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Article

Automated classification of nebulae using deep learning & machine learning for enhanced discovery

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SUMMARY

There are believed to be ~20,000 nebulae in the Milky Way Galaxy. However, humans have only cataloged ~1,800 of them even though we have gathered 1.3 million nebula images. Resources like the Hubble telescope can automatically explore space, discover new artifacts, and capture new images. Still, their classification is a human skill, which ultimately is interminable and subject to human error. Classification is important as it helps scientists understand the chemical composition of a nebula which in turn helps them understand the material of the original star. Our research on nebulae classification aims to make the process of classifying new nebulae faster and more accurate using a hybrid of deep learning and machine learning techniques. Our hypothesis is that the application of machine learning and deep learning methodologies effectively classifies nebulae based on images. Using a dataset primarily of images from the European Space Agency, we experimented with a range of artificial intelligence techniques such as featurization and color conversion and then determined the deep learning network/ machine learning algorithms that produced the best results. The main conclusions reached from our research were that (a) the artificial intelligence (AI) was not dependent on color to classify nebulae, (b) dropping specific categories increased accuracy, and (c) featurization is the most effective technique to classify nebulae accurately. Automated classification of nebulae will help us discover, identify, and classify these marvels much faster and more accurately to expand our understanding of nebulae.

INTRODUCTION

For much of history, humans have marveled at astronomical bodies in the night sky. The universe is a vast mystery about which we still know little, but we continue to learn more about it everyday thanks to new and more advanced technologies. Since the Hubble telescope mission started in 1990, over 1.5 million observations have been made (1). In addition, there are believed to be around 20,000 nebulae in the Milky Way Galaxy, but only 1,800 of them have been cataloged (2). Telescopic resources like the Hubble telescope can automatically explore different areas of space and discover new artifacts including nebulae. Nevertheless, the nebulae categorization process remains a human endeavor, inherently susceptible to the potential for human inaccuracies. Classification remains a barrier to achieving higher levels of automation in this field. Although there are not any specific studies regarding human error in misclassification of nebulae, human labeling of data is often prone to mistakes as demonstrated in medicine (3).

In addition, comprehensive and accurately labeled datasets are fundamental for training these artificial intelligence models effectively. However, the scarcity of such extensive and precise data specifically tailored for nebulae poses a challenge.

Classifying nebulae helps scientists gain a clearer understanding of their chemical composition, contributing to a more comprehensive knowledge of the materials present in the original star. (4). The presence of certain elements such as carbon or nitrogen can reveal details about the processes within a star during its lifetime (4). In addition, the makeup of a nebula can contain critical information about potential life on other planets (5). Recently, the Orion Nebula helped scientists learn that the abundance and distribution of phosphorus (an essential element for life) are more random than we thought (5).

Each nebula possesses unique visual attributes that permit classification into five main categories: planetary, supernova remnants, emission, reflection, and dark (6). The variations in these visual characteristics stem from the diverse types of gases released by the expiring star, leading to distinct light emissions in each nebula category (6). Emission nebulae, such as Orion, are formed of ionized gases emitting light of notably red/pink tints, with high-temperature gas clouds ranging from 100-10,000 solar masses and temperatures up to 20,000 K (6). Supernova remnants, expanding ionized gas shells, are left behind after the dramatic end of a massive star (6). Reflection nebulae, with blue/gray colors from Rayleigh scattering, do not create their own light but reflect light from nearby stars, bright enough to illuminate the surrounding dust (6). Dark nebulae are interstellar clouds with high dust concentrations, often present in star-rich regions (6). Made of hydrogen molecules, water, and carbon dust, these nebulae are dense enough to obscure visible wavelengths of light from objects behind them (6). These nebulae are characterized by their irregular formations and temperature range from 10-100 Kelvin (6). Planetary nebulae, created when a star blows off its outer layers, are often in a ring or bubble shape (6). Consisting of hydrogen, helium, and oxygen, these nebulae are observed in more distant galaxies, yielding valuable information about their chemical abundances and the sun's life (6).

Neural networks are a crucial component of the research due to their ability to discern intricate patterns and relationships within complex datasets (7). Their use allows for the automated recognition of nuanced characteristics and variations in nebulae, aiding in more precise and efficient

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classification. They are a series of algorithms that attempt to recognize underlying relationships in a dataset by mimicking how the brain works (7). Some parts of neural networks include neurons, hidden layers, output layers, and synapses (7). Neurons take the output one or more layers behind of it and apply a weight to this input (8). Hidden layers are between input and output layers, where neurons take in a set of weighted inputs and produce an output (8). The output layer is the last layer of neurons that makes the output (8). Lastly, synapses connect neurons and layers in a neural network, similar to how synapses work in our brains (8).

