Contributions of Machine Learning and Image processing to Astronomical data

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Abstract

Astronomy is in a data-driven era due to technological advancements in photography and machine learning. This study aims to show the significant contributions of machine learning and computer graphics to the field of astronomy. That is by investigating the process of astronomical data collection by telescopes. It goes in-depth with the steps and different image processing methods in both the spatial and frequency domains. This is while showing some popular machine learning algorithms that are used for studying and analyzing data. The study has shown the significant integration of computer science in astronomy, making it easier to study larger data sets.

I. Introduction

Project Galaxy Zoo is a project where volunteers classify galaxies according to their type. Eighty-seven thousand volunteers did about 5 million classifications in the last decade. However, with the rapid growth of the data collected, this method becomes ineffective. This is when machine learning comes into place, solving most real-world problems associated with big data sets.

Machine learning has played a major role in different fields in recent years. From the medical field, security, and military to cosmology and space. It is even more necessary in astronomy as telescopes send up to 30 TB of data per night, which increase even more as technology advances.

Machine Learning is used in many aspects of astronomy and astrophysics. It is used in reforming low-quality simulations into super, higher ones. Furthermore, machine learning is used in the image processing phase to filter data captured by telescopes and determine whether they must be discarded or sorted.

According to Chandra NASA, electromagnetic waves are detected through special types of detectors fixed to telescopes. After that, this data is transferred to the Earth; most of the time, data is then translated into greyscale images using 8-bit color depth. The photos are then colorized depending on the type of radiation captured. For example, infrared and ultraviolet rays are then translated to the closest visible light ranges. So they become as close to what the human eye retina would see as possible. Then the images are processed by adjusting the brightness and colors and removing noise from them via machine learning algorithms.

II. History of Machine Learning

In the last decades, scientists had a deep interest in machine learning for what it serves them. The 18th century is considered to be the first contribution to machine learning. In 1763, the English mathematician Thomas Bayes set out the mathematical theorem in probability known as Bayes theorem; it’s the base for most of the machine learning algorithms and models. The start of the real interest in machine learning came in 1950 by the computer scientist and mathematician Alan Turing. He had published a paper that was asking about whether a machine is intelligent or not; he put some questions that had to be asked to the machine, and it required the machine to give convincing answers to be considered intelligent. The first use of neural networks was in 1957 by the psychologist Frank Rosenblatt. After that, Gerald Dejong introduced the concept of EBL (Explanation

Based Learning), in which a machine analyses data and conducts a general rule to follow in other situations; this was published in 1985. A year later, David Rumelhart and James McClelland published Parallel Distributed Processing, which advanced the use of neural network models for machine learning. The first time to introduce a new kind of machine learning was in 2006 when Geoffery Hinton created the “deep learning” term; this term had new algorithms and methods of learning than before, and machines could distinguish between texts, photos, and videos. [1], [10]

III. The start of the journey, telescopes.

Telescopes had evolved over the course of history since it was first invented by Danish opticians in the 17th century; it was a lens only then an eyepiece used for magnification till they had been used in orbits outside the Earth. Two types of telescopes are used in astronomy: refracting and reflecting telescopes. [4]

Figure 2 represents a refractor. Refracting telescopes, also known as refractors, use lenses to create an image. First, light beams emitted from distant objects are passed through a lens that concentrates all the light beams at one point; this point is called the focal point which lies at a distance from the lens called the focal length. To have more magnification of the created photo, another lens was used as an eyepiece to magnify the photo. The ability of the refractors to collect light is

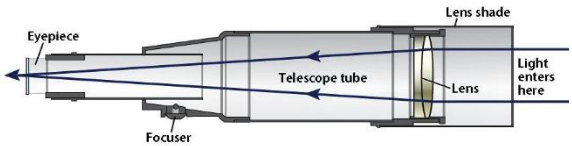


Figure 2 shows components of a refractor

called the light-gathering power of a lens; this can be calculated using the following formula:

$\boldsymbol{P \propto d^2}$, where P is the light-gathering power, and d is the diameter of the lens.

