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Intelligent system for bar detection based on Non-negative Matrix Factorization Algorithms

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ABSTRACT

In this paper, a new automated machine supervised learning method for bar detection scheme in spiral galaxies based on the Nonnegative Matrix Factorization algorithm have been presented. Non-negative matrix factorization has been introduced in this paper to detection bar in spiral galaxies, which is very easy to use, and gives us a good accuracy. Detection bar in spiral galaxies is the main objective of this research. WE describe an entirely automated method that extract feature from spiral galaxies and then automatically bar detection. The algorithm is trained using manually bared and non-bared images of spiral galaxies. The algorithm show that the bar in spiral images from the EFIGI catalog can be detected automatically with an accuracy of 97.3% with an average processing time of 0.37 s per galaxy compared to bar detection carried out by other authors and manually detection.

Keywords:

Spiral Galaxies, barred spiral classification, Nonnegative matrix factorization (NMF), image processing, Machine learning.

1 INTRODUCTION

Since the creation of the universe 13.7 billion years ago galaxies are a pretty mysterious creation that consist of dust, billions of stars, and gas which is known by the Big Bang theory which lead to all the different types of galaxies. In our big universe we reached very important clues and information about its origin and developmental stages by investigating and Studying galaxies properties and types, [1]. Astronomers used shape and general visual semblance of galaxies to know more information about their development and their structure, [2]. The first step towards a super perception understanding of the origin and formation process of galaxies is study the shape and structure of galaxies which is an important role in the large scale to understanding the provenance and developments in the universe, [3]. Astronomers deduce that bar detection is a trouble because it is often considered as a suitable way to differentiate between two kinds of spiral galaxies that have different physical properties. We have huge datasets of images due to growing size of telescopes and the CCD camera, [4]. In modern sky surveys containing millions of galaxies, there are too much data to feasibly anatomize manually, the Sloan Digital Sky Survey one of the most famed examples of this. Morphological analysis of huge galaxy image databases needs for robust methods, [5]. Artificial neural networks (ANNs) have recently been utilized in astronomy for a wide range of problems, e.g., from adaptive optics to bar detection in spiral galaxies. Lately the improvements in mathematical tools and algorithms have started to allow automatic analysis of spiral galaxy morphology according to the different Hubble types, [6]. In the past astronomers classified galaxies and detection bar in spiral galaxies manually into categories based on their visually guise. Thus, automated detection algorithms will evidence precious for the analysis of such datasets, but these algorithms are yet to be applied on such scales. According to growing quantity of spiral galaxies is a very hard problem for astronomers Therefore, the dimension reduction methods is needed before apply bar detection method, [7]. Since galaxies images are represented by its light intensity and it is measured by a nonnegative value. In recently years, the nonnegative matrix factorization (NMF) has become a popular dimension reduction method. The NMF refers to the problem of approximating a nonnegative matrix by a product of two nonnegative matrices. The main goal of this paper is to develop an algorithm for bar detection of galaxies images based the NMF method. The proposed algorithm is compared with human classifications and other algorithms. The NMF extract a list of features for galaxy images based on some nonnegative constraints are imposed. Therefore, the image can be reconstructed from this list of features, [8].

The paper is organized as follows: we introduced spiral galaxies in section 2. Section 3 Related work and gives an introduction of Nonnegative matrix factorization in section 4. The used algorithms are described in section 5. and the experimental results described in section 6. We presented the conclusion and the future work in section 7.

2 SPIRAL GALAXIES

2.1 Spiral Galaxies schema

Spiral galaxies are composed of a central concentration of stars known as a bulge and a flat, rotating disk containing stars, gas, and dust. Edwin Hubble in his 1936 presented spiral galaxies from a class of galaxies originally described in work The Realm of the Nebulae [9], and as such are part of the Hubble sequence as shown in figure 1.

Spiral galaxies are named by their spiral structures that extend from the center into the galactic disc. The spiral arms are sites of ongoing star formation and are brighter than the surrounding disc because of the young, hot OB stars that inhabit them. Roughly two-thirds of all spirals are observed to have an additional component in the form of a bar-like structure, extending from the central bulge, at the ends of which the spiral arms begin. The proportion of barred spirals relative to bar less spirals has likely changed over the history of the universe, with only about 10% containing bars about 8 billion years ago, to roughly a quarter 2.5 billion years ago, until the present, where over two-thirds of the galaxies in the visible universe (Hubble volume) have bars, [10].

The Milky Way is a barred spiral, although the bar itself is difficult to observe from Earth's current position within the galactic disc. The most convincing evidence for the stars forming a bar in the galactic center comes from several recent surveys, including the Spitzer Space Telescope.