For nebulae, prior research is limited to the classification of specific nebula types. For instance, a planetary classification model using a Bayesian neural network has been created (9). Planetary nebulae have been classified using tree modeling and deep transfer learning (10-11). Our experiments deal with a specific astronomical body (nebulae), while most previously held research is broader. Focusing on nebulae specifically allow for a more detailed and comprehensive analysis of these intricate celestial bodies, aiming to deepen our understanding of their unique characteristics and potentially contribute specialized insights to the field of astronomy.

The goal of our research is to make the process of classifying nebulae more efficient and accurate. Our hypothesis is that machine learning and deep learning techniques can effectively classify nebulae from images. To evaluate our hypothesis, we assembled a dataset consisting of five categories of nebulae and evaluated a mix of deep learning and machine learning with featurization techniques and color conversion, using accuracy as the metric of effectiveness. By utilizing advanced featurization methods and a diverse dataset, we explored how these methods can enhance the accuracy and efficiency of nebulae categorization. Initial findings suggested that color independence, selective category omission, and featurization considerably improve classification accuracy. The subsequent sections will delve into a detailed analysis of the methodology and results, focusing on the exploration and assessment of machine learning and deep learning techniques for the classification of nebulae, providing a clearer understanding of their efficacy and potential implications.

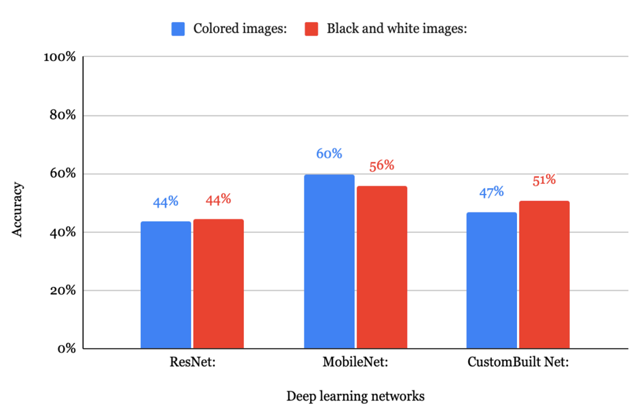

Figure 1: Deep Learning Network Color Conversion Results. Accuracy of ResNet, MobileNet, and CustomBuilt Network for colored images v.s. black and white images. Blue indicates colored images, Red indicates the black and white images. The accuracy is displayed above each bar. Color conversion experiment is shown where we analyzed the effect of changing the color of the nebula images for the deep learning networks.

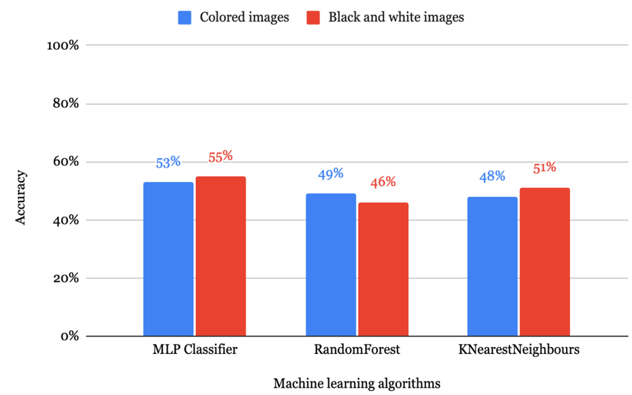

Figure 2: Machine Learning Algorithms Color Conversion Results. Accuracy of MLP Classifier, RandomForest, and KNearestNeighbours for colored images v.s. black and white images. Blue indicates colored images, Red indicates the black and white images. The accuracy is displayed above each bar. Color conversion experiment is shown where we analyzed the effect of changing the color of the nebula images for the machine learning networks.