Another aspect to be calculated is the magnification power of the refractor. This measures how much can a telescope magnify the objects in the sky. The magnification power can be calculated through this relation as shown in **Figure 1**:

$$\boldsymbol{M = \frac{\textit{The angular diameter of object through a telescope}}{\textit{The angular diameter of object through the naked eye}}}$$

Figure 1 shows magnification power of telescope

here M is the magnification power of a telescope. Another formula for the magnification power uses the ratio between the focal length of the objective lens and that of the eyepiece.

Refractors, which were a great invention, had some disadvantages which made them less used by scientists. One of the most severe issues was a chromatic aberration. This issue appears in lenses as they bend different colors when light is passed through; this is similar to what happens in a prism. Opticians worked in solving this problem in the 19th century till it was solved in the late 1800s. Unfortunately, many other issues had appeared in the lenses which made them used only by amateur astronomers. [4]

Reflecting telescopes depends on the idea of reflecting light using mirrors instead of using lenses. They’re better than refractors in weight, efficiency, and volume. Refractors require lenses with large diameters to give considerable results, and the larger the diameter, the thicker the lens, and in turn the heavier it would be. Furthermore, lenses’ diameters have limits and beyond them, the photos would be blurred. In contrast, reflecting telescopes

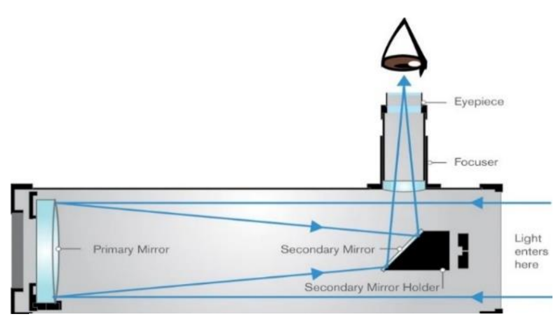


Figure 3 illustrates a Newtonian telescope has no limits to their diameter, and they can be as thin as millimeters, and they would give the same results.

As seen in **Figure 3**, a reflecting telescope consists of a large mirror called the primary mirror to reflect light to another mirror called the secondary mirror which in turn reflects it to an eyepiece to be magnified before being seen. To get the best results from a reflecting telescope, a spherical mirror should be used with a correcting lens as shown in **Figure 4.** The correcting lens is used to adapt the angle by which the light rays fall on the primary mirror.

To capture the collected photos, an additional part is used with the telescopes; this additional part is the Charged-Coupled Device or the CCD. This part is mainly made of semiconductors in the form of cells, and every individual consists of pixels that are sensitive to photons of light. In comparison with normal films, CCDs respond to 70% of the light while films respond only to 2%.[4] These pixels build up electric charges according to the number of

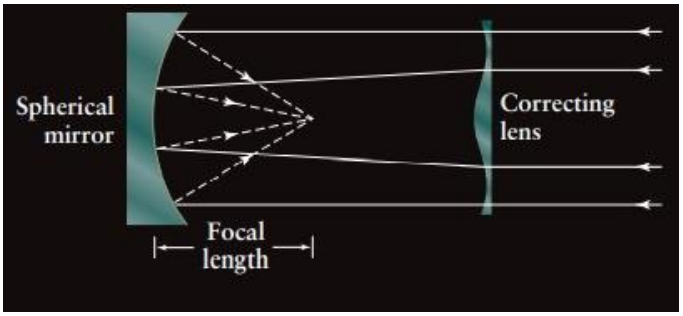


Figure 4 shows correcting lens which shows the optimal results of reflection

photons that stroke each pixel; these charges are translated to real photos using computers. In this stage, some basic image processing is done to the images.

IV. But what happens to the data?

i. Digital Images

To understand how images are processed, it is necessary to understand what digital images are. *Digital images* are the images that are sent by telescopes to be stored digitally. Unlike photographs, digital images consist of pixels. They are stored in memory as arrays. Each array consists of a header with general information about the image, such as its format, width, and height. Besides, it consists of a long row of pixels, where each pixel is stored as several bits. Grayscale images, for example, have pixels that each store 8 bits, while colour images store 24 or 32 bits. Colour images are larger because they consist of more than one layer; they are made of 3 layers, where each layer is a grayscale image with pixels holding a value between 0 and 255. These values represent red, blue, or green intensity. Therefore, this format is called the RGB format that is based on the primary colors the human eyes can see. [1]

a. Astronomical Data Collection

1- Image Acquisition:

Image acquisition is the first step into image processing. This procedure usually consists of data mapping and read/write operations. The digital data for the image can be loaded into computer memory or hard drive, which is a step generally to ensure that data is digitized and ready to be used. [12]

2- Image Transport:

Astronomical data comes in large volumes. Thus, a standard format for these large images is necessary, which is why the FITS standard was chosen in 1979. FITS provides the type of support to be used for transporting images. [12]

3- Image Archive:

Image archives have (the) essential functions of storing images and retrieving them. These functions depend on the destination of the archive, which could be either online/offline storage or a computer mass storage. In this step, images are stored on either of the three storage systems mentioned. [12]

4- Image Presentation:

This is the process of displaying the images. It is a fundamental part of astronomical image processing, as images require visual monitoring. There are many different ways of image presentation. [12] However, they are not going to be covered

5- Basic Image Processing:

Basic image processing in astronomy includes standard image arithmetic, geometrical, and intensity mapping. It also includes sub-images extraction, interpolation, approximation of images, linear and nonlinear filtering, statistics and data compression. [12]

V. Preprocessing

After storing, visualizing, and basic data processing, the preprocessing part starts. As shown in **Figure 5,** preprocessing happens before more image processing techniques are used to classify and detect objects, such as stars and galaxies, in the images. These techniques are used to either filter out unwanted things, or to enhance the overall quality of data. [13]

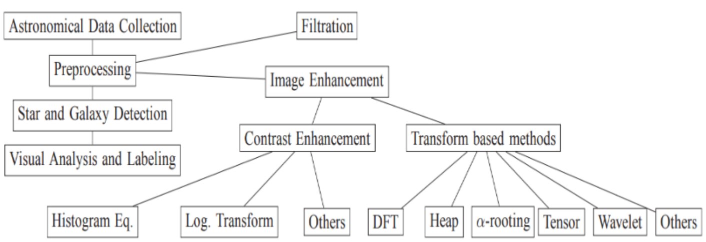


Figure 5 Shows the step of preprocessing in Astronomy [13]

i. Image enhancement/Filtration (Spatial domain)

1- Point processing:

Point processing is a spatial image processing technique, where each pixel/point is changed individually. The process is very straightforward and it is mathematically represented as $s = T(r)$, where s is the processed pixel, r is the original pixel, and T is the process, filter, or effect that is applied to the pixel.

2- Neighborhood processing:

Unlike point processing, which is concerned with applying different processes to each pixel individually, Neighborhood processing works with several pixels simultaneously, called a “neighborhood”. It is mainly in the shape of a square or a rectangle.

3- Simple techniques used in astronomical spatial image processing:

There are various methods and techniques used for image processing in the spatial domain, as shown in **Figure 6**, some of which will be covered in this paper.

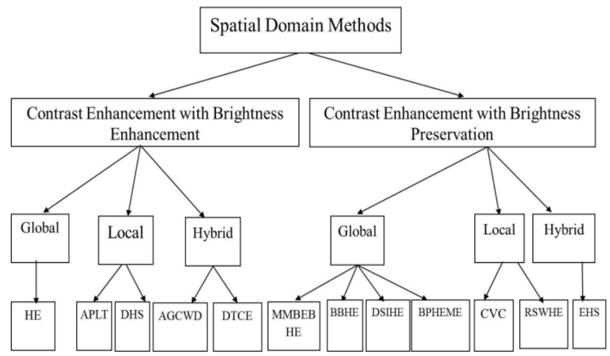


Figure 6 Shows methods of enhancement in the spatial domain [14]

a. Histogram Equalization (HE):

Histogram Equalization is a common technique based on representing the intensity of each pixel of the image on a histogram. The histogram is of values between 0 and 1, where 0 is the least intensity (black) and 1 is the highest intensity possible (white). Histogram Equalization manipulates the values of the intensity of pixels stretching or compressing them, as shown in **Figure 7**. [8,] [16]