Together with irregular galaxies, spiral galaxies make up approximately 60% of galaxies in today's universe. They are mostly found in low-density regions and are rare in the centers of galaxy clusters.

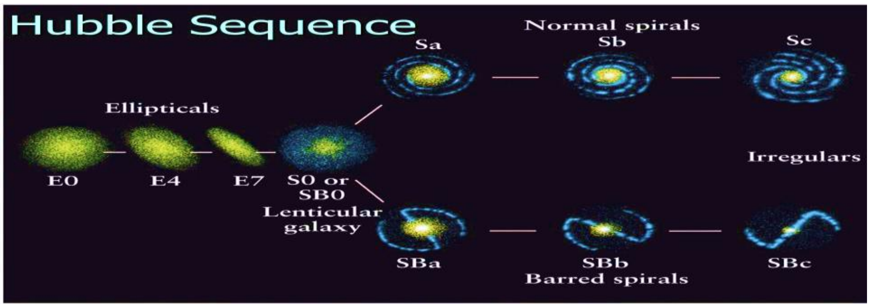

Figure 1. Hubble's Classification Scheme shows that spiral galaxies divided to two branches Spiral galaxies with bar and spiral galaxies without bar

Hubble sequence schema in 1959 updated by Gérard de De Vaucouleurs system In 1960. De Vaucouleurs system classified spiral galaxies, based on the three basic morphological characteristics: As shown in figure (2).

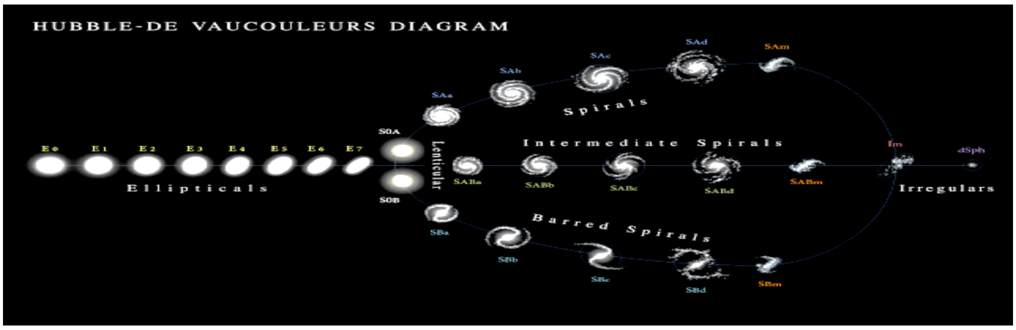

Figure 2. De Vaucouleurs Classification Scheme

- Bars, galaxies division is based on the presence or absence of a nuclear bar. De Vaucouleurs introduced the notation SA to define spiral galaxies without bars, an intermediate class SAB was also introduced to denote weakly barred spirals [11], and he also used the notation S0 to describe Lenticular galaxies that are impossible to tell whether they have a bar or not, and for barred Lenticulars he used the notion SB0 while he used the notion SAB for unbarred Lenticulars.
- Rings. Galaxies with ring-like structures (denoted „(r)‟) and those without rings (denoted „(s)‟). While „transition‟ galaxies are given the symbol (rs).
- Spiral arms. Hubble's scheme categories spiral galaxies into classes based on the tightness of their spiral arms, De vaucouleurs extended the spiral classes by adding several additional classes, these additional classes were classified in Hubble's scheme as Irregulars Irr, De Vaucouleur used the notions: Sd (SBd), Sm (SBm), Im. In addition, the Sd class contains some galaxies from Hubble‟s Sc class.

2.2 Bars in Spiral Galaxies

Bars are among the most common morphological features of disk-shaped galaxies. Unlike spiral arms, bars cross the "spiral-S0 divide" in the Hubble sequence and are abundant among spirals (at the 50-70% level) when both SAB and SB types are considered. The bar fraction has cosmological significance and many estimates of the nearby galaxy bar fraction have been made from both optical and IR studies. Bars are fairly well-understood features of galaxy morphology that have been tied to a natural instability in a rotationally supported stellar disk. The long-term maintenance of a bar in a mostly isolated galaxy is thought to depend on how effectively it transfers angular momentum to other galaxy components, such as the halo. Bars are thought to be transient features that, in spiral galaxies, may dissolve and regenerate several times over a Hubble time. Alternatively, bars may be long-lived density wave modes that drive secular evolution of both the stellar and gaseous distributions. The possible secular evolution of bars in S0 galaxies is discussed by Buta et al. . Bars are also thought to drive spiral density waves.