RESULTS

We first investigated the effect of color conversion to black and white on accuracy of the neural networks and algorithms. Accuracy is the number of correctly predicted images divided by the total number of images. These accuracies are after tuning the hyperparameters with all five categories; ResNet50 improved its accuracy with the gray images (+0.71%), MobileNetV2's accuracy decreased (-3.94%), and the custom-built network's accuracy improved (+4.05%) (**Figure 1**). MLP Classifier's accuracy improved with gray images (+1.36%), Random Forest's accraucy decreased a little (-3.02%), and KNearestNeighbours improved its accuracy (+3.25%) (**Figure 2**). Since the range of accuracy is a hundred, these accuracy differences are relatively small. These were the best accuracies after manipulating hyperparameters. The experiment that converted images to black and white was able

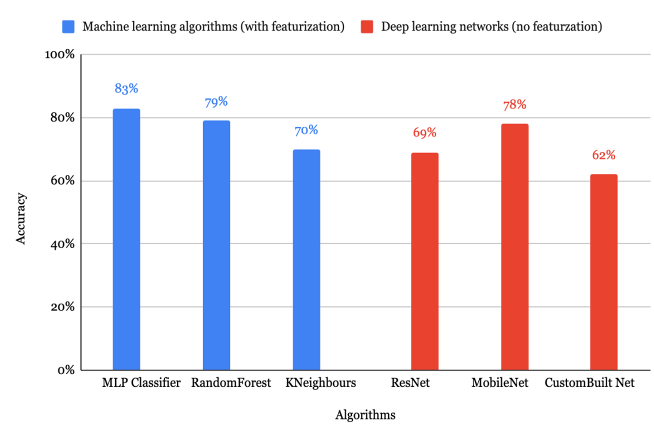

Figure 3: Machine learning algorithms v.s. deep learning networks performance. Accuracy of MLP Classifier, RandomForest, and KNearestNeighbours, ResNet, MobileNet, CustomBuilt Net. Red indicates a deep learning network (no featurization) and blue indicates a machine learning algorithm (featurization applied). The accuracy of each model is displayed above the bar. The featurization experiment is shown where we analyzed the effect of featurization on images, allowing us to use machine learning algorithms. All models were trained on colored images.

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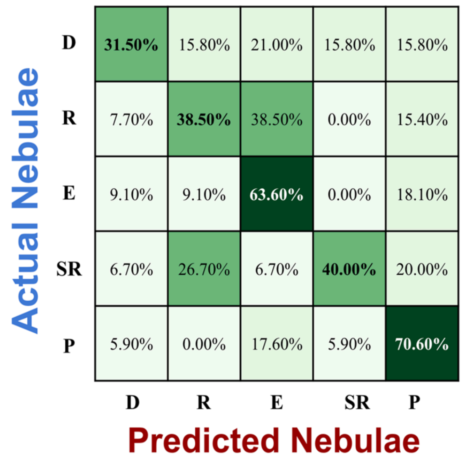

Figure 4: Confusion Matrix. Confusion matrix of KNeighboursClassifier of featurized, colored images. D stands for dark nebulae, R for reflection nebulae, E for emission nebulae, SR for supernova remnants, and P for planetary nebulae. The percentage for each box indicates the percent of times the model predicted the indicated category was incorrect.

to show us that the artificial intelligence was not dependent on the color of the images to classify a nebula.

Next, we featurized the images, which is a technique utilized to use machine learning algorithms, by converting the images into vectors. We compared the accuracies of the machine learning algorithms and deep learning networks after removing the poor performing categories, which is elaborated upon in greater detail in the subsequent section (**Figure 3**). We observed improvement in accuracy with featurization. The best accuracy in the neural network was 78%, and after featurization with machine learning algorithms, it increased significantly (+5).

Finally, we used a confusion matrix to analyze the specifications of performance. A confusion matrix, a visual representation of the performance of a classification mode, provides a comprehensive picture of how well the model has predicted different classes within a dataset. Upon close inspection, we noticed the confusion matrix was beneficial as it showed us the first and second rows seem to be random guessing (**Figure 4**). The rows represent the valid values, while the columns represent the predicted values. The dark category is the 1st row. We observed the artificial intelligence only predicted that it was a dark nebula 6 out of 16 times. Similarly in the reflection category (second row), we noticed our artificial intelligence model only predicted a reflection nebula 5 out of 13. The model only predicted about 37% for these two categories correctly. Knowing this, we dropped the two randomly guessing categories, and models rerun without them to see how the accuracy would be affected. In the machine learning models, MLP Classifier and Random Forest's accuacies improved by 30%, while KNearestNeighbours' accuracy improved by 22% (**Figure 5**). In the deep learning networks, ResNet's accuracy improved by 25%, MobileNet's accuracy increased by 18%, and the custom-built network's accuracy improved by 15% (**Figure 5**).