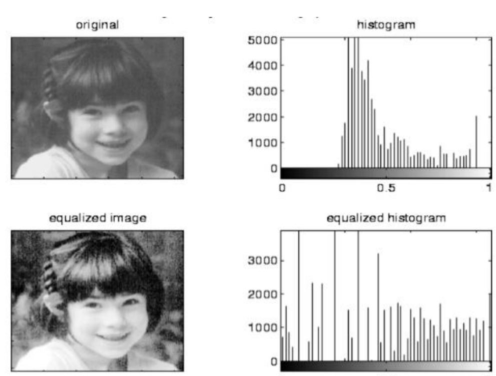
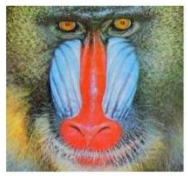


Figure 7 shows the effect of HE on images [16]

b. Brightness preserving Bi-Histogram Equalization:

Histogram Equalization has one flaw that BBHE solves. This flaw is mean-shift, which means that the average brightness of an input image may change, causing an over-enhancement problem in the output image. BBHE uses the mean values of the image to separate the histogram, therefore transforming each pixel. The over-enhancement problem is reduced, while the mean remains constant, as shown in **Figure 8**. [8], [16]

The way BBHE reduces the flaw is by decomposing the input image into two sub-images. One of the images represents the set of samples less than or equal to the mean, while the other is the set of samples greater than the mean. The two images are then equalized with their respective histograms. [16]



Original image

HBBE image

Figure 8 shows input image and HBBE enhanced output

. Some different methods and techniques are associated with image de-nosing, smoothing, blurring, and many more; however, they are not going to be reviewed in this paper.

1- Image enhancement/Filtration in frequency image processing:

a. Fourier Transform:

Fourier transform is a mathematical operation that turns functions that are in the spatial domain into functions in the frequency domain. For example, for a periodic function $f(x) = A\sin(B\ (x + C)) + D$, it is possible to represent this same function in the frequency domain as shown in **Figure 9.** To represent a periodic function in its frequency domain [14], it is represented as shown in **Figure 10**:

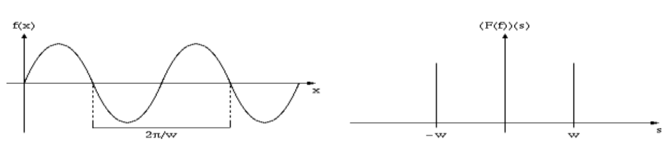


Figure 9 shows the function f(x) in both the spatial and frequency domains.

$$F(u) = \int_{-\infty}^{\infty} f(x)\, e^{-i2\pi ux}\ dx$$

Note that: $e^{ik} = \cos(\mathrm{k}) + i\ \sin(k)$

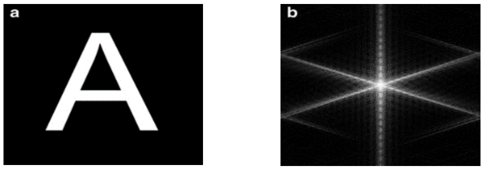
Figure 10 shows the equation representing the transform of spatial to frequency domain

This process is also used in digital images in many ways such as image analysis, image filtering, image enhancement, and compression. However, since images have two dimensions, Discrete Fourier Transform, which is the most used in digital image processing, is used. It is sampled, meaning it does not contain all frequencies forming an image. However, it contains a set of samples that describe the spatial domain image in a more general way. This, however, is done with a number of frequencies corresponding to the number of pixels in the spatial domain image [8], [14]. For example, for an image of the size $M \ \times N$, the two-dimensional DFT is given in **Figure 11** by:

$$F(k,l) = \sum_{i=0}^{M-1}\sum_{j=0}^{N-1} f(i,j)\ e^{-j2\pi(\frac{ki}{M}+\frac{lj}{N})}$$

Figure 11 shows how an image is given by 2-dimensional DFT

What happens is that at index (k, l) there is a pixel, and it needs to be transformed into the frequency domain. However, it is necessary to know how this pixel relates to every other pixel in the image. Thus, for transforming one pixel of the input image, the function goes through every pixel, and this process is done repeatedly until the whole image is transformed. The input and transformed images can be seen as shown in **Figure 12**. This type of transform is called “low-pass” as it only lets low frequencies pass, where the low frequencies – white parts – represent the details on the image.



