Computer Vision for Astronomical Image Analysis

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2021 IEEE International Conference on Progress in Informatics and Computing (PIC) | 978-1-6654-2655-8/21/$31.00 ©2021 IEEE | DOI: 10.1109/PIC53636.2021.9687023

***Abstract*—Computer Vision (CV) is undoubtedly one of the most popular forms of Artificial Intelligence (AI) and its implementation has gained considerable ground in all aspects of our lives, from security and automotive, to the night sky observation and astronomy. In general, CV uses pattern recognition techniques for identifying objects in visual media (both static and moving images). The current archetype in CV is largely based on supervised AI, which uses large data sets of human-labelled images for training. Machine Learning (ML) and Deep Learning (DL) models in computer vision have undergone a period of extremely rapid development in recent past years; in particular for object recognition and localisation tasks. An area of study with great interest in practical applications that concerns this essay, is astronomical images analysis. However, one of the main challenges facing researchers these days is the existence of large quantities of annotated data sets, in the appropriate resolution and scale. This challenge consequently asks for huge amounts of storage and high computational power. In this paper, we systematically review and analyze different challenges faced by astronomers and continue with state-of-the-art methodologies that were conducted over the last decade.**

***Index Terms*—Computer Vision, Image Analysis, Astronomy image analysis**

I. Introduction

Over the past years, space and astronomical research have grown rapidly in terms of research data size and complexity. This attentiveness for discovery and sustainability created the need of Astronomy introduction to a Big Data era, as higher computational requirements were required. To satisfy this trend, a variety of telescopes are commonly used: (1) telescope LSST is expected to start in 2022, it is estimated that will generate approximately 20TB of data per night and will detect more than 20 million of galaxies with the use of 3.2 Gigapixel camera [31]; (2) integral field units (IFUs) are generating 60GB of data per night while imaging instruments are generating 300GB per night [24]. Furthermore, past estimates conducted by NASA sized the universe at around two trillion galaxies. However, a recent study [6] adjusts this gargantuan number to only a ”few” hundred billions, making it a significant amount of objects that need detection and classification. In light of data complexity, it has been proven that the most image data discovered night by night, needs to be processed and requires the adoption of complex technological instruments. Dealing with this growth, astronomers are developing automated tools to detect, characterize, and classify objects using rich and complex datasets gathered by different facilities. In that case, Machine learning algorithms and Computer Vision have gained increasing popularity among astronomers.

Computer vision algorithms have become powerful tool in astronomical image analysis. A major area of research in the last decade is raised by the combination of CV with Machine Learning techniques. This area brings in computer science the human capabilities for data sensing, understanding and processing, where amplified with Deep Learning methods based on artificial neural networks. In general, Computer Vision can be defined as a subset of Artificial Intelligence that focuses on simulating the human perception and understanding of an image, with the aim of extracting useful information from enormous image data. On the other hand, Machine Learning is a tool for data gathering, analyzing and data training. The purpose of this essay is to elaborate on how CV, when combined with ML and DL techniques, can assist in solving traditional astronomical images analysis problems, optimizing processes that require manual labor e.g. images labelling, and research new frontiers. The target is to present relevant literature and show the current interest in CV for astronomical images analysis over the last decade, find sources of data and any room for improvement in existing practices.

In this context, the review focuses on the most common problems of astronomical image processing and aspects of astronomical images analysis that computer vision can assist in coping with; and presents a systematic study where ML and DL models are applied to address an image classification problem in astronomy. The present structure consists of four axes, where next to introduction, the research methodology will be presented. Next, the research interest in the topic over the last decade, followed by a brief summary of the Machine Learning and Deep Learning techniques applied in the Computer Vision area for astronomy. In the end, the available data sets as well as the discussion and summary sections will be presented.