3 RELATED WORK

Different automated classification techniques use different methods. Depending on the increasing amount of data, there is a common problem facing many of the science of astronomy today. This makes classification a difficult issue. Therefore, before applying the classification method, we have to do the dimensional reduction methods. Because images of galaxies are represented by their light intensity and are measured by a non-negative value. In recent years, non-negative matrix factorization (NMF) has become a popular way to reduce dimensions. NMF refers to the problem of approximation of a nonnegative matrix by a product of two nonnegative matrices. The main objective of this article is to develop an algorithm for the automatic detection of spiral galaxy image bars using the NMF method. The proposed algorithm is compared to human bar detection and other algorithms. The NMF imposes certain nonnegative constraints to extract a list of features for images of galaxies.

Selim et al (2022) presented a new logically structured modular algorithm that analyzes the morphological raw brightness data of galaxies to automatically detect the visual center, region and classification of galaxies. First, a new threshold of selective brightness is used to eliminate the effect of brilliant background stars on the detection of visual centers of galaxies. Second, a technique to detect the area of galaxies is developed. The technique has been tested by a collection of 1000 galaxies of the EFIGI catalogue. The results of the classification of galaxies showed a high success rate of current technology. The current technique correctly classifies 97.2% of galaxies, which is higher than nearly all the techniques considered. In addition, the technique results in very short processing times, averaging 0.37 seconds per galaxy, which would give it an advantage in real-world applications, [1].

Abraham et al (2018) use a deep convolutional neural network to introduce an automated method of detecting the structure of bars in optical images of galaxies. They used a sample of 9346 galaxies in the redshift range 0.009-0.2 of the Sloan Digital Sky Survey, which has 3864 blocked galaxies, the rest being un brayed. Using the trained network, they reached a peak precision of 94 percent to identify the bars in galaxies, [12].

Selim and Abd el aziz (2017), employed a nonnegative matrix factorization algorithm to create an automated supervised machine learning system for the categorization of galaxies. Using two separate datasets of galaxy imaging data, this method was tested. The accuracy of the small data set, which had 110 photos, was roughly 93%. The enormous data set, which had 700 photos, had a 92% accuracy rate, [13].

Abd el aziz et al. (2018) suggested a brand-new machine learning method for classifying galaxies. The method consists of three steps. Gegenbauer moments were used in the first stage to extract properties including scale, rotation, and invariant. As previously said, each of these traits is important. In the second stage, an artificial bee colony (ABC) swarm method is used to choose important attributes. With its few parameters, ABC would quickly reach the overall solution. A support vector machine is used in the third stage to assess the effectiveness of particular characteristics in galaxy categorization. The highest accuracy recorded was 94.6%, [14].

Gonzalez et al. (2018) introduced a model for automatically detecting and classifying galaxies that was built on a fresh data augmentation technique. Deep learning and convolutional neural network techniques are used in the model. Using several datasets, the detection and classification model was trained and had an accuracy rate of roughly 81%, [15].

An automatic galaxy classification technique based on image retrieval was presented by Abd el aziz et al. (2017). This method identifies the type of galaxy present in an image and the majority of related photos. It performed well against the EFIGI catalog, with a 94.2% accuracy rate, [4].

4 THE NON NEGATIVE MATREX FACTPRIZATION ALGORITHM

The nonnegative matrix factorization (NMF) approximates a given nonnegative data matrix

$A \in R^{m\times n}$: $A \approx WH$ by using reduced rank nonnegative factors $W \in R^{m\times k}$ and $H \in R^{k\times n}$ with (problem defendant) $k \ll \min\{m, n\}$.

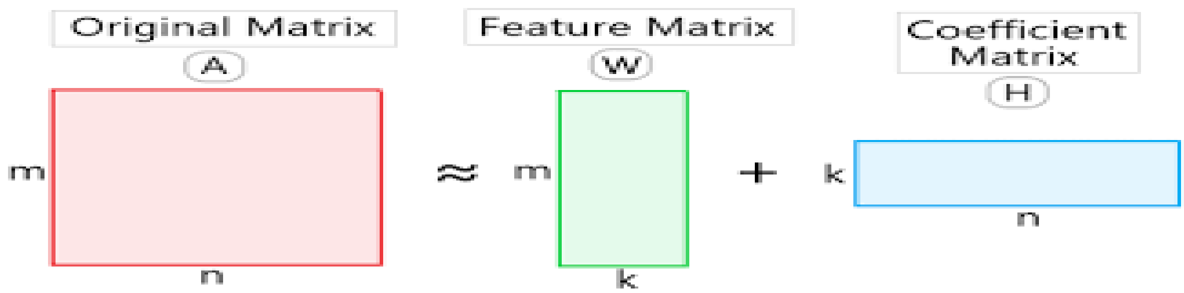

Figure 3. Non negative matrix factorization

The entries in A, W, and H must all be zero or positive in order to satisfy the non-negativity conditions. The product WH is referred to as a nonnegative matrix factorization of A even though it is merely a rough factorization of A of rank at most k.. The non-linear optimization problem underlying NMF can generally be stated as