original image in spatial domain

image represented in frequency domain

Figure 12 shows image after applying DFT to it

2- Quaternion Algebra:

Quaternion numbers are four-dimensional hyper-complex numbers that consist of a real (scalar) part, and 3 complex (vector) parts. They are represented in Cartesian form as in **Figure 13**:

$$\boldsymbol{q = a + ib + jc + kd}$$

Figure 13 shows the Cartesian form of a quaternion number

There is a relation between its imaginary parts i, j, and k, as shown in **Figure 14**:

$$\boldsymbol{i^2 = j^2 = k^2 = ijk = -1},$$

$$\boldsymbol{ij = -ji = k; jk = -kj = i; ki = -ik = j}.$$

Figure 14 shows the relation between the imaginary parts of the number

The magnitude of a quaternion is defined as in **Figure 15**:

$$|q| = \sqrt{\|q\|} = \sqrt{a^2 + b^2 + c^2 + d^2}$$

Figure 15 defines the magnitude of a quaternion q

When the real part of the quaternion is equal to zero, it is referred to as a pure quaternion; however, when the magnitude of the quaternion q is equal to 1, it is said to be a unit quaternion.

One last property of quaternions is that if we have two quaternions, p and q, as shown in **Figure 16**, it is said that:

$$pq \neq qp \; OR \; pq = qp$$

Figure 16 shows commutative property of quaternions

Thus, in quaternion algebra, the product of two quaternions may or may not be commutative. [11], [13]

3- Representing color images in quaternion space:

It is possible to represent RGB color images in the quaternion space as pure quaternions. This is as because they have three or four channels, where the fourth channel is usually used as padding or represents the transparency of the image.

For example, let f (x, y) be an RGB image function as in **Figure 17**. Each pixel of the image can be represented as a pure quaternion, in which:

$$f(x,y) = f_R(x,y)\boldsymbol{i} + f_G(x,y)\boldsymbol{j} + f_B(x,y)\boldsymbol{k}$$

Figure 17 representing images as pure quaternions (where the real part equals 0)

Where $f_R(x,y), f_G(x,y), f_B(x,y)$ represent the RGB components respectively. **Figure 18** shows a representation of the RGB colors in the quaternion space. [6]

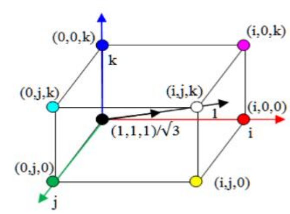


Figure 18 shows RGB color cube in the quaternion

One of the main reasons for using quaternions for representing images is that they take less space in the computer memory, and they make it easier to do computational and arithmetic operations compared to the representation of images as matrices.

4- 2-D Quaternion Discrete Fourier Transfer (QDFT):

Due to the unique property of quaternion numbers, the concept of QDFT can be defined in two different ways as shown in **Figure 19**.

$$F(p,s) = \sum_{n=0}^{N-1}\sum_{m=0}^{M-1} W_j{}^{np} q W_k^{ms}$$

where

$$W^{np} = \cos np\emptyset - j\sin np\emptyset \text{ and}$$

$$W^{ms} = \cos ms\varphi - k\sin ms\varphi$$

$$\emptyset = \frac{2\pi}{N} \text{ and } \varphi = \frac{2\pi}{M}$$

Figure 19 the mathematical definition of QDFT

Again, it is going through every pixel in the $N \times N$ image; however, it cuts it into two 1-D QDFTs going through each row/column separately. [15]

5- Alpha-Rooting Transform & QDFT:

The alpha rooting method is an image enhancement method for gray-scale images. It can also be used for color images stored as quaternion numbers. Mixing the 2-D QDFT method with the alpha rooting method results in high-quality color images. In this method, the magnitude of the frequency representation of the image is transformed as shown in **Figure 20**.

$$\left|F_{p,s}\right| \to \left|F_{p,s}\right|^{\alpha}$$

Figure 20 image in frequency domain with alpha rooting

This transform is for each frequency point (p, s), where α lies between 0 and 1. The best alpha value may be adjusted via trial or it could be found automatically. This is as shown in **Figure 21** [7], [11], [13].

