A Learning-Oriented AI Framework for Identifying Basic Galaxy Morphologies from Small-Telescope Images

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Abstract - Understanding galaxy morphology is a critical part of extragalactic astronomy. However, most students study galaxies only through professional images rather than the data they collect themselves by doing research. This research paper presents a learning-based framework that uses artificial intelligence to help students identify basic galaxy types from images captured with small, low-cost telescopes or from publicly available sky data. This system uses broad categories such as spiral, elliptical, and irregular galaxies and provides simple explanations rather than high-precision scientific labels. The goal isn't automated discovery, but guided learning that helps students connect real data with galactic structure concepts. This paper describes the system design, classification approach, educational focus, and limitations. The research indicates that simplified AI-assisted analysis can facilitate an early understanding of galaxy morphology without supplanting human interpretation.

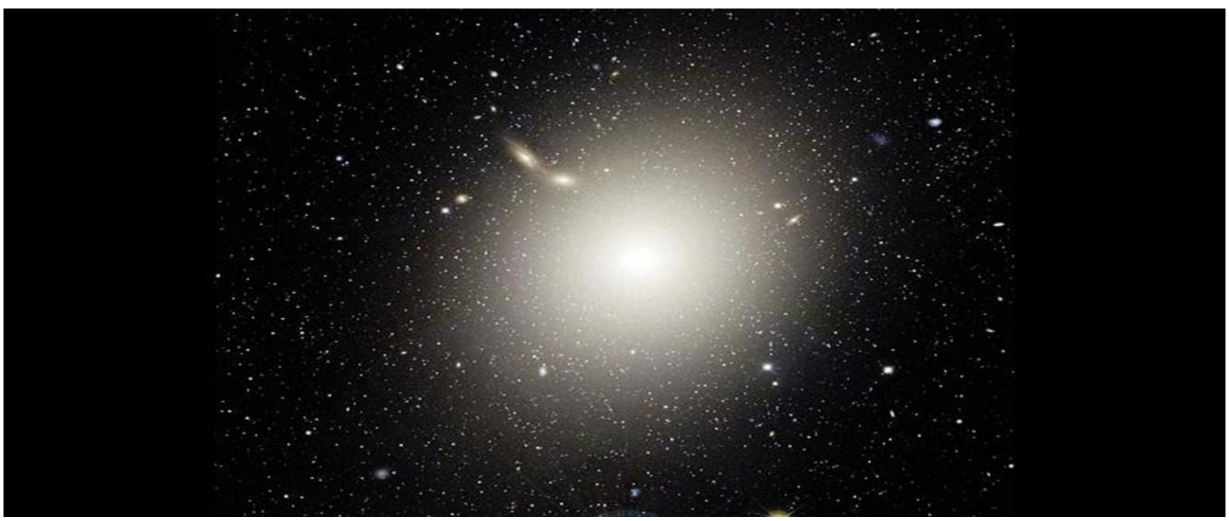

Figure 1. Representative examples of spiral, elliptical, and irregular galaxies from sky survey data. Visible structural differences form the basis of broad morphological classification.

I. INTRODUCTION

Galaxies are complex systems made up of stars, gas, dust, and dark matter. Studying their shapes and structures can help astronomers understand how galaxies form and evolve. One of the most common ways to introduce this topic is through galaxy morphology, which groups galaxies based on their structure.

In school-level astronomy education, galaxy morphology is usually taught using images from large sky surveys. While these images are scientifically valuable, students rarely interact with raw data themselves. This creates a gap between theory and observation.

Recent progress in artificial intelligence has made image classification more accessible. When used carefully, AI can help students analyze astronomical images without removing the need for human thinking. This paper demonstrates a simple AI framework designed to help students identify basic galaxy types from small datasets while focusing on learning rather than research automation.