II. Methods

A. Goal and Research Questions

The goal of this study is to investigate and evaluate in detail the benefits of Computer vision on astronomical image analysis problems, including the image understanding and processing. This paper will also examine the way the sides of Computer Vision, Machine Learning and Deep Learning can be combined to address image classification problems in astronomy.

Initial research has been focused to review a list of papers dedicated to the current research area of Computer Vision in Astronomy. The method of systematic review was used. Keyword selection includes a variety of search techniques using databases Google Scholar, Scopus and SAO/NASA Astrophysics Data System (ADS) [24], a digital library portal for researchers in astronomy and physics, operated by the Smithsonian Astrophysical Observatory (SAO) under a NASA grant. Several methodologies were studied and the current review was divided into three steps: 1) define primary research questions, 2) extensive search in the CV topic using the appropriate databases, 3) selection and content analysis of publications. In particular, this study aims to address the following primary research questions:

- What problems does the CV have to solve in Astronomy?
- What methodologies and models have been proposed for each problem and with what performance?
- What type of astronomical datasets are available for these purposes?

In order to answer the above questions, the following search queries were designed on Scopus and Google Scholar databases:

- TITLE-ABS-KEY ("COMPUTER VISION" AND for AND astronomical AND image AND analysis) that returned 27 papers,
- TITLE-ABS-KEY ("COMPUTER VISION" AND ASTRONOMY) that returned 107 papers.

After combining and originally screening the results, we concluded at a total of 52 papers.

A quick search in SAO/NASA Astrophysics Data System (ADS) using the query (computer vision and astronomical images analysis) and year limitation period: 2010-2021 brings forth 88 results showing the growing interest for astronomical images analysis and Computer Vision over the recent years. Figure 1 shows the increase of total refereed and non refereed papers over the last ten years; with research growth from 2019 which ends up decreasing in 2021 probably due to the COVID-19 pandemic period.

The segments of the visualization in Figure 2, represent groups of papers from the result set described above which cite similar papers. The thicker the grey connection is, the more unique references they share. Deep learning and Big Data models share evidently more citations with astronomical images analysis in the examined literature of the last ten years.

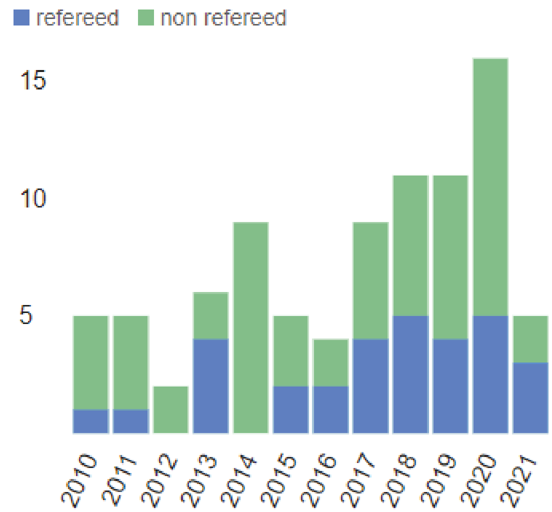

Fig. 1. Number of total refereed and non refereed papers over the last decade in ADS

