28	June 4	Exploring Classification Task and Related Data
June 5	June 12	Implementing Various Models and Techniques for Classification
June 13	June 20	Classification Models Tuning and Comparisons
June 21	June 28	Classification Task Documentation and Final Results
June 29	July 6	Exploring Regression Task and The Possibility of using the Classification model in Regression
July 7	July 14	Beginning of Implementation for Regression Models + Prepare for MT Evaluation
July 15	July 22	Regression Models Tuning and Comparisons + Results of using same classification model and Full Documentation
July 23	July 30	Exploring Anomaly Detection Task and Related Data
July 31	August 7	Implementing Various Models and Techniques for Anomaly Detection
August 8	August 15	Anomaly Detection Models Tuning and Comparisons
July 16	August 23	Anomaly Detection Task Documentation and Final Results
August 24	Augst 28	Final Conclusions, Feedback Enhancements and Preparation for Final Evaluation

Future Deliverables

- Provide a well-documented, easy to use library for the specified tasks, with customization options as possible.
- A large-scale evaluation and comparison between the chosen models for each specific task, as a companion to the library.
- Being in a college with a large population and students, I will keep trying advice other students to join GSOC or other open-source projects.

Concurrent Commitments in Summer

Even being a student, I am not attending any lectures on campus, nor having any exams due to personal reasons, the only thing I am currently committed to is working on another open-source project (to be mentioned later)

So, I will give 30-35 hours weekly to the project in the duration between 29 May to 28 August, except for the duration between 26 June to 4 July because of the holidays.

You and The Project

I have been learning, working in Machine Learning and Deep Learning fields for about 2 years, I have taken many Academic, and non-academic courses from reputable organizations like DeepLearning.ai, and applied this knowledge in many projects.

Beside this, I am currently working with my team to develop Labelmm[8], a large open-source project to provide the next generation of Annotation Tool for Computer vision Tasks, that uses SOTA models to increase the throughout of the annotation process.

From our team's search, Labelmm is the second to none, of both open and closed source annotation tools for Computer Vision tasks.

References

[1] Tan, M., & Le, Q. (n.d.). EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks.

[2] Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., Dehghani, M., Minderer, M., Heigold, G., Gelly, S., Uszkoreit, J., & Houlsby, N. (2021). *AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE*

[3] *Wang, Y., Li, G., Xu, S., & Oguri, M. (2021). Vision Transformer for Strong Gravitational Lensing Parameter Estimation*

[4] Liu, Z., Lin, Y., Cao, Y., Hu, H., Wei, Y., Zhang, Z., Lin, S., & Guo, B. (n.d.). *Swin Transformer: Hierarchical Vision Transformer using Shifted Windows*

[5] Anomaly Detection using Autoencoders | by Renu Khandelwal | Towards Data Science

[6] Kingma, D., & Welling, M.(n.d.) *Auto-Encoding Variational Bayes.*

[7] Makhzani, A., Shlens, J., Jaitly, N., Brain, G., Openai, I., &Frey, B. (n.d.). *Adversarial Autoencoders.* Retrieved April 3, 2023, from

[8] GitHub:Labelmm