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A Deep Learning Approach for Detecting Unusual Celestial Phenomena in Astronomical Datasets

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Abstract

Detection of Unusual Celestial Phenomena in Astronomical Datasets is a deep learning -powered project implemented using ResNet50, a Convolutional Neural Network (CNN) model, and TensorFlow. Utilizing these it efficiently scans big open-source datasets such as NASA (National Aeronautics and Space Administration), SDSS (Sloan Digital Sky Survey), ESA (European Space Agency), etc, to identify asteroids, galaxies, exoplanets, supernovae, and other irregularities. Conventional human analysis is time-consuming and prone to errors, whereas current automated solutions are not affordable and scalable. Our solution combines FastAPI and cloud hosting (Render) for real-time use, making it affordable for students, researchers, and startups. The system uses consumer GPUs, making space research more democratic with an affordable, scalable, and open-source approach.

Keywords: Deep learning, ResNet50, TensorFlow, FastAPI, cloud deployment.

I. Introduction

The amount of astronomical data has grown exponentially in recent decades with missions such as the Sloan Digital Sky Survey (SDSS), Gaia, and space observatories adding billions of images and observations. As much as this data explosion presents new frontiers for discovery, it also creates formidable challenges to conventional analysis techniques. Detection of rare celestial phenomena, like new star types, supernovae, or galaxies, within such huge datasets has become more and more challenging to achieve through manual inspection alone. Deep learning, especially Convolutional Neural Networks (CNNs), has transformed the examination of image-based data in numerous scientific fields. In astronomy, CNNs provide effective means for the automation of anomaly detection and classification in space images. Of different architectures, ResNet50 is notable for its capability to achieve high performance with solutions to vanishing gradient problems, and thus it is very suitable for the intricate textures in astronomical data.

Background of the Project:

The system suggested in this project utilizes a fine-tuned ResNet50 model that was trained on datasets curated from NASA, ESA, SDSS, and SpaceNet sources. The images are preprocessed — resized, normalized, and converted to grayscale — for uniformity and to improve model accuracy during inference. Apart from the deep learning model, there is a light and efficient deployment framework created with FastAPI to facilitate real-time interaction via web-based interfaces. This allows users to upload images and receive immediate predictions about potential anomalies.

Intended to be affordable and accessible, the system is especially ideal for schools, research laboratories, and startups that might not have the infrastructure of larger astronomical research centers. This makes

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advanced data analysis tools more accessible to a wider population, encouraging greater participation in space research.

II. Literature Review

1. Title: Object Detection on Space-Based Optical Images Leveraging Machine Learning Techniques
Authors: Sebastian Samuele Rizzuto, Riccardo Cipollone, Andrea De Vittori, Pierluigi Di Lizia, Mauro Massari
The paper describes a convolutional neural network (CNN)-based system for detecting artificial space objects and orbital debris based on optical satellite imagery. Manually annotated datasets were used to train the model, which then demonstrated highly accurate real-time detection for artificial objects.

2. Title: Predicting Galaxy Morphology Using Attention-Enhanced ResNets
Authors: Akshit Gupta, Kanwarpreet Kaur, Neeru Jindal
The paper describes a convolutional neural network (CNN)-based system for detecting artificial space objects and orbital debris based on optical satellite imagery. Manually annotated datasets were used to train the model, which then demonstrated highly accurate real-time detection for artificial objects.

3. Title: Application of Machine Learning Methods for Detecting Atypical Structures in Astronomical Maps
Authors: I.A. Karkin, A.A. Kirillov, E.P. Savelova
This study used unsupervised clustering algorithms, including k-means and DBSCAN, to mark anomalous structures in Cosmic Microwave Background (CMB) maps. The method effectively picked up out-of-the-ordinary patterns, evidencing the capabilities of machine learning in revealing concealed traits in astronomy data.

4. Title: From Chaos to Clarity: Time Series Anomaly Detection in Astronomical Observations
Authors: Xinli Hao, Yile Chen, Chen Yang, Zhihui Du, Chaohong Ma, Chao Wu, Xiaofeng Meng
The research presents AERO, a two-stage system integrating Transformer-based encoder-decoder structure and Graph Neural Networks (GNNs) to detect anomalies in astronomical time-series data without supervision. AERO can identify normal temporal patterns from anomalies efficiently and alleviate false alarms triggered by co-existing noise.