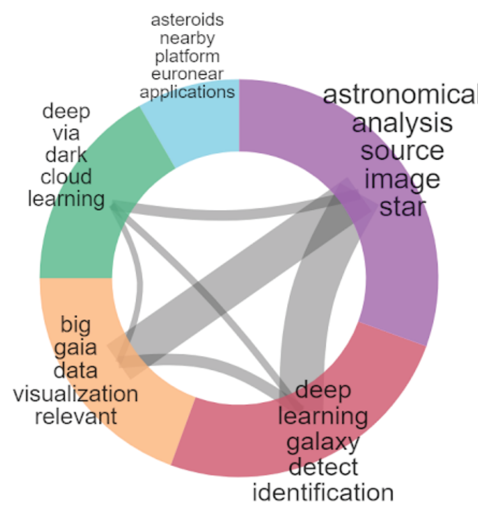

Fig. 2. Paper Network

III. Related Work

Astronomical object classification could be star, galaxy or even stellar halo classification [18], in which the object is identified using images. This process is easier in case of bright objects, but is more difficult when galaxies appear as point-like objects. These objects should be separated in order to derive more accurate notions of their size and scale. Galaxies may be separated into the following classes: elliptical, spiral, lenticular and irregular. We can identify galaxies that are colliding using galaxy images (Merge Galaxies), which can help us understand their evolution. Besides this, we can categorize the shape of galaxies (Galaxy Morphology), which can help us understand their form and evolve. The classification problem becomes harder when adding sub-classes [52].

Astronomers use either spectroscopy or photometric surveys to collect data from objects in the sky. Spectroscopy can collect data from thousands of frequency bands but for a single object at a time. While photometric surveys can collect data for many objects at a time but from only a few frequency bands. In order to make sense of all this data, the need arises to use Machine Learning (ML). Many of ML works focus on processing pre-processed astronomical data. On the other hand there are only a few works that address problems in object classification.

Thus, the latest advances are based on neural networks or well-known classifiers, and on hand-crafted feature extraction techniques. More recent works use Deep Learning techniques, such as Deep Convolutional Neural Networks (ConvNets), which take raw pixel values and extract features directly from the data during training, minimizing the need for input from human experts. Besides this, some works are based on Transfer Learning, which takes a ConvNet to solve a problem applying it to images of different domains.Recent notable Machine and Deep Learning applications are presented in the following paragraphs:

A. Deep Learning

Recently, there have been works that successfully use Deep Learning (DL) techniques.The latest advances in Machine Learning enables CV engineers to use deep convolutional neural networks and allow machines to automatically learn the features directly from the data, by minimizing the need for input from human experts. Compared to traditional techniques, DL enables CV engineers to achieve greater accuracy level in image classification, semantic segmentation and object detection.

Some case studies in Deep Learning applications are presented below: The Authors in [49], [50] use Convolutional Neural Networks (ConvNets), to classify astronomical objects which take raw pixel values and learn how to extract features during training. Kim and Brunner [49] utilized CNNs for star-galaxy separation in the SDSS and CFHTLenS photometric images and achieved an accuracy score of 99.5%. ConvNets [52] for Astronomical Object Classification achieve accurate and well-calibrated probabilistic classifications that are competitive with conventional machine learning techniques. Another competition of ImageNet Large Scale Visual Recognition Challenge (ILSVRC) took place and different image classification techniques were evaluated over a very large data set consisted of more than 1000 categories. Beginning from the CNN development of AlexNet [52] which achieve accuracy level of 52% with total 62,378,344 parameters, many other CNN architectures have been proposed by authors, aiming to improve accuracy on ImageNet and reduce model complexity using different number of parameters.

B. Data Augmentation

The authors in [48] describe a technique for automatically detecting and classifying galaxies that incorporates a unique data augmentation approach that strengthens trained models when it comes to data from various sensors and contrast-stretching algorithms. This technique is demonstrated as part of AstroCV, a rapidly expanding open source project in computer vision repository for processing and analyzing large astronomical datasets, including high-resolution astronomical images. In the fields of image processing and computer vision, high-performance Python and C++ methods are employed. A sample of Sloan Digital Sky Survey (SDSS) galaxies [1] from the Galaxy Zoo Project was used to build the classification model [17]. The authors presented a data augmentation method based on several extra filters to convert FITS (see Astronomical image data chapter) data from various bands into RGB color scale, which shows a significant improvement over standard training methods based on a single color scale conversion.

