AstroVision: Advancing Astronomy with AI

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Introduction and Purpose

Astronomers generate an immense volume of data from modern telescopes and observational instruments, often presenting complex challenges in accurately classifying celestial objects. The high data complexity and low-intensity signals often mandate powerful, heavy hardware along with expert analysis. Traditional manual image classification requires an immense time commitment and professional expertise, yet struggles to keep pace with the growing volume of images and often leads to human error in labeling. AstroVision aims to improve the classification accuracy of Google's MobileNet architecture, a lightweight yet powerful deep learning model. We employed Knowledge distillation with Meta's Hiera to improve astronomers' ability to analyze noisy images and interpret data from space. Prompting further groundbreaking discoveries about the cosmos and inspiring new advancements in space exploration.

Dataset and Experimental Setup

Dataset: The dataset we used is the EFIGI galaxy dataset, which was compiled by the IAP, the LTCI and the LRDE in Paris, the LAM in Marseille, the OMP in Toulouse and the CRAL in Lyon. It provides the computational aspects of galaxy morphometry and a robust and scalable solution to measure galaxy morphologies.

- Images mapped using EFIGI's galaxy attributes data using script
- Dataset consists of 4 classes: Sprials, lenticulars, ellipticals and irregulars
- Dataset contains noisy and unprocessed images for practicality
- Data augmentation was used to prevent class imbalance

Figure 1. Different types of galaxies

Model

Teacher-Student Model Architecture: The proposed model uses a Knowledge Distillation framework. The Hiera transformer (teacher model) transfers feature representations to MobileNetV3-Small (student model). Hiera's attention and hierarchical feature extraction mechanism efficiently capture long-range spatial dependencies, allowing for robust feature extraction across image scales. MobileNetV3-Small employs a small, lightweight but powerful architecture that integrate Squeeze-Excitation Attention blocks and Hard-Swish activations. Despite having only 2.5 million parameters, it achieves 67.7% Top-1 accuracy on ImageNet-1K, making it suitable for resource-constrained settings.

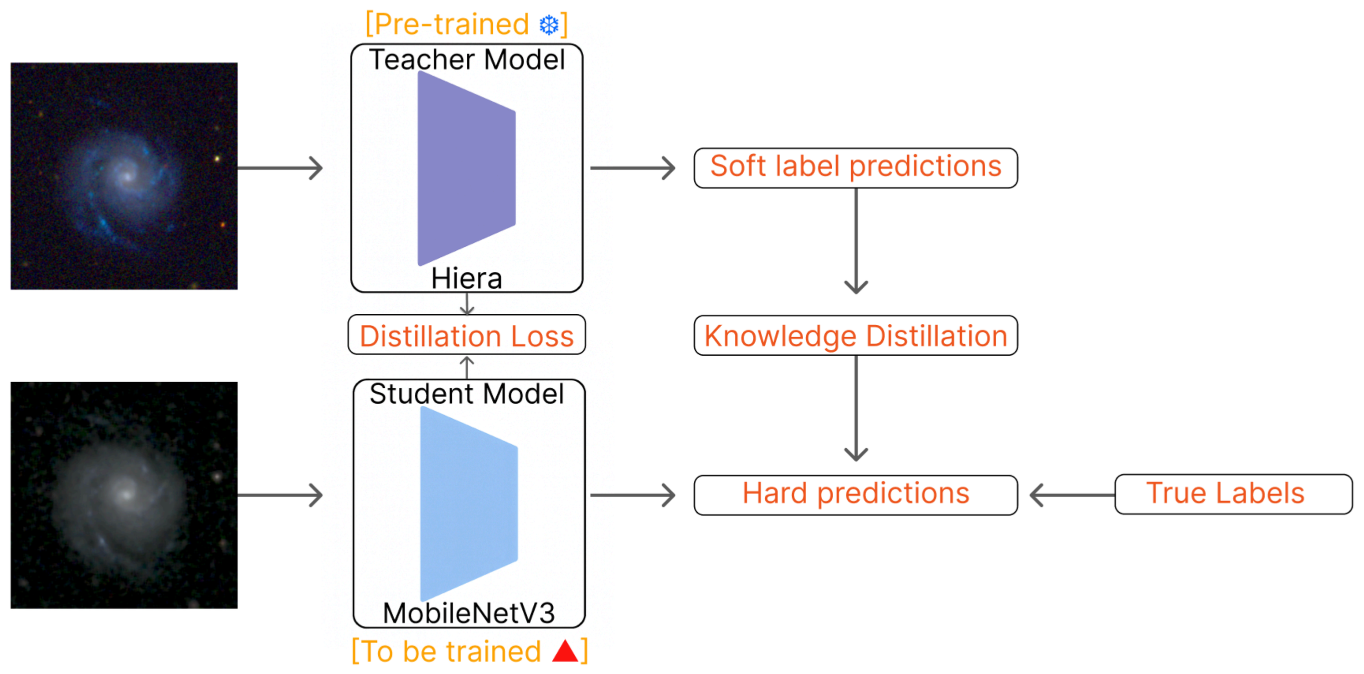

Figure 2. Teacher-Student Distillation Model Architecture

Results

Model Training: The Hiera Vision Transformer teacher model was trained with a learning rate of $1e^{-4}$. For a more lightweight student model we trained a MobileNetV3-Small model with a learning rate of $1e^{-3}$.