5. Title: Exploring the Universe with SNAD: Anomaly Detection in Astronomy
Authors: Alina A. Volnova, Patrick D. Aleo, Anastasia Lavrukhina, Etienne Russeil, Timofey Semenikhin, Emmanuel Gangler, Emille E. O. Ishida, Matwey V. Kornilov, Vladimir Korolev, Konstantin Malanchev, Maria V. Pruzhinskaya, Sreevarsha Sreejith
The SNAD project is aimed at the detection of astronomical anomalies in large-scale surveys through active learning and machine learning algorithms. The project has led to the discovery and classification of several astronomical phenomena and pushed the frontiers of the application of machine learning in astrophysics.

6. Title: Multi-Class Deep SVDD: Anomaly Detection Approach in Astronomy with Distinct Inlier Categories

Authors: Manuel Pérez-Carrasco, Guillermo Cabrera-Vives, Lorena Hernández-García, Francisco Forster, Paula Sánchez-Sáez, Alejandra Muñoz Arancibia, Nicolás Astorga, Franz Bauer, Amelia Bayo, Martina Cádiz-Leyton, Marcio Catelan

This work introduces Multi-Class Deep Support Vector Data Description (MCDSVDD), an extension of the algorithm Deep SVDD, adapted to anomaly detection in multi-category astronomical datasets. The approach projects data into hyperspheres associated with particular inlier categories, successfully recognizing anomalies from various classes.

7. Title: A Deep Learning Approach for Active Anomaly Detection of Extragalactic Transients
Authors: V. Ashley Villar, Miles Cranmer, Edo Berger, Gabriella Contardo, Shirley Ho, Griffin Hosseinzadeh, Joshua Yao-Yu Lin

The authors created a variational recurrent autoencoder (VRAE) model for rare extragalactic transient event detection in astronomical observations. The model, trained on a portion of the PLAsTiCC dataset, sorts events by anomaly scores and effectively identifies rare transients for follow-up study in real time.

8. Title: Astronomaly: Personalised Active Anomaly Detection in Astronomical Data
Authors: Michelle Lochner, Bruce A. Bassett

Astronomaly is an active learning framework that is purpose-built for anomaly detection in big astronomical datasets. Utilizing machine learning paired with human-in-the-loop approaches, it offers tailored recommendations, actually detecting compelling anomalies in diverse data types like images, light curves, and spectra.

9. Title: A Comparison Between Unsupervised Deep and Machine Learning for Anomaly Detection on KiDS Data
Authors: Maurizio D'Addona, Giuseppe Riccio, Stefano Cavuoti, Crescenzo Tortora, Massimo Brescia

This research is a comparison of the use of classical machine learning techniques, i.e., Support Vector Machines and Random Forests, to deep learning techniques like autoencoders for detecting anomalies in the Kilo-Degree Survey (KiDS) dataset. The results show that deep learning-based models perform better than the traditional techniques, particularly when dealing with big data.

10. Title: Surprise Detection in Multivariate Astronomical Data
Authors: Kirk D. Borne, Arun Vedachalam

The article presents probabilistic modeling methods such as density estimation and Gaussian Mixtures for identifying rare and unexpected objects in high-dimensional astronomical data. The method is intended to detect outliers that could be new astrophysical events.

11. Title: Classification and Anomaly Detection for Astronomical Survey Data
Authors: Marc Henrion, Daniel J. Mortlock, David J. Hand, Axel Gandy

This study uses supervised classification and cluster-based anomaly detection techniques to the data from astronomical surveys. The work proves preliminary success in distinguishing anomalies and highlights the use of combining classification and anomaly detection methods in astrophysics.

12. Title: Finding Anomalous Periodic Time Series
Authors: Umaa Rebbapragada, Pavlos Protopapas, Carla E. Brodley, Charles Alcock
The authors present PCAD, a technique for unsupervised anomaly detection in large collections of unsynchronized periodic time-series data, e.g., light curves of variable stars. PCAD identifies both global and local anomalies efficiently, enabling the discovery of new categories of astronomical objects.