$$\min_{W,H} \ \mathrm{f}\,(\mathrm{W},\mathrm{H}) = \frac{1}{2}\,\|A - WH\|_f^2 \qquad (1)$$

where ||.|| F is the Frobenius norm ($\|A\|_F = \left(\sum \left|a_{ij}\right|\right)^2)^{\frac{1}{2}}$. Although the Frobenius norm is commonly used to measure the error between the original data A and WH, other measures are also possible, for example, an extension of the Kullback-Leibler divergence to positive matrices, a convergence criterion based on the Karush- Kuhn-Tucker (KKT) conditions, or an angular measure based on the angle θ_i between successive basis vectors $w_i^{(t+1)}$ and $w_i^{(t)}$. The NMF is not unique, in contrast to the SVD, and convergence is not assured for all NMF algorithms. If they do, they often only reach local minima (potentially different ones for different algorithms). Fortunately, it has been established that the data compression obtained using simply local minima is of significant quality for many data mining applications. Due to its non-negativity constraints, NMF produces so-called “additive parts-based” (or “sum-of-parts”) representations of the data (in contrast to many other representations such as SVD, PCA or ICA). This is an important benefit of NMF since it makes the interpretation of the NMF factors much easier than for factors containing positive and negative entries and enables NMF a non-subtractive combination of parts to form a whole. For example, the features in W (called “basis vectors”) may be topics of clusters in textual data, or parts of faces in image data, [16].

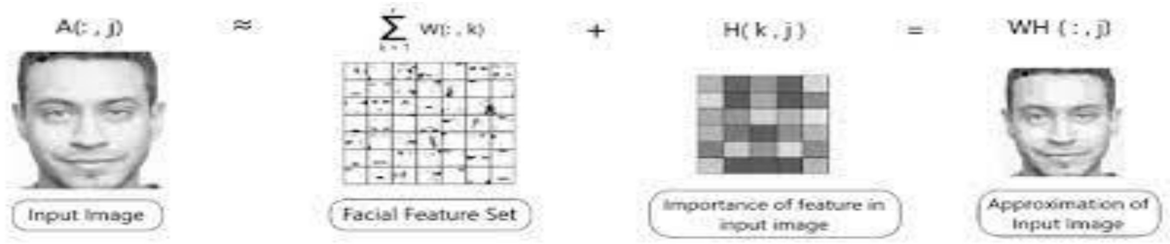

Figure 4. feature extraction by non-negative matrix factorization

5 PROPOSED METHOD

The accuracy of the spiral bar galaxy detection depends on the accuracy of the images itself, the experience of galaxies experts (specialists in galaxies science) and further image processing. It's well known that the noises introduced during the practical image acquisition will greatly affect the accuracy of the classification, so there are many studies and approaches to enhance the accuracy of galaxies classification for un-specialists and reduce the noise on the galaxy images. The task in galaxy image processing involves removing the image background, noise and illustrating the existence of bar in the galaxy. Figure. 3 shows the overall proposed new bar detection proposed method. This method go throw three main tears.

5.1 Nun negative matrix factorization (NMF) normalization.

The *standard-NMF* decomposes a non-negative matrix $\boldsymbol{X} \in \mathrm{R}m\times n$ into two non-negative factors $\boldsymbol{A} \in \mathrm{R}m\times k$ and $\boldsymbol{Y} \in \mathrm{R}k\times n$ (where $k < \min\{m; n\}$), that is

$$\boldsymbol{X}_+ = \boldsymbol{A}_+\boldsymbol{Y}_+ + \boldsymbol{E}$$

Where, E is the error (or residual) and M+ indicates the matrix M is non-negative. Its optimization in the Euclidean space is formulated as

$$\min_{A,Y} \frac{1}{2} \|X - AY\| \frac{2}{F} \text{ , subject to , A, Y } \geq 0.$$

Statistically speaking, this formulation is obtained from the log-likelihood function under the assumption of a Gaussian error. If multivariate data points are arranged in the columns of X, then A is called the basis matrix and Y is called the coefficient matrix; each column of A is thus a basis vector. The interpretation is that each data point is a (sparse) non-negative linear combination of the basis vectors. It is well-known that the optimization objective is a non-convex optimization problem, and thus, block-coordinate descent is the main prescribed optimization technique for such problem, [17].