C. Galaxy Morphology Classification

The inherent difficulty of characterizing spiral galaxies especially when not face-on, has meant that most work focuses on ellipticity in the galaxies under study. A recent paper on Morphological classification [12] of astronomical images, presented an effective semi-supervised approach for galaxy morphology classification task, based on active learning of adversarial autoencoder (AAE) models. For a binary classification problem (top level question of Galaxy Zoo 2 decision tree) it achieved accuracy 93.1% on the test part with only 0.86 millions markup actions. The researchers at MIT-IBM Watson AI Lab developed ObjectNet with the goal of removing the biases that exist in current image data sets. Instead of curating photos from existing sources on the web, the researchers crowd sourced the photos on Mechanical Turk, Amazon's micro-task platform.

D. List of models and applications in CV, ML and DL

While galaxies exhibit a wide variety of shapes, colors and sizes, the need for computational analysis [13] to astronomical images analysis has been in researchers' interests for decades. An attempt to solve this problem is the use of advanced data mining [32], machine learning and computer vision techniques and applications, mostly thanks to advancements in AI and deep learning. A quick list of the models and applications with their challenges on image classification techniques is presented in Table I.

Ultimately, both computer vision and astronomy are concerned with images, and both can work supplementary to enhance the astronomical images analysis process.

IV. Taxonomy

A. Image Acquisition

The first step in computer vision is the data acquisition where information is obtained through the camera. Generally, Image acquisition in astrophotography is similar to terrestrial photography. An optical system captures light and then focuses onto an electronic sensor or photographic plate. It uses a mount to keep the camera steady and improves the appearance of the image [34]

B. Image Processing

Night and day, telescopes attached to orbital satellites and ground-based observatories are taking millions of pictures of numberless astronomical objects [11]. The images taken by telescope are always in gray scale; however sometimes they contain some color information. Planetariums, in turns, represent these objects in digital ways and may form the galaxies in color for educational and entertainment ends. These image data of stars, planets and galaxies provide an invaluable

TABLE I
LIST OF THE MODELS AND APPLICATIONS IN CV/ML

Reference	Year	Type	Description	Dataset	Accuracy
[12]	2021	CV	Semi-supervised algorithm, modernization of the adversarial autoencoder by Makhzani et al.	Kaggle Galaxy Zoo dataset	95.5%
[15]	2020	ML	A new model for generating pixel-level morphological classifications of astronomical sources.	7629 galaxies sampled	91.4%
[16]	2020	ML	An astronomical target detection and classification framework based on deep neural networks	Data obtained by WFSATs	94%
[19]	2018	ML	An edge detection algorithm based on Extreme Learning Machine (ELM)	Cassini astronomy images	93.7%
[20]	2017	ML	The algorithm combines a series of algorithmic steps that first remove other objects (stars, galaxies) from the image and then enhance the line to enable more efficient line detection with the Hough algorithm	SDSS data structure	80%
[21]	2016	ML	Structure-from-motion (SfM) is a computer vision method that enables the recreation of a 3D object by combining images of that object from many different angles	7,872 images of Jupiter from AstroBin	Successful reconstruction of a 3D mesh model of Jupiter
[22]	2014	ML	Developed a pipeline combining multiple computer vision feature detectors and machine learning regression, and experimented the performance using cross validation technique	Data from Galaxy Zoo containing more than 60,000 human-classified galaxy images as training set	90%
[49]	2016	ConvNets	Star–galaxy classification framework that uses ConvNets for classifying stars and galaxies in the SDSS and CFHTLenS on the reduced, calibrated pixel values	Photometric and spectroscopic data sets with different characteristics and compositions	95%
[51], [52]	2012,2014,2016,2016,2017,2017	ConvNets	Development of large, deep convolutional neural network classification systems for galaxies with employment of regularization method and selected CNN architectures for ImageNet	1.2 million high-resolution images in the ImageNet LSVRC	57%, 71%, 80%, 77%, 77%, 75%

resource to space researchers and astronomy for data analysis. However, one of the biggest problems is that until the data is annotated, or human-labelled, it's incredibly difficult to put them in good use. [23] In fact, the astronomical images we see in the media can be described as 'pretty pictures' that are already processed and refined. ML techniques seem to be very useful in a variety of tasks in Astronomy; however many algorithms are not designed to deal with raw astronomical datasets directly. This data usually contains complex formats such as noises, gaps or under enhancements the image size increases. Thanks to the significance of image processing techniques, raw data can be easily stored and transmitted.