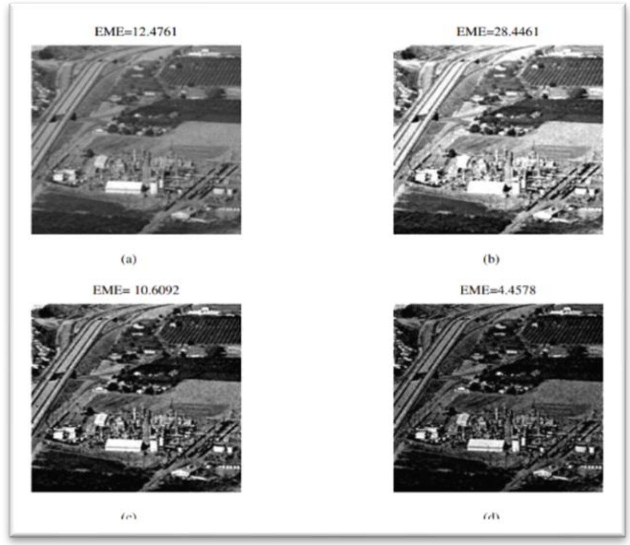


Figure 21 shows the effect of different alpha values

VI. Machine learning and Data analysis

These images are analyzed, studied, and classified. All of which are usually done with the help of various machine learning algorithms.

i. Supervised and Unsupervised learning:

Three stages need to be completed to construct such a successful model. The first stage is the training stage, in which the hyper-parameters of the model are set and trained using an input set called the training set. The second stage is the validation stage; this stage is required for specifications. In this stage, the hyper-parameters are costumed according to predefined functions. Sometimes, different sets of inputs are used to optimize the hyper-parameters. Many optimizations happen to the hyper-parameters until reaching the best-performing ones. The latter stage is the test stage; this stage is required to check the model's performance. In this stage, the model is exposed to a dataset called the test set to check whether it would achieve the target variables or not. Once these stages are finished, the model is ready to be used on unseen datasets. [2]

Supervised machine learning algorithms are used mainly with two types of tasks in astronomy, classification tasks and regression tasks.

In classification tasks, the model is given a dataset that needs to be classified into different categories. An example is classifying stars into "OBAFGKM" according to their surface temperature and luminosity. For the regression tasks, the target variables are continuous; they change as a function of time. An example is estimating the redshift using photometric measurements.

In contrast, unsupervised machine learning algorithms are not constructed based on complete datasets but on inputs for specific parameters. Unsupervised machine learning algorithms are considered a general term for a large number of tools that are used in statistics. Generally, unsupervised models are used in explorations and collecting data stages, not in the specifications; they reveal the unseen and unnoticed objects in the heavens. An example of their usage is cluster analysis. In this analysis, the model tries to reveal distinct planet clusters. The analysis suggests that both clusters had different formation channels. [3]

Dealing with unsupervised models has to be too sensitive, as these models give massive sets of results that must be filtered and revised before use. In addition, external parameters affect the model heavily; they result in significantly different results for the same dataset, making many calculations errors.

ii. Semi-Supervised Learning:

Unlike other machine learning algorithms, semi-supervised does not have a wide-range usage to date. However, this approach holds considerable potential to be used for the upcoming astronomical and photometrical surveys. A supervised machine learning algorithm requires datasets to be trained, and scientists neither use it for exploration nor for producing new classes. On the other hand, an unsupervised machine learning algorithm doesn’t require datasets or parameters to be used, but it cannot be used for specifications; it gets unexpected results and data and requires sensitive usage. The semi-supervised machine learning algorithm takes the best of the two previous algorithms and uses them. [17] A semi-Supervised machine learning algorithm can be used to explore and produce new classes based on datasets and parameters so that the randomness percentage is very tiny compared to an unsupervised machine learning algorithm.

A semi-supervised model is shown in **Figure 22**. The model shows labeled and unlabeled data together on the diagram. Numbers represent the labeled data from 1 to 4, and unlabeled data are represented by the U letter with a number from U1 to U4. [17]
Semi-Supervised machine learning algorithm applications in astronomy are mainly focused on the area of photometry and spectroscopy. It uses the specifications and limitations of spectroscopic models to extrapolate the purely unlabeled photometric data; this opens gates to new data in the photometric realm. In addition, semi-supervised machine learning allows collaborations and overlapping between scientists in Astronomy, Computer Science, and Statistics. [17]

Semi-Supervised machine learning algorithm has different approaches according to the required task. Some approaches may work efficiently for one task but poorly for other tasks. This allows overlapping between different fields of science to determine suitable approaches for specific tasks.