Model Evaluation: Our Hiera ViT yielded a high accuracy at 96%. The student model had an accuracy of 94%, increasing the accuracy of MobileNetV3 by 11% without compromising computational efficiency.

Model Metrics: The student model was evaluated by an accuracy score of the classifications made by the model. This accuracy is equal to the number of correct predictions divided by the total number of predictions.

Model	Accuracy
MobileNetV3 (Baseline without knowledge distillation)	83%
ResNet152V2	84%
Vision Transformer	79%
Hiera Vision Transformer	96%
MobileNetV3-small (with knowledge distillation)	94%

Table 1. Summary of Accuracy for Different Models

Analysis

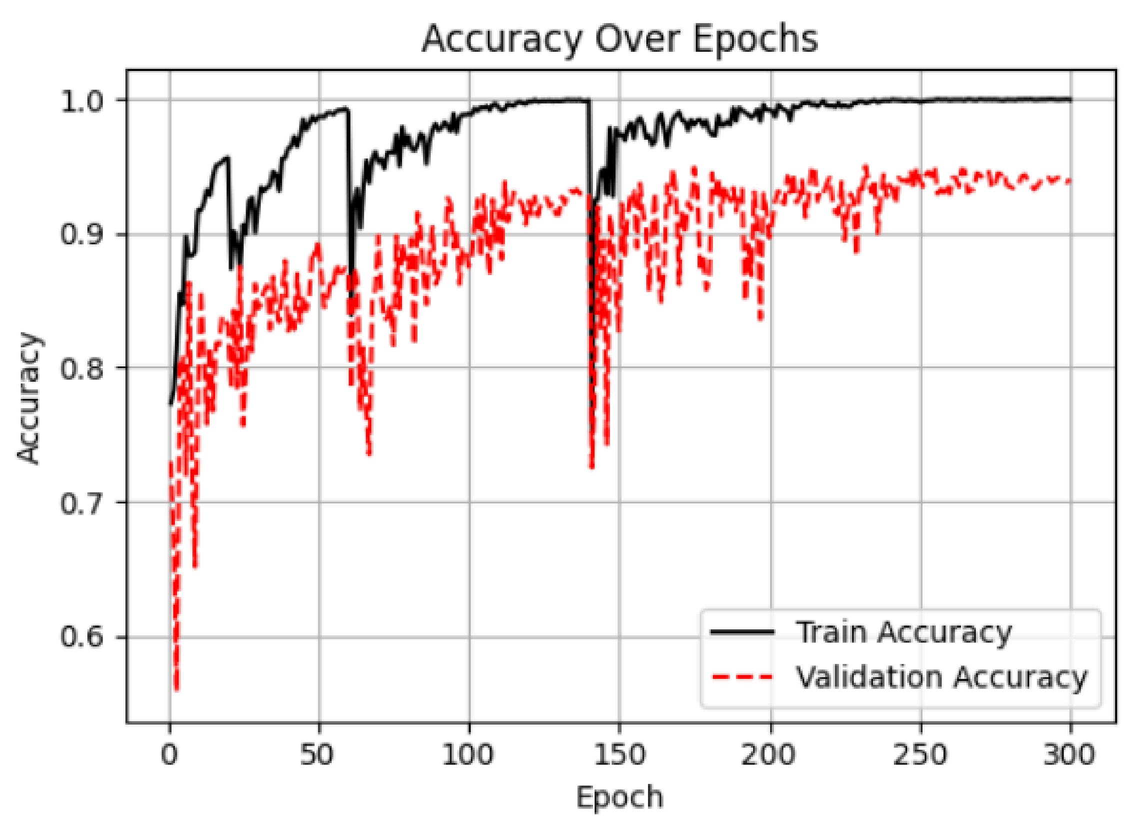

Figure 3. Training and Validation Loss Graph

Accuracy Over Epochs: Figure 3 illustrates the model's performance throughout the training period. After applying knowledge distillation techniques, the model's accuracy improved significantly, going from 83% to 94%.

Conclusion

Our model, AstroVision, demonstrated that by employing Knowledge Distillation with Meta's Hiera and Google's MobileNetV3-Small, we significantly improved classification accuracy on astronomical images. The approach achieved an accuracy of 94%, outperforming the baseline MobileNetV3 model by 11% without increasing computational costs. This cutting-edge model highlights the potential of lightweight, efficient architectures for processing noisy astronomical datasets and offers a promising solution to support future discoveries in space exploration.

References

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