III. Comparative Analysis of Research Papers on Anomaly Detection in Astronomical Data

Sl. No	Paper Title [Year]	Author(s)	Methods	Findings
1	Object Detection on Space-Based Optical Images Leveraging Machine Learning Techniques [2025]	Sebastian Rizzuto et al.	Utilized CNN-based models for the detection of objects in optical satellite imagery; learned from manually labeled datasets.	Met high real-time detection accuracies for space debris but identified only artificial objects.
2	Predicting Galaxy Morphology Using Attention-Enhanced ResNets [2024]	Akshit Gupta et al.	Trained Attention-Augmented ResNet50 models to predict various galaxy morphologies with supervised learning.	Enhanced classification accuracy of complex galaxy morphologies over vanilla CNNs.
3	Application of Machine Learning Methods for Detecting Atypical Structures in Astronomical Maps [2024]	I.A. Karkin et al.	Implemented unsupervised clustering algorithms (such as k-means, DBSCAN) to find anomalies in CMB maps.	Were able to detect unusual structures, but test limited to CMB maps.
4	From Chaos to Clarity: Time Series Anomaly Detection in Astronomical Observations [2024]	Xinli Hao et al.	Constructed a two-stage framework with the integration of Transformer Networks and Graph Neural Networks (GNNs) for analyzing light curves.	Successfully identified transient anomalies in time-series but not for static image data.
5	Exploring the Universe with SNAD: Anomaly Detection in Astronomy [2023]	Alina Volnova et al.	Applied outlier detection techniques (Isolation Forests, Random Cut Forests) along with human feedback.	Successfully identified rare transient phenomena in sky surveys, but only for transient detection.
6	Multi-Class Deep SVDD: Anomaly Detection Approach in Astronomy with	Manuel Pérez-Carrasco et al.	Extended Deep SVDD to multi-class scenario with tailored loss functions.	Accomplished anomaly detection between different celestial object types but needed prior class information.

	Distinct Inlier Categories [2023]			
7	A Deep Learning Approach for Active Anomaly Detection of Extragalactic Transients [2021]	V. Ashley Villar et al.	Developed Variational Recurrent Autoencoders (VRAEs) to identify extragalactic transients.	Identified rare transient anomalies with success; scope was restricted to sequential data.
8	Astronomaly: Personalised Active Anomaly Detection in Astronomical Data [2020]	Michelle Lochner et al.	Applied unsupervised learning with t-SNE visualizations and human-in-the-loop labeling refinement.	Identified previously unknown anomalies but relied on manual validation to refine results.
9	A Comparison Between Unsupervised Deep and Machine Learning for Anomaly Detection on KiDS Data [2020]	Maurizio D'Addona et al.	Compared SVM, Random Forest, and Autoencoder-based anomaly detection models across astrophysical datasets.	Found deep learning models (autoencoders) surpass conventional methods, particularly with big datasets.
10	Surprise Detection in Multivariate Astronomical Data [2012]	Kirk D. Borne et al.	Employed probabilistic modeling (density estimation, Gaussian Mixtures) for outlier detection.	Detected surprising objects but struggled with scalability as feature dimensions grew.
11	Classification and Anomaly Detection for Astronomical Survey Data [2012]	Marc Henrion et al.	Applied supervised classification together with clustering-based anomaly detection to sky surveys.	Reported early success in separating anomalies but concentrated primarily on known object classes.
12	Finding Anomalous Periodic Time Series [2009]	Umaa Rebbapragada et al.	Implemented clustering and distance-based scoring to identify anomalies in periodic astronomic time series.	Successful for periodic anomalies but unsuccessful for non-periodic or irregular signals.