As all images, astronomical images are an array, or a matrix, of square pixels (picture elements) arranged in columns and rows. Electronic detectors, such as a CCD (Charge Coupled Device), are commonly used to capture images of celestial objects. Ordinary digital cameras use similar detectors. Although telescope pictures are almost usually greyscale, they do include some color information. A color filter can be used to capture an astronomical image. Different detectors and telescopes are generally sensitive to different colors in different ways (wavelengths).

Image processing techniques starting from Image Smoothing, Noise removal, Edge Detection and Contour Mapping to Object Segmentation will be a powerful tool for astronomical data analysis. Recently, It seems that some problems [8] identified from the perspective of applications engineering to algorithmic image processing and pattern recognition techniques, continue to trouble researchers. Some common problems are object searching and classification in photometry [9], the classification of galaxies on the basis of their morphological shapes, the classification of stellar spectra and the specific problems that were expected for Hubble Space Telescope image data which are being dealt with nowadays, through ground-breaking technologies. In addition, based on the authors of the [10] book, the most common and similar problems that astronomical images face during their analysis are:

- Filtering
  Noise is existent in all data of the physical world. In fact, the galaxy images captured by modern cameras are inevitably degraded by noise, which leads to low image quality. Thus, It is of great importance to effectively separate the signal from noise. Computer Vision has the main role to assist in this task, by replacing each pixel by the average of its neighbors assuming that neighboring pixels are similar, and the noise to be independent from pixel to pixel.
  For general sky survey telescopes, different smart data processing methods have been recently tested on images with various PSFs and have successfully proved their robustness. At [35] authors introduce the centered dictionary learning (CDL) method and study its performance for astronomical image denoising. CDL outperforms wavelet or classic dictionary learning denoising techniques on astronomical images, and a comparison of the effects of these different algorithms on the photometry of the denoised images is shown. The authors of [36] propose a denoising scheme for astronomical color images/videos corrupted with Poisson noise. The concept of Exponential Principal Component Analysis and sparsity of image patches is employed to convert the color space RGB to YCbCr and K-means clustering is applied on luminance component only. Simulation results verify the significance of the proposed scheme in both visual and quantitative manner. The survey at [37] presents an overview of impulsive noise filtering methods and compares their efficiency for the purpose of astronomical image enhancement resulting in a very efficient solution for denoising the astronomical images using the (Laplacian Edge Detection Filter (LED) algorithm.
  The comparative analysis of denoising algorithms for extragalactic imaging surveys [38] gives a thorough examination of the performance of noise-reduction (denoising) methods; concluding that denoising algorithms improve the detection of dim objects and the scientific yield of existing and future extragalactic surveys significantly. Among the 20 approaches evaluated in that research, the most promising denoising algorithms are ATVD-TVL2, Bilateral, Perona-Malik, TV Chambolle, Starlet, and b-UWT(7/9)+Wiener because they perform well in the various tests proposed, and they are closely followed by BM3D.
- Deconvolution
  Deconvolution is a key area in signal and image processing. It can include deblurring of an observed signal to remove atmospheric effects. More generally, it means correcting for instrumental effects or observing conditions. It is used for objectives in signal and image processing that include the following:
  - Deblurring,
  - Removal of atmospheric seeing degradation,
  - Correction of mirror spherical aberration,
  - Image sharpening,
  - Mapping detector response characteristics to those of another,
  - Image or signal zooming,
  - Optimizing display.