1- Tear one: Image preprocessing, which includes images resizing to (200 * 200 pixels), rotating, and filtering.

2- Tear two: Image normalization, in which morphological features are extracted using non-negative matrix factorization to minimize the dimensionality of galaxy data.

3- Tear three: Bar Classification procedure using k-nearest neighbors, to classify the images into two categories with-bar and without-bar.

The proposed method algorithm

Input	Galaxy data (Images and labels "With-bar and Without-bar") – Test images
Output	The labels for test images (With-Bar, Without-Bar).
Step 1:	Read Bar-Galaxy data (Images and labels)
Step 2:	Resize the images to 200 * 200 pixel images.
Step 3:	Image filtering to enhance the probabilities of desired pixels.
Step 4:	K-mean clustering with k=7, to cluster the pixels to seven groups.
Step 5:	NNM factorization with 50 iterations
Step 6:	Train KNN with with-bar and without-bar data (W matrix – the result of NNM)
Step 7:	Classify unclassified galaxy images to with-bar and without-bar.

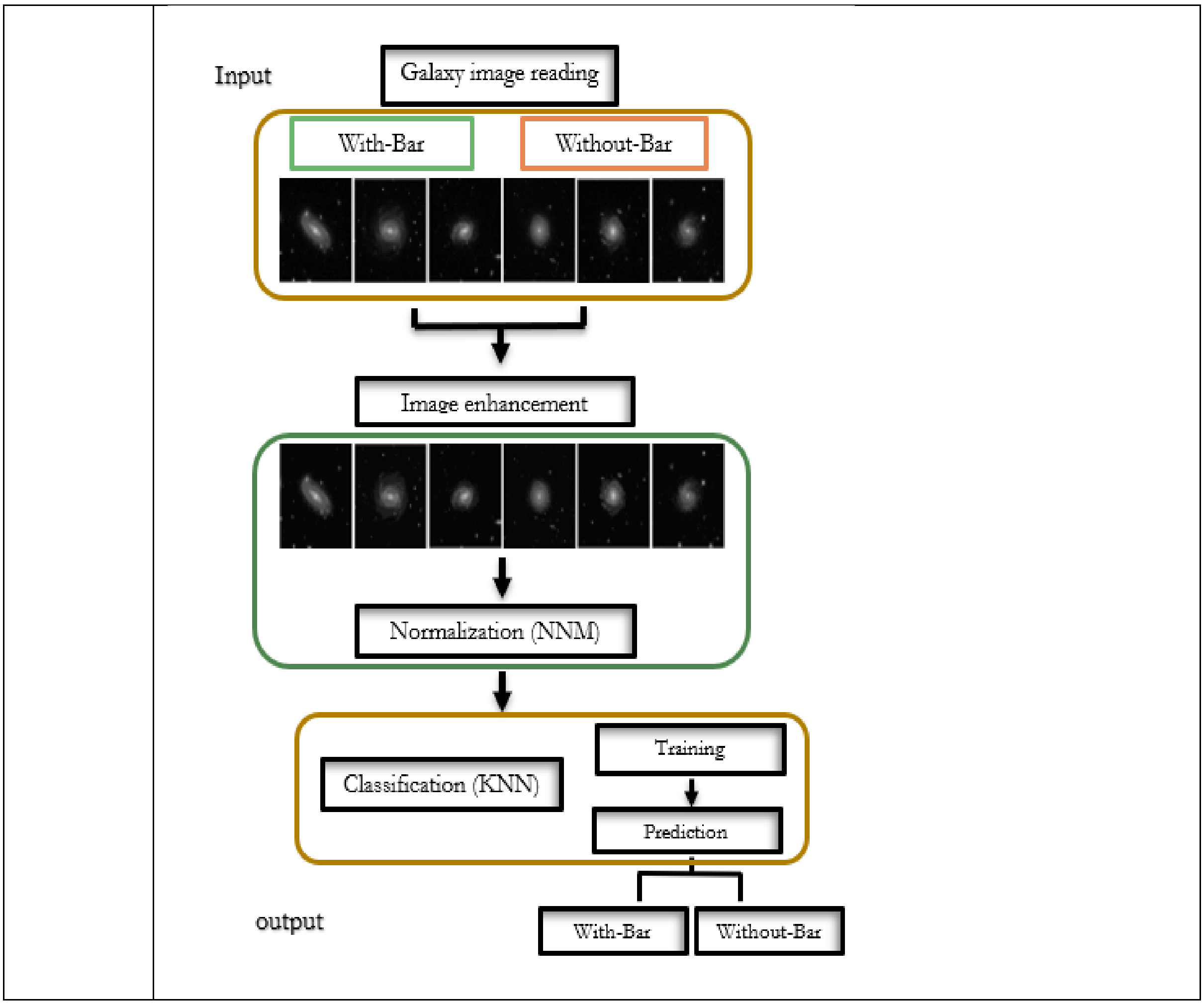

Figure 5. Shows the flowchart of the proposed method

5.2 K-means clustering.

K-means clustering Galaxy images (KMG). Attempt to cluster the pixels of an image into five groups to illustrate the existence of a bar in the galaxy images (we use the parameter k=5 after many experimental attempts). Thus, in KMG, the feature vector is reduced to a single variable in the Euclidean one-dimensional space. The first step of KMG consists of initializing the class label for each pixel and calculating the mean for each cluster, [18].

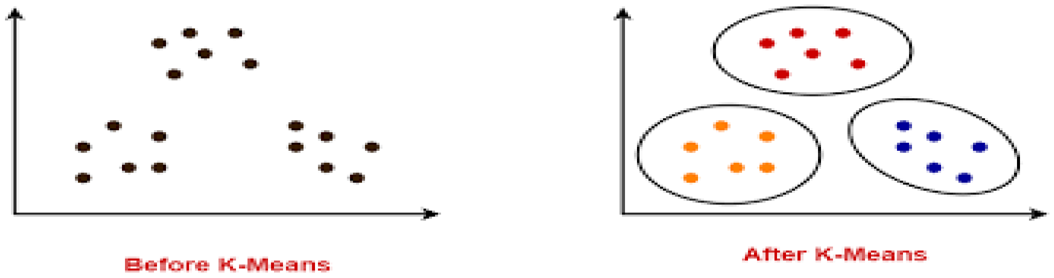

Figure 6 show differences between after and before k mean[18]

K-mean algorithm.

Input	Galaxy image x_i
Output	The clustered galaxy image y_i
Step 1:	For $k = 5$, let x_1 and x_5 be the minimum and maximum values for the intensities in the Galaxy image.