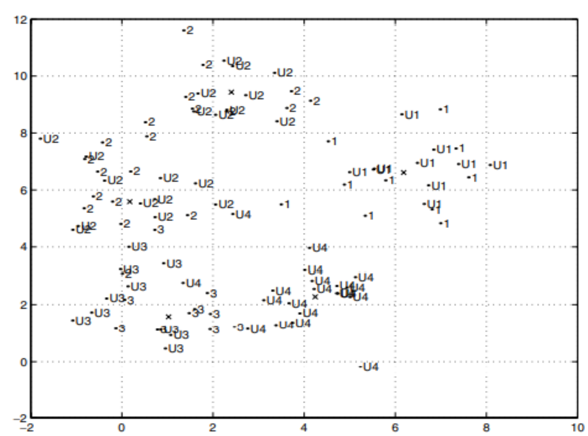


Figure 22 Shows semi supervised model

iii. Decision Tree & Random Forest Classifiers

Decision trees – which are shown in **Figure 23** – are a type of machine learning algorithm that is widely used in the field of astronomy. It is mainly used for galaxy and star classification. The way it works is by attempting to classify data based on specific features that each data point has. It then starts from the "root node" comparing the data points to the condition at each node; it, therefore, classifies the data according to whether or not it meets the requirement.

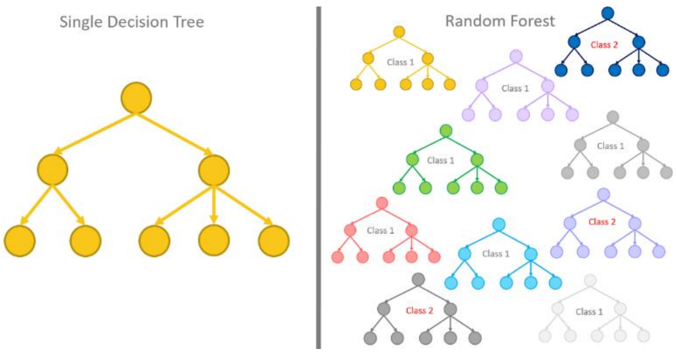


Figure 23 Shows Decision trees and Random Forests

Decision trees use information theory to decide the next step for classification, where it calculates the entropy of each decision and chooses the one with the highest entropy [5]. For simplification purposes, think of it as a "Hot or Cold" game, where decisions that have a value closer to "Hot" are chosen, and decisions with values that are closer to "Cold" are avoided.

Decision trees have a problem, however, which is that they are very sensitive to the set of data that they are trained on. This makes it hard for them to generalize what they learn. Thus, as an attempt to solve this problem, Random Forest classifiers were created. Random forest classifiers, as the name identifies are a group of decision trees. They work using two simple principles, Bootstrapping and Aggregation. *Bootstrapping* is dividing the training data into chunks randomly. Each of these chunks is then used for training a decision tree. After that, comes the aggregation part. The same data set is then given to each of these trees, and the classification happens with each tree giving an output. The outputs may differ from one tree to the other, thus, the choice of the majority is the one considered. This process is known as aggregation [5], [2].

Galaxy and star classification is a process in which decision trees are used in. Where they are usually classified according to either their spectroscopic information – information concerning the wavelength range according to the electromagnetic spectrum – or photometric attributes – the total brightness as seen by a human eye – or both [2].

iv. Artificial Neural Networks:

Neural networks are techniques that were originally designed to simulate the human brain. They were not used, however, until the 1990's during the 3D video games demand which encouraged major companies to create GPUs. Graphical Processing Units specialize in doing matrix operations; therefore, they made it possible for scientists to create and develop neural networks.

They have the ability to recognize patterns and learn from them. The way neural networks do that is by taking data x^d and generate a function h(x) which gives an output. Due to their large potential, neural networks have become a point of interest in many different fields.

