Harnessing Convolutional Neural Networks to Discover Exoplanets

Convolutional Neural Networks from *The Worlds I See*

In the book, "*The Worlds I See"* by Fei Fei Li, convolutional neural networks (CNN), such as AlexNet, are a powerful machine learning tool that helped advance computer vision and image processing. As CNN uses biological vision patterns and receptive fields, it can classify millions of images using deep learning algorithms. By leveraging CNN, larger and more complex datasets can be analyzed, particularly from telescopes and space missions, to revolutionize our understanding of the universe.

Abstract

Somewhere in the universe, there are distant Earth-like planets that could harbour life. These exoplanets can help us understand the origin, evolution and future of life and how solar systems and planets are formed. But a question arises: how can we find these distant worlds? The answer lies in convolutional neural networks.

In the book "*The Worlds I See"* by Fei Fei Li, we are introduced to the concept of convolutional neural networks (CNN) with the application of AlexNet and ImageNet. Since Dr. Li developed ImageNet, the world's largest labelled dataset of images, her work provided an essential ingredient for advancing computer vision and image processing with CNN. She believed the key to building better AI models is larger datasets, and this concept with using a large ontological structure of images, helped AlexNet have a 10% advantage over other algorithms. You may know that CNN has become a popular model in image recognition and natural language processing, but these algorithms can also be used to solve problems in astrobiology.

Problem

Exoplanets are challenging to observe within habitable zones, since they can be small, located many light-years away, and the brightness of stars can hide them. NASA currently uses planetary transits, radial velocities, gravitational microlensing and direct imaging from telescopes to detect exoplanets, as stated by New Space Economy. However, manually analyzing this data would also be time-consuming and inefficient. As such, how can neural networks be used to replace these methods to better analyze patterns in astronomical data?

Firstly, let's define how CNN works. To illustrate this, take a moment to look around you. As you notice the different objects, your brain is consistently analyzing and processing visual stimuli in the background. Chapter 5 in Li's book describes how the complexity of perception and intelligence evolved, and how we can use this idea to design AI to simulate biological vision patterns. In Chapter 8, we learned that our eyes use thousands of receptive fields that work in layers, so from a basic level, you can identify simple features (edges, shapes and textures), whereas at higher levels, you recognize complex and abstract patterns.

The result is an algorithm that behaves like a retina, gazing out into the surrounding environment. Like a real eye, its outermost layer applies thousands of receptive fields to the pixels of a photograph, each tuned to a unique, tiny pattern and activating when it encounters it—a diagonal edge tilted at a certain angle, a fuzzy blend between two shades, a pattern of stripes or alternating intensities, and so on (page 196).

Similarly, CNN applies a series of filters across an image to differentiate planets from other space objects and backgrounds. According to Pinecone, CNN has three main layers made up of neurons, the convolutional, pooling and fully connected layers, which increase in complexity to identify larger portions of the image.

Convolutional Neural Network Architecture
An article by IBM states how neural networks take in input (such as a light curve or direct imaging) as a 3d matrix of pixels with a height, width and depth. This layer will have a filter, which is typically a small 3x3 matrix that moves or convolves across the image. A dot product is calculated between each 3x3 block of the image and the filter. The output of this layer is a matrix of these dot products, which will then be passed as input into the next layer. The final output is reduced to a single vector of the probability of whether a given dataset contains an exoplanet.

Applications of CNN in Astrobiology
According to an article published by PubMed Central, a CNN model named Astronet can accurately distinguish exoplanets from other transiting and eclipsing objects with 90% accuracy and 96% precision. Recently, NASA's neural network called ExoMiner has discovered 301 exoplanets using the Kepler spacecraft's dataset. ExoMiner was more precise in ruling out false positives and identifying genuine signatures of exoplanets, which proved to be more reliable than existing machines and human biases and errors in manual observation.

By discovering exoplanets beyond our solar system, we can use AI ethically in scientific research to learn more about planetary systems. Ultimately, Li's goal was for AI to be used in a way that benefits humanity and advances our understanding of the world. Thanks to CNN, we can accelerate our search for life in other worlds more efficiently than ever before.

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