Step 2:	Set $x_{3=}$ x_1/ x_5 , $x_{2=}$ x_1/ x_3 and $x_{4=}$ x_3/ x_5.
Step 3:	If $\lvert x_i – x_2\rvert > \lvert x_i – x_1\rvert$, x_i is labeled "1" else If $\lvert x_i – x_3\rvert > \lvert x_i – x_2\rvert$, x_i is labeled "2" else If $\lvert x_i – x_4\rvert > \lvert x_i – x_3\rvert$, x_i is labeled "3" else If $\lvert x_i – x_5\rvert > \lvert x_i – x_4\rvert$, x_i is labeled "4" else x_i is labeled "5"

5.3 KNN classifying

K-Nearest Neighbor is one of the best Machine Learning calculations based on Administered Learning technique. K-NN calculation accept the closeness between the unused case/data and accessible cases and put the new case into the category that's most comparative to the accessible categories. This calculation stores all the accessible information and classifies a modern information point based on the likeness. This implies when unused information shows up at that point it can be effectively classified into a well suite category by utilizing K- NN algorithm. K-NN calculation can be utilized for Relapse as well as for Classification but mostly it is utilized for the Classification problems. K-NN may be a non-parametric calculation, which implies it does not make any presumption on basic data. KNN calculation at the training phase fair stores the dataset and when it gets unused information, at that point it classifies that information into a category that's much comparative to the unused data, [19-20].

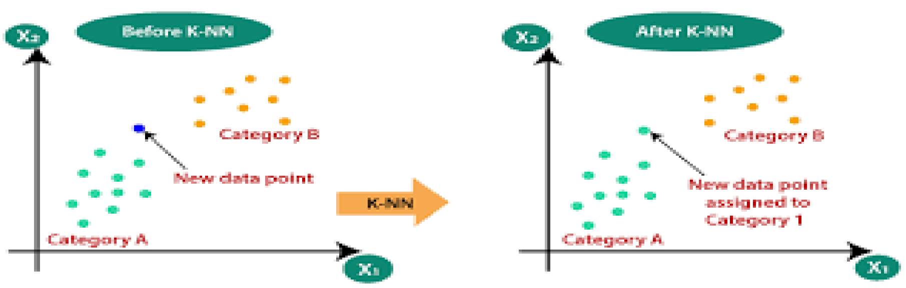

Figure 7. show how k-nn work

KNN algorithm

Input	Galaxy image x_i
Output	The result of classification process (With- Bar or Without-Bar)
Step 1:	Determine the number of the neighbors (K =8).
Step 2:	Calculate the Euclidean distance of eight neighbors
Step 3:	Select the nearest eight neighbors.
Step 4:	Count the number of the data points in each category.
Step 5:	Assign the new image to that category for which the number of the neighbor is maximum.