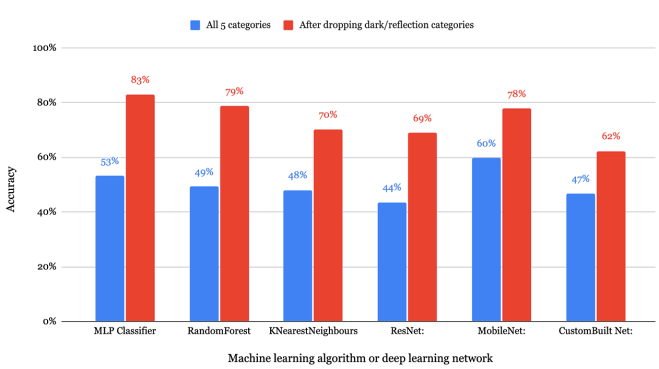

Figure 5: Dropping categories results. Accuracy of MLP Classifier, RandomForest, and KNearestNeighbours, ResNet, MobileNet, CustomBuilt Net. Blue indicates the model was trained with all 5 categories while red indicates the model was trained after dropping the dark and reflection categories). The accuracy of each model is displayed above the bar. The dropping categories experiment is shown where we analyzed the effect of dropping the two problematic categories. All models were trained on colored images.

DISCUSSION

Our study aimed to expedite and enhance the accuracy of nebulae classification through the fusion of machine learning and deep learning techniques applied to image data. The central question of our research revolved around whether a hybrid AI approach could efficiently categorize nebulae based on images and whether specific methodologies within this hybrid model would notably impact classification accuracy. Utilizing a dataset primarily sourced from the European Space Agency, we conducted a series of experiments, implementing various artificial intelligence techniques, such as featurization and color conversion, to discern the optimal approach for accurate classification. The overarching conclusions drawn from this research are twofold. Firstly, the successful application of machine learning and deep learning techniques in nebulae classification substantiates the potential of AI in swiftly and accurately categorizing celestial objects, thereby expediting scientific exploration in astronomy. Secondly, the discovered insights regarding color independence, category selection, and the effectiveness of featurization not only optimize the current classification process but also lay a foundation for future studies to refine and advance AI methodologies in classifying nebulae.

The machine learning and deep learning techniques utilized in our research reached the best accuracy of predicting nebula of 82.97%, showing that it is possible to effectively classify nebulae from images with artificial intelligence, confirming our hypothesis. Beyond this, the results revealed several observations.

The first conclusion from our research that can be made is that artificial intelligence is not dependent on the color of the nebula images to classify it. Our research on the different nebulae revealed that some nebulae had a certain luminosity or color associated with them. The research investigated whether the artificial intelligence was only dependent on color to classify or whether it had identified other features to distinguished. The validation accuracies for the black/white and colored datasets were about the same. The black and white experiment was not an effective technique to increase the effectiveness of the artificial intelligence. Secondly, we learned that dropping specific categories was beneficial overall. The artificial intelligence was not able to classify the

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dark and reflection nebulae. This may be because there were few features that distinguished these nebulae. Reflection and dark nebulae may also require more information than a picture to classify them, such as wavelengths of the light coming out of them.

Lastly, the main observation that can be reached from the research is that the featurization of images is the most effective technique at improving performance. The assertion that image featurization stands as the most effective technique stems from its capacity to capture intricate visual patterns and convert them into a format understandable to machine learning algorithms. It's the extraction of these complex visual elements that facilitates a more robust and accurate classification, offering a plausible explanation for why featurization emerged as the most effective technique in our research. The technique of using featurization and dropping the two problematic categories, dark and reflection, led to a maximum accuracy of a 82.97% using MLP Classifier. The metric table includes the validation accuracy, precision, recall, and F1 (combination of precision and recall) of many different combinations of dropping categories and featurization (**Table 1**).