  A number of papers address and analyze older and modern deconvolution techniques. Specifically, [39] examines various deconvolution techniques. Deconvolution is extremely tough because of the all-pervasive presence of noise. Blind deconvolution approaches are presented in the papers [40], [41], [42] the point spread function's (PSF) lack of knowledge is tackled through the use of these methods.
- Edge detection
  Edge detection is defined as mathematical methods that aim in identifying edges, curves in galaxy images; in which the brightness of images changes sharply. Information extraction for these images is a fundamental step

for astronomers. For example, in order to build catalogs, the stars and galaxies must be identified and their position and photometry must be estimated with good accuracy. Various methods have been proposed in the past to achieve such results.
A standard source detection approach, consists of the following steps:

– Background estimation.
– Convolution with a mask,
– Detection,
– Deblending/merging,
– Photometry and
– Classification

Over the years, a significant number of papers on the topic have been published. The authors in [45] describe how object detection and star/galaxy classification in astronomy can be automated by neural networks because the nature of the problems is that of pattern recognition. More pattern recognition challenges are presented at [46] through two instances, one of an automated star-galaxy classification in complicated and diverse panoramic imaging datasets, as well as an automated, iterative, dynamical categorization of transient events identified in synoptic sky surveys. A more recent paper [47] provides a new method for finding items of interest in astronomical imagery (galaxies and stars). Following the application of a global detection approach, the image is further refined by employing the watershed segmentation method to divide the entire image into numerous unevenly sized sub-regions, resulting in higher successful detection rates.

- Image Compression
From year to year, the quantity of astronomical data increases at an ever growing rate. In part, this is due to very large digitized sky surveys in the optical and near infrared, which in turn is due to the development of digital imaging arrays such as CCDs (charge-coupled devices). The size of digital arrays is also continually increasing, pushed by the demands of astronomical research for ever larger quantities of data in ever shorter time periods. The following papers describe image compression techniques for the complex nature of astronomical images [43]. Specifically in [44], the authors examine, on a large sample of astronomical photos, a plethora of lossless image compression methods and show how the amount of noise in the images affects the compression ratios and speeds of the algorithms, showing that the Rice compression algorithm achieves the best balance of compression and computational efficiency by being 2–3 times faster and producing about 1.4 times greater compression than GZIP.
- Multichannel Data
A new generation of detectors produce multichannel data, i.e. a set of images taken with different filters. The challenge for multi-channel data filtering and restoration is to have a data representation which takes into account at the same time both the spatial and the spectral (or temporal) correlation.
The processing of multi-channel information is more complex. In [29] this work sets the basis for the application of the Bayesian paradigm to restore multi-channel astronomical images. A more recent work [30] addresses for the first time, the aspect of distributed data storage for multi-channel observations and specifically a solar telescope. This work presents the current data storage solutions for astronomical observations and the basic requirements such as, secure and reliable storage, archiving and accessibility on demand. Concluding that, for contemporary telescopes, the storage of enormous observational data is a crucial concern. After analyzing the requirements for NVST's storage system, the researchers built a distributed storage system, based on real-time observational data for data storage using the Lustre distributed file system.

C. Feature Matching

Features matching or Image matching is a part of many computer vision applications, such as image registration, camera calibration and object recognition that determine certain feature matches between image data. A common approach identifies a set of points of interest from image data through the feature extraction technique. Image matching then determines some preliminary correspondences between two images of the same scene/object. The final image data enters a trained model.in order to be classified as a pattern.

V. Datasets

A. Astronomical image raw data

A great variety of open astronomical image data is available for analysis. The most common file format used in Astronomy is the Flexible Image Transport System (FITS), which is an open standard that designates the digital file format applicable to storage, transmission and data processing. Since FITS was specifically created for Astronomy, it considers measures such as description of photometric and spatial calibration information, along with image origin metadata.