Neural networks consist of "neurons" or "nodes", which are simple processing units that are connected by unidirectional connections. These nodes are arranged in a series of layers, the first and last being input and output layers. That is in addition to "hidden layers" in the middle, as shown in **Figure 24**. The input layer acquires input that it

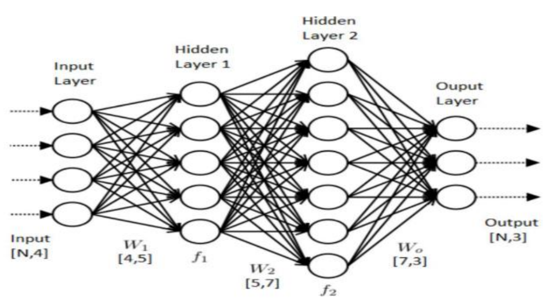


Figure 24 shows the different layers of an artificial neural network distributes to the nodes of the next layer, where each input is given a weighted value that specifies how much impact this input has on the output.

Although Neural networks have been utilized for speech recognition for AIs such as Apple's Siri and Amazon's Alexa, they were also utilized for image recognition as they are sometimes called "Computer Vision" algorithms when dealing with image data [5], [9].

Neural networks use both supervised and unsupervised learning methods to learn. Hybrid neural networks that use both methods were also developed. These systems were used in many applications and many areas of research in astronomy. Its main applications are object classification, satellite systems, and adaptive telescope optics.

One of the most used types of neural networks in astronomy is Convolutional Neural Networks (CNNs). They are a type of network that is made specifically for pattern recognition. Like other neural networks, CNN is made of an input layer, a hidden layer, and an output layer. The hidden layer, however, contains "convolutional layers" that can recognize an image's patterns.

Once the input data is given to the layer, a kernel/filter is added to the data. A filter is a matrix multiplied by each image block to produce a pixel in the output image. This process is done to specify certain parts of the image, such as edges, squares, corners, or circles. The more layers the network has the more sophisticated shapes and objects it can recognize. It can get as complicated as recognizing objects such as ears and eyes or even more complicated recognizing creatures such as dogs or cats [5].

The way filters work is shown in **Figure 25,** where the input image has four different filters. Each number in the filters represents a color, where the negative one is black, one is white, and the zero is gray. As the filters are multiplied by each block of pixels in the image, the network creates more recognizable shapes, such as its edges, as shown in **Figure 26**.

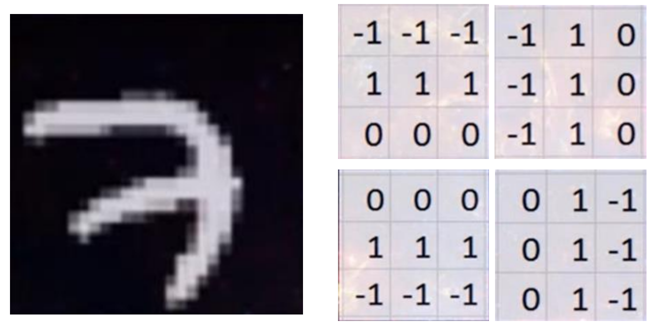


Figure 25 Shows image and four different filters which are represented

Figure 26 Shows the effect of the four filters on the image.

The filters have different effects on the picture; however, they do the same task: showing the edges of the image. Once the filters are applied to the input, a pooling layer is used to reduce the data quality. This process is done to reduce the data size so it does not take as much memory for doing arithmetic operations as it usually would. After that, and after the first layers use simple filters to recognize edges, corners, and simple geometrical figures, deeper layers are used to recognize more complicated objects and patterns. [5]

VII. Conclusion

For centuries, humans have always been concerned about studying the heavens. This mysterious field has been revolutionized across the centuries by different discoveries. Like how centuries ago, mathematics was used to describe astronomy, and physics was used to go to outer space, computer science is the current revolution in astronomy. With image processing and machine learning, it is possible to analyze and study large data sets. As for this fast development rate, we decided to review the contributions of these two technologies in the field of astronomy. This was done by going through data collection, image processing, and analysis methods in sequence. Different methods and techniques of image processing and machine learning used in astronomy were shown and explained. In the end, this all shows the rapid growth at which the fields of astronomy and computer science are advancing.

VIII. References

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