6 EXPREMANTEL RESULTS

Datasets

Two hundred sixty of spiral galaxy images with-bar and without-bar from the National Research Institute of Astronomy and Geophysics (NRIA) are employed for the evaluation of the proposed technique. The following table 1 describe the probertites of the galaxy database (One hundred images of type with-bar, One hundred images of type without-bar and sixty images for test). Hence the original images have different sizes, we resize all the images to 200*200 pixels.

Table 1: The properties of the galaxy database.

	Image Name	Size of Original Image	Label
1	fpC-000752-40-5-0462-0275.jpg	242 * 242 Pixel	With-Bar
2	fpC-000752-40-6-0359-0074.jpg	678 * 678 pixel	With-Bar
3	fpC-000752-40-6-0489-0232.jpg	484 * 484 pixel	With-Bar
4	fpC-000756-44-1-0462-0029.jpg	318 * 318 pixel	With-Bar
5	fpC-000756-44-1-0464-0057.jpg	320 * 320 pixel	With-Bar
6	fpC-000752-40-4-0315-0061.jpg	264 * 264 pixel	Without-Bar
7	fpC-000756-44-1-0333-0132.jpg	374 * 374 pixel	Without-Bar

8	fpC-000756-44-2-0311-0025.jpg	328 * 328 pixel	Without-Bar
9	fpC-000756-44-2-0552-0161.jpg	322 * 322 pixel	Without-Bar
10	fpC-000756-44-4-0565-0192.jpg	368 * 368 pixel	Without-Bar
11	fpC-000756-44-6-0590-0191.jpg	270 * 270 Pixel	unknown
12	fpC-000756-44-2-0729-0184.jpg	314 * 314 pixel	unknown
13	fpC-000756-44-4-0265-0062.jpg	574 * 574 pixel	unknown
14	fpC-001035-40-3-0077-0254.jpg	328 * 328 pixel	unknown
15	fpC-001140-40-2-0264-0162.jpg	228 * 228 pixel	unknown

The previous table 1 present five images from one hundred of type with-bar, five images from one hundred of type without-bar and five images from sixty test images. The sixty test images divided to twenty images of type with-bar, twenty images of type without-bar and twenty images of unknown types.

The description of the databases used to evaluate our model is presented in table 1. All of these images were resized to 200 * 200 pixels, then each image clustered to five regions using K-mean algorithm, the output of KNN applied to NMF to extract a list of features for galaxy images based on some nonnegative constraints are imposed. Therefore, the image can be reconstructed from this list of these features. Finally, the images classified to With-Bar and Without-Bar images using KNN. The following two tables present the accuracy of our proposed method using the K-mean algorithm and without it and figure (8) show that.

Table 2: the accuracy of bar detection using our proposed method

	No. of galaxies	Accurately classified	Accurately classified	Accuracy
Bared spiral gal	600	584	16	97.3%
Non bared	400	389	11	97.25%
total	1000	973	27	97.3%

Table 3 :the accuracy of bar detection without using k means

	No. of galaxies	Accurately classified	Accurately classified	Accuracy
bared spiral gal	600	557	43	92.8%
Non bared	400	368	32	92%
total	1000	925	75	92.5%