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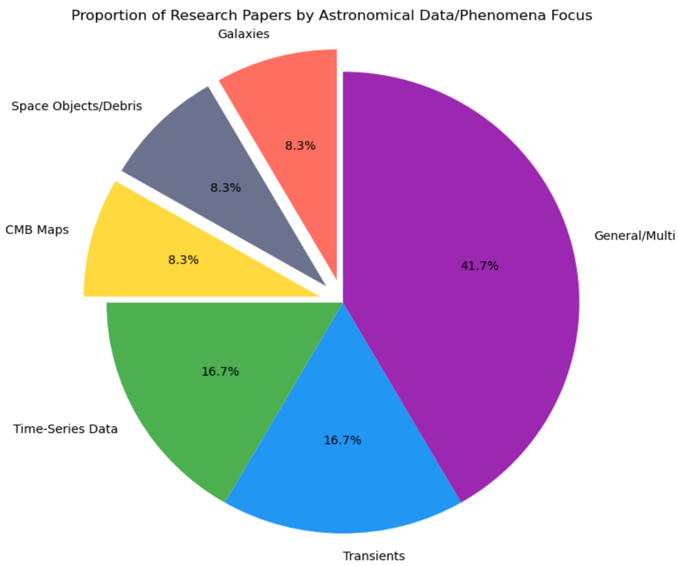

IV. Research Gaps

1. Adaptive Learning for Evolving Data

The majority of current anomaly detection systems are trained on static data sets and do not have the ability to learn incrementally from new astronomical data. As celestial surveys change over time, so do the patterns in the data. The inability to learn incrementally limits the usefulness of the model in long-tern research applications. A system with continuous or online learning would greatly enhance anomaly detection over updated data sets.

2. General-Purpose Anomaly Detection

Most models in the literature, including those in SNAD, are designed to identify a particular kind of anomaly, such as supernovae or periodic variables. But astronomy encompasses wide-ranging anomaly types ranging from structural, temporal, and spectral to even new visual patterns. A very real research deficiency is building a common model to identify wide-ranging classes of anomalies across heterogeneous astronomical sources.

3. User-Friendly Deployment and Scalability

While many deep learning models show good performance in testing environments, very few are adapted into software accessible to the broader community. The lack of API-based, real-time, or browser-deployable platforms restricts utilization by educators, students, and early-stage researchers. Lightweight, scalable platform building is an untapped requirements for democratizing anomaly detection in astronomy.

V. Proposed Methodology

The suggested method presents a system based on deep learning to identify anomalous celestial events through a Convolutional Neural Network (CNN) known as ResNet50. The steps start with the retrieval of open-source astronomical images from resources like NASA, ESA, and SDSS. The images are preprocessed by resizing them, converting them to grayscale, normalizing, and reshaping to maintain homogeneity prior to being input into the model. The ResNet50-based CNN is trained to recognize images as normal or anomalous based on labeled data. After training, the model is served using a FastAPI backend so that users can upload images through a web interface and obtain real-time anomaly predictions. Such a system is made modular, scalable, and user-friendly so that researchers, students, and small institutions can identify unusual space phenomena effectively without needing powerful computing facilities or specialized machine learning knowledge.

VI. Conclusion

The system proposed hereby brings forth an accessible and pragmatic deep learning-based approach for the identification of unusual celestial phenomena within astronomical datasets. Through the use of Convolutional Neural Networks (CNNs) like ResNet50, together with a light-weight FastAPI interface, the system simplifies the entire process of anomaly detection—from preprocessing to real-time prediction—within space imagery. The simplicity of the model, low expenses, and web deployment make it especially advantageous for students, academic researchers, and space-enterprise startups. This piece of work not only solves current limitations in conventional manual and static approaches but also provides a strong foundation for implementing scalable AI-powered astronomy tools within research and educational settings.

VII. Future Scope

The suggested system provides a basis for automatic anomaly detection in astronomical images; however, it has promise for various useful improvements. Future endeavours may consider self-supervised learning (SSL) methods such as contrastive learning and masked autoencoders to decrease reliance on annotated datasets and enable the model to learn more elaborate representations from enormous quantities of unlabeled space data. Furthermore, the integration of hybrid architectures that mix CNNs with transformer-based architectures like Vision Transformers (ViTs) can assist in enhancing detection accuracy by learning both spatial local and global features.

Additional developments could include adding incremental or online learning abilities in order to enable real-time adjustment based on updates from new astronomical information. Running on edge devices such as Jetson Nano or Raspberry Pi would also facilitate offline computation in remote sites, further enabling wider use for educational and research purposes. These developments are intended to realize greater scalability, accuracy, and usability—ultimately serving the larger objective of democratizing AI-facilitated astronomicalexploration.

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