Below list of data sources provides an indicative example of the image data availability:

- The SIMBAD database of astronomical objects at Strasbourg Observatory contains data on 3 million objects, based on 7.5 million object identifiers. Constant updating of SIMBAD is a collective cross-institutional effort. A categorization of object types in SIMBAD is referred to [4] and [5].
- The Hubble Space Telescope is a collaboration between ESA and NASA [7]. It's a long-term, space-based observatory. The observations are carried out in visible, infrared and ultraviolet light. In many ways Hubble has revolutionised modern astronomy, by not only being an efficient tool for making new discoveries, but also by driving astronomical research in general.

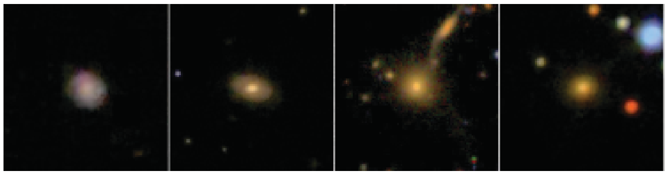

Fig. 3. Random images from dataset

- VizieR provides the most complete library of published astronomical catalogues –tables and associated data– with verified and enriched data, accessible via multiple interfaces. Query tools allow the user to select relevant data tables and to extract and format records that match given criteria.
- Sloan Digital Sky Survey (SDSS) [28] a major multi-spectral imaging and spectroscopic redshift survey is conducted using a dedicated 2.5-m wide-angle optical telescope at Apache Point Observatory in New Mexico, United States.
- Galaxy Zoo Challenge [25], [33], which contains 61,578 images of galaxies with corresponding labels in jpg format. The Galaxy Zoo [2], [3] is defined as a crowd-sourced project devoted to annotating galaxies in support of scientific discovery and exploration. In fact, it is classified as a crowd sourcing project, where volunteers are invited to vote a series of questions about the images they are looking at. Through the corresponding answers they assist in forming a decision tree that covers a wide range of morphological categories [14]. Galaxy Zoo is part of the Zooniverse, a group of citizen science projects. Figure 3 shows 3 randomly images from the available data set.
- Next Generation Virgo surveys (NGVS) [26] a comprehensive optical imaging survey of the Virgo cluster, from its core to its virial radius - private data sets.
- Next Generation Fornax surveys (NGFS) [27] an ongoing multipassband optical and NIR survey of the Fornax Galaxy cluster - private data sets.

Generally, it is observed that astronomical images are very noisy and contain a large area of dark background, which can not be handled by traditional computer vision techniques. In order to capture the unique characteristics of galaxy images, data analysis and image processing techniques are essential.

Discussion

Computer Vision, Machine Learning and Deep Learning are three important areas for academic and commercial research in astronomy where a combination and cooperation of them, helps astronomers to deal with complex astronomical images processing and analysis problems. ML and DL algorithms are both gaining equal popularity in astronomy and have already been able to address many issues of feature extractions, training and processing in Computer Vision. However, due to data image size and data complexity, algorithms are highly sensitive to the noise properties and there will always be a growing demand and need for more image sets. In order to generalize this problem, Computer vision can undertake this role very efficiently. The current trends show a vested interest in advanced Deep Learning models and the need for more effort in coping with the elaborated challenges and open issues like performance and storage needs. The most promising models, in some cases, show an accuracy level of 95% thus allowing for a very small margin of improvement.The vastness of the universe allows for great research and discoveries opportunities that open new frontiers.

Conclusion

This paper demonstrated the extent that Computer Vision has penetrated to the domain of astronomy. In fact, how advanced Machine Learning and Deep Learning models enhance the implementation of Computer Vision models and techniques to astronomical images analysis. On the one hand, by presenting in theory the main problems that astronomers face when an images analysis challenge comes and how recent models and technology advances help in resolving them. On the other hand, a plethora of data sources for future experimentation were listed and the ground for further development and research was laid.

Acknowledgment

This work was supported by the MPhil program “Advanced Technologies in Informatics and Computers”, hosted by the Department of Computer Science, International Hellenic University, Greece.

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