However, our research does not come without limitations. One significant limitation is the reliance on enhanced images for analysis, as opposed to utilizing raw images captured directly by telescopes. These telescopes possess the capability to capture light beyond the visible spectrum, which may contain valuable information for nebula classification. By using processed images, we may limit the richness of data available to our tool. This limitation highlights the importance of further exploration into the integration of raw telescope images into our classification framework, potentially enhancing the power and accuracy of our tool. Another limitation is the decision to drop two specific categories during model training

	Accuracy	Precision	Recall	F1
ResNet50 - All categories	43.55%	52.5%	38.33%	45.4%
MobileNetV2 - All Categories	59.68%	61.02%	57.92%	59.47%
Custom Built Net - All Categories	46.77%	44.19%	53.85%	49.02%
MLP Classifier - All categories	53.33%	52.03%	53.06%	52.55%
Random Forest - All Categories	49.33%	50.98%	50.01%	50.49%
KNN - All Categories	48.00%	49.44%	46.21%	47.83%
ResNet50 - Dropped Categories	68.89%	77.47%	63.83%	70.65%
MobileNetV2 - Dropped Categories	77.78%	79.23%	74.17%	76.70%
Custom Built Net - Dropped Categories	62.22%	64.11%	62.13%	63.12%
MLP Classifier - Dropped Categories	82.97%	85.33%	80.14%	82.73%
Random Forest - Dropped Categories	78.72%	79.54%	77.20%	78.37%
KNN - Dropped Categories	70.21%	70.42%	69.69%	70.05%

Table 1: Summary of machine learning and neural networks performance. Shows the metrics across dropping category experiments (before v.s. after dropping categories) in both machine learning algorithms and deep learning networks.

to improve overall performance. While this approach led to higher accuracy rates (from ~40% to ~80%), it also means that our tool cannot be applied universally to the complete set of nebulae images. This limitation necessitates consideration of strategies for incorporating these excluded categories into future iterations of our model.

Our research holds promising implications in the vast field of astronomy, especially in the context of the evolution of telescopic instrumentation. The Hubble telescope has been reported to decay by mid-2030 (12). Our study, focused on aiding the classification of nebulae through a hybrid of deep learning and machine learning techniques, offers a versatile framework that is inherently adaptable. It represents a step toward promoting further research in the application of machine learning and deep learning in nebulae classification. By incorporating these classification techniques into the next generation of astronomical endeavors, we help to bridge the gap between the capabilities of existing instruments and the rapid discovery, identification, and classification of the hundreds of marvelous nebulae waiting to be discovered.

Several studies have explored the application of artificial intelligence in space object classification from galaxies to stars to planets. The work of Dang Pham demonstrated the use of machine learning in color classification of Earth-like planets (13). Similarly, Moonzarin Reza utilized neural networks for galaxy morphology classification showing the potential of automated techniques in handling extensive astronomical datasets (14).

Drawing parallels to existing research, our research aligns with the trend of astronomical research leveraging artificial intelligence for efficient and accurate classification. The successful application of machine learning and deep learning techniques in nebula classification confirms the potential of artificial intelligence in categorizing celestial objects. Further engagement with related works and methodologies with foster further advancements in astronomy.

MATERIALS AND METHODS

Approach

The approach undertaken in the research is depicted (**Figure 6**). First, we collected nebula image data. Next, we either featurized the images, converted the images to black and white, or directly applied deep learning algorithms. After featurizing the photos, machine learning algorithms (MLP Classifier, KNearestNeighbours, RandomForest) can be used to classify the nebulae. Converting the images to black and white was an experiment and afterwards, we trained the images using the deep learning neural networks or machine learning algorithms. Next, we dropped categories as necessary and tuned the hyperparameters. Lastly, we observed and evaluated the results by using the testing dataset to look at the validation accuracy and confusion matrices, tables to show exact performance across categories.

Data

Data collection was the first step. The data consisted of a massive variety of nebulae across the five categories: emission, dark, reflection, supernova remnants, and planetary. Data was gathered from the European Space Agency (ESA) (15). The website consisted of many nebula images taken by the Hubble Telescope and documented the nebula type. This was insufficient data, so more images were collected