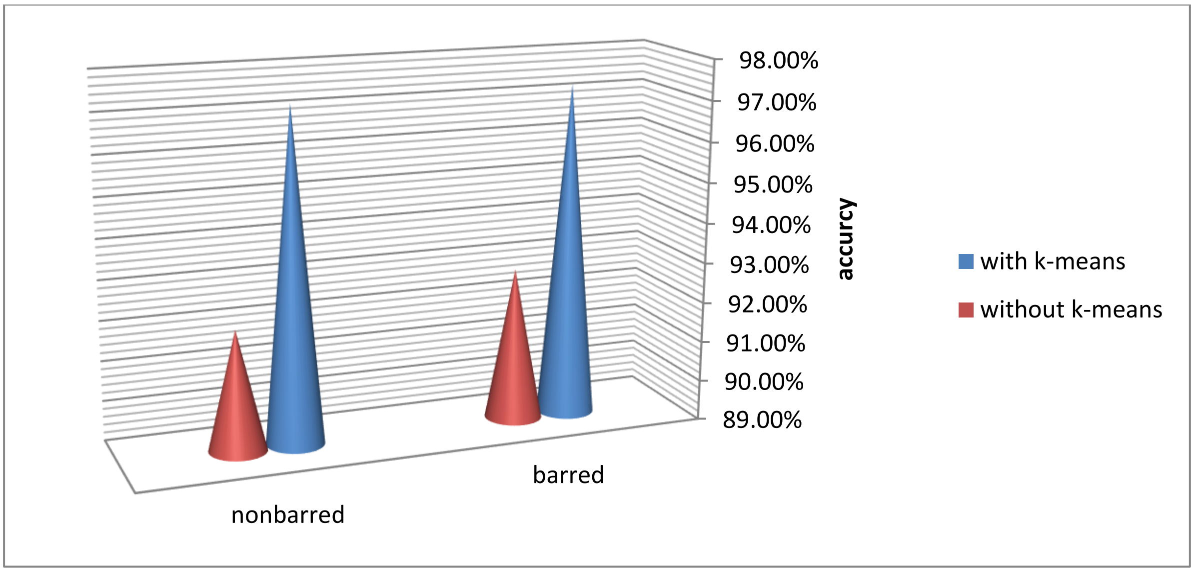

Figure 8. show the accuracy of using k means and without using k means

K-means algorithm hybrid with NMF algorithm to enhance the quality of reconstructed images, Hence the result of classification using the hybrid algorithm is better than other methods.

Our proposed algorithm has been compared with previous bar detection method shown in table 3.

Table 4: Comparative results for galaxy classifications

Related work	Year	Employed technique	Accuracy
P.A. Patsis	2009	Chaos	92%
C. Garcia-Gómez	2017	Fourier analysis	95%
Abraham	2018	a Deep Convolutional Neural Network	94%
Our model	2022	K means and nmf	97.3%

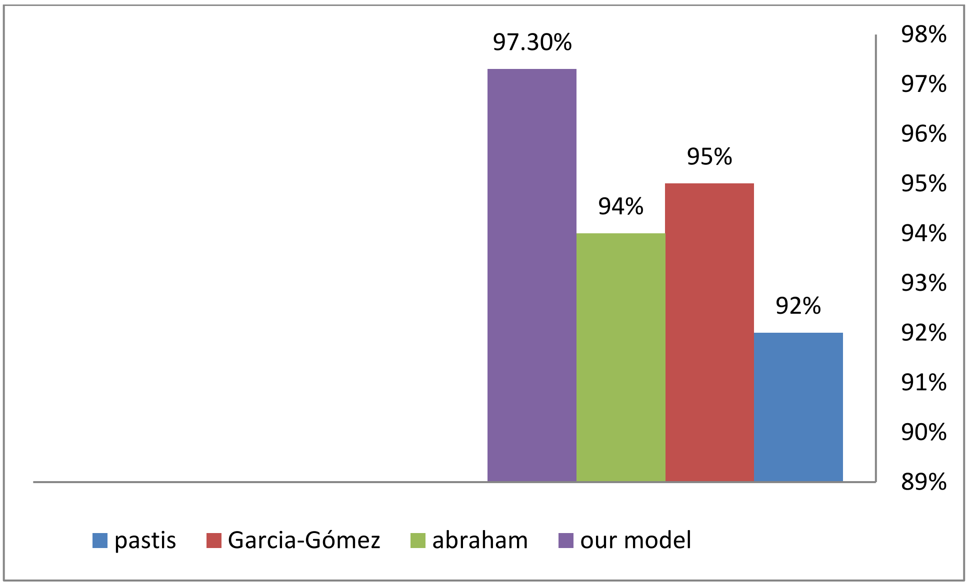

Figure 9. show accuracy of our model and previous method

7- CONCLUSION

We have shown the benefit of a non-negative matrix factorization algorithm for detecting bars in galaxies from SDSS images with a top precision of 97.3 percent. The main advantage of using a non-negative matrix factorization algorithm extraction of features from the raw images. With a base sample size of a few thousand, we have made use of the rotated images of example galaxies to generate the large amount of data required for training the model. We were able to train the model to high accuracy. In this study, we have not attempted to classify the different types of galaxies. We are detecting bar in spiral galaxies .Even though the samples used in this study mainly consisted of a mixture of strong, weak, and short barred galaxies, our algorithm was able to determine the presence and absence of bar in spiral galaxies.

Another advantage of the Non-negative matrix factorization is that this same model cans be used as a feature extractor for studying the different types of bars. Also, the model can be retrained to detect those specie types without the need of having a large training set. This kind of retraining is often known as transfer learning.

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