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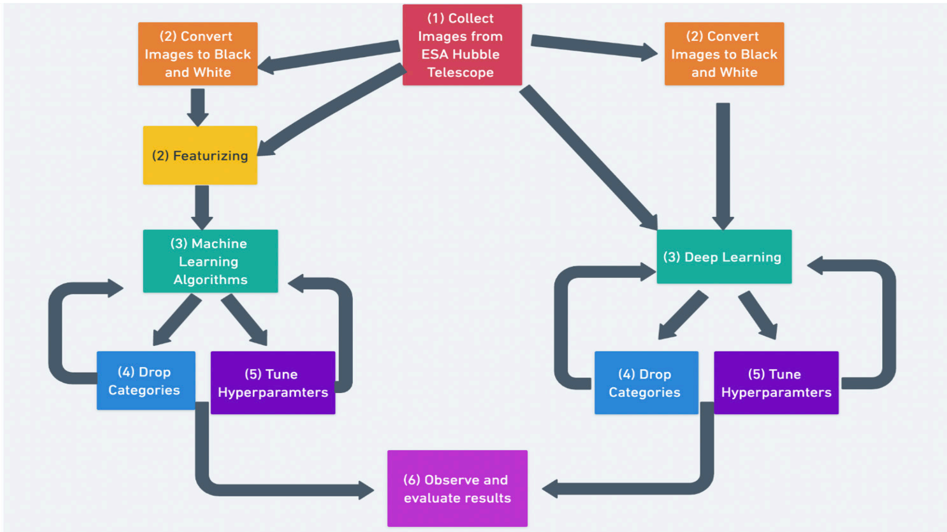

Figure 6: Flowchart of the research methodology. The first was collecting images from the ESA Hubble Telescope. We converted the images to black and white. We then applied featurization for machine learning algorithms. We trained the deep learning models and the machine learning algorithms. We dropped categories and tuned hyperparameters and rerun the deep learning networks and machine learning algorithms. Lastly, we observed and evaluated the results.

from Google Images. When collecting Google images, it was essential to ensure that it was the correct category by checking the source because otherwise, the data would be inaccurate. Around 80% of the data was collected from the ESA and only 20% from other miscellaneous sources. All images were converted to 224 by 224 pixels before training.

The frequency table shows about 70-80 images for each type of nebula (dark, reflection, emission, planetary, supernova remnants), with a total of 376 unique nebula images (**Table 2**). It was critical to have approximately the same number of pictures for each category so the artificial intelligence would not be biased toward one class. In addition, there had to be sufficient images for the artificial intelligence to learn about every category. 80% of the data was used for training the artificial intelligence, while the remaining 20% was used for testing. N-fold cross validation was used using sklearn's StratifiedKFold.

Color Conversion

Raw nebula images are typically originally black and white and then color is added for visual effects. We converted the images to black and white to determine the effect on the AI's effectiveness in classifying nebulae using the python PIL library.

Type of Nebula	# of Nebula of That Type in the Dataset
Dark	68
Reflection	72
Emission	72
Planetary	78
Supernova Remnants	86

Table 2: Number of images in each category of nebula.

Featurization

Featurizing images involves extracting essential visual patterns or characteristics from the images, which are transformed into a high-dimensional representation. In our study, this process utilized a pre-trained MobileNetV2 model, which converts the images into a 1280-dimensional vector or image representation. These 'features' extracted from the images could encompass complex visual elements, such as edges, textures, shapes, or higher-level concepts within the image. These features, when translated into a numerical format, allow us to apply various machine learning algorithms, enabling the computer to 'understand' and classify images based on these extracted visual patterns. Featurization was utilized to effectively use relatively small sets of labeled images that would not be sufficient to train a deep network from scratch (16). The featurization took a base model (MobileNetV2) that was previously trained using ImageNet and then added the global average pooling layer. Unlike ResNet50 and MobileNetV2, however, the softmax was not added. The featurization took the output of the MobileNetV2 (2400 values), and instead of converting it into the five categories of prediction, it took the intermediate values and used that as a feature vector for the machine learning algorithms.

Dropping Categories

A confusion matrix is a specific table layout that visualizes the performance of a machine learning classification model by showcasing the model's predictions and their alignment with the actual data. It organizes and displays the model's classification outcomes, detailing the number of correct and incorrect predictions for each class within a dataset. Essentially, it provides insight into the model's accuracy by showing the relationship between predicted and actual classifications, enabling a detailed evaluation of the model's performance. In the context of our research, the confusion matrix serves as a crucial tool to assess the accuracy and effectiveness of our classification methods for different types

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of nebulae, helping us analyze and refine the performance of our machine learning models in categorizing these celestial objects accurately.

The decision to drop a category was determined by analyzing that particular category's confusion matrix row. Checking the row and how often it was incorrectly predicted as another category indicated whether the model was randomly guessing for that category. Algorithms and neural networks were rerun after dropping categories. The decision to drop a specific category was based on a comprehensive analysis of that category's confusion matrix row obtained during the evaluation of the model's predictions. Upon observing frequent incorrect predictions for that category, indicated by a high number of misclassifications as another category, it suggested potential ambiguity or randomness in the model's predictions for that particular class. As a result, to refine the model's performance and accuracy, we made the decision to exclude that specific category from further analysis and re-ran the algorithms and neural networks.

Algorithms

There are many different deep learning networks, but we focused on MobileNetV2, ResNet50, and a custom-built one. These specific neural networks, MobileNetV2 and ResNet50, were chosen for their established performance in image classification tasks and their balance between accuracy and computational efficiency, while a custom-built network was developed to address the specific complexities of the nebulae dataset. MobileNetV2 is a convolutional neural network that is 53 layers deep (17). MobileNetV2 is unique because it has very little computation power to run or apply transfer learning. ResNet50 50 V2 (residual network) is a specific neural network that uses 50-layer and significantly enhances the performance of neural networks with more layers (17) The custom-built network is different from ResNet50 and MobileNetV2 as there is no pre-trained model, to begin with. The custom neural network was a sequential model consisting of three convolutional layers followed by a single dense layer. The final layer of the network was softmax with five neurons, one for each category.

MLP Classifier (Multi-layer Perceptron classifier) is a machine learning algorithm that relies on an underlying fully connected Neural Network to perform the task of classification (18). It is notably more straightforward than the neural networks described above. KNearestNeighbours is a classification technique that takes the k neighbors data points to determine the category. Lastly, RandomForest uses many decision trees to predict a class.

We used TensorFlow and Scikit Learn run in Google Collab. TensorFlow is a software library used typically for deep learning algorithms such as ResNet50 and MobileNetV2 (19). The use of TensorFlow in the code is to create a plethora of deep learning neural networks to classify nebulae. Scikit Learn is another valuable library for machine learning algorithms (20). The use of Scikit Learn in the code is to run various machine learning algorithms after the featurization of the images to classify nebulae. Code used for analysis is available on GitHub (21). In addition, some machine learning algorithms (Multilayer Perceptron Classifier, KNearestNeighbours, RandomForest) were run in Amazon Web Services (AWS) as well.

ResNet50	MobileNetV2	Custom Built Net	MLP Classifier	KNeighbours	Random Forest
Batch Size: 45	Batch Size: 40	Batch Size: 40	Hidden layers: 140	k: 20	Num trees = 20
Epochs: 50	Epochs: 45	Epochs: 45	Max Iterations: 200		Max Depth = 5
Learning rate: 0.0007	Learning rate: 0.001	Learning rate: 0.007	Learning Rate: 0.007		
Accuracy: 68.89%	Accuracy: 77.78%	Accuracy: 62.22%	Accuracy: 82.97%	Accuracy: 70.21%	Accuracy 78.72%

Table 3: Best hyperparameters for the colored images and the featurized colored images

Hyperparameters

There are unique hyperparameters for all the different neural networks and algorithms. The primary hyperparameters we manipulated in the deep learning networks are the batch size, learning rate, and epochs. The batch size was kept around 30-40 images per batch, the learning rate was usually around 0.0001 to 0.007, and the epochs were around 40-50 (a full cycle of dataset in units of batch size).

For MLP classifiers, the primary hyperparameters were the hidden layers and the learning rate. The hidden layers were around 150 to 225, while the learning rate spanned from 0.0001-0.0005. In KNearestNeighbours, the only hyperparameter used is k (the number of nearest neighbors to use for making predictions). The range for k we used was around 16 to 35 neighbors. Lastly, RandomForest takes in the number of trees and an optional hyperparameter, maximum depth. The num_trees spanned from around 20 to 80 trees. Playing around with the hyperparameters helped me achieve the best possible results. The hyperparameter shows the best hyperparameters for the colored images and the featurized colored images (**Table 3**).

Tuning and Metrics

The confusion matrix helps determine the effectiveness of an algorithm or neural network. The confusion matrix of an algorithm can tell us information about how it is performing. Looking at the rows helps identify where an algorithm may be predicting for a particular category. This can help us determine whether to drop a category or not.

Another method is to adjust hyperparameters to achieve the best validation accuracy. There are many different hyperparameters that depend on the neural network/algorithm used. Previous hyperparameters were kept track of to do this most effectively.

The metric in the research is validation accuracy. It's a percentage indicating how well artificial intelligence could classify new images. We also noted the precision, recall, and F1 scores of the performance. It's also helpful to distinguish which categories are performing well.

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