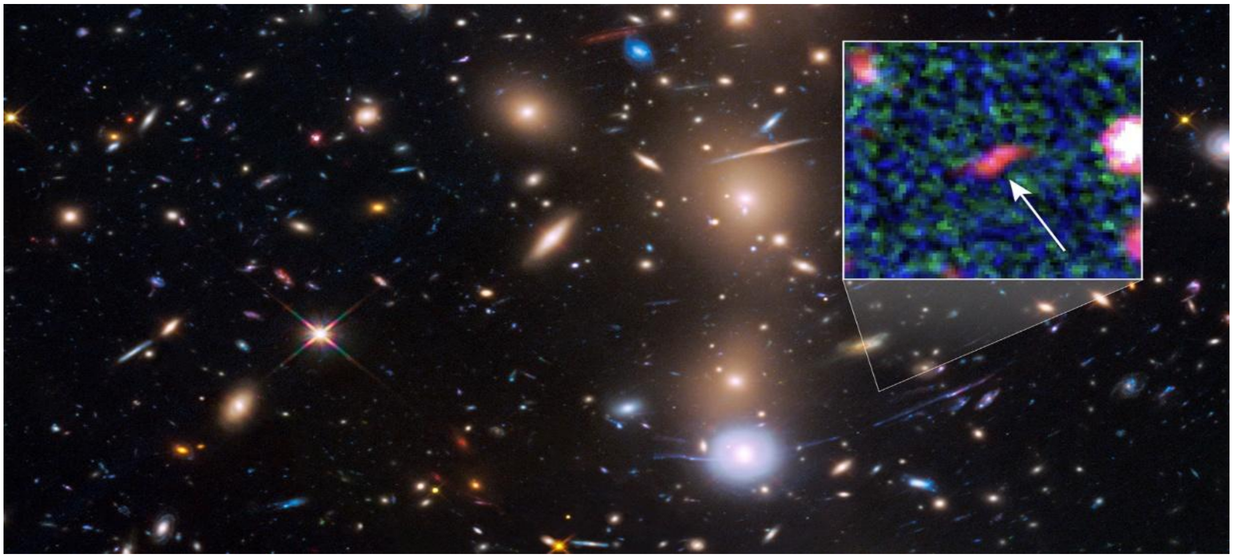

Figure 2. Example of a faint galaxy image captured using a small-aperture telescope. Structural features are visible but less defined compared to professional survey data.

II. BACKGROUND AND MOTIVATION

Galaxy morphology is commonly divided into broad categories such as spiral, elliptical, and irregular galaxies. Professional classification requires high-quality data and expert knowledge, but basic visual differences can be understood at an early level.

Students face several challenges:
1. Galaxy images may appear unclear or noisy
2. Structural features are hard to recognize
3. Most learning uses finished datasets instead of raw, half-baked images

Projects like visual galaxy classification have shown that human pattern recognition is valuable, especially at early stages. However, beginners often lack confidence in their observations. A simple AI system can act as a guide by highlighting features and suggesting broad categories without making final decisions.

III. RESEARCH OBJECTIVE

How can an AI-assisted system help students identify basic galaxy morphologies from small telescopes or public survey images while preserving active learning and human needs?

Data Sources and Image Preparation

This framework is designed to work with:
1. Publicly available galaxy images from sky surveys
2. Small telescope images where galaxies are faint but visible

Images are prepared using these simple steps:
1. Cropping around the target galaxy
2. Contrast adjustment to improve visibility
3. Noise reduction to remove background artifacts

These steps improve clarity without changing any content

IV. AI-ASSISTED CLASSIFICATION FRAMEWORK

Design Approach

The system does not aim for precise scientific classification. Instead, it focuses on:
1. Broad morphology categories
2. Visual feature recognition
3. Simple explanations for decisions

Classification Categories

The system identifies three main groups:
1. Spiral Galaxies: Visible arms or disk-like structure
2. Elliptical Galaxies: smooth, rounded light distribution
3. Irregular galaxies: no clear or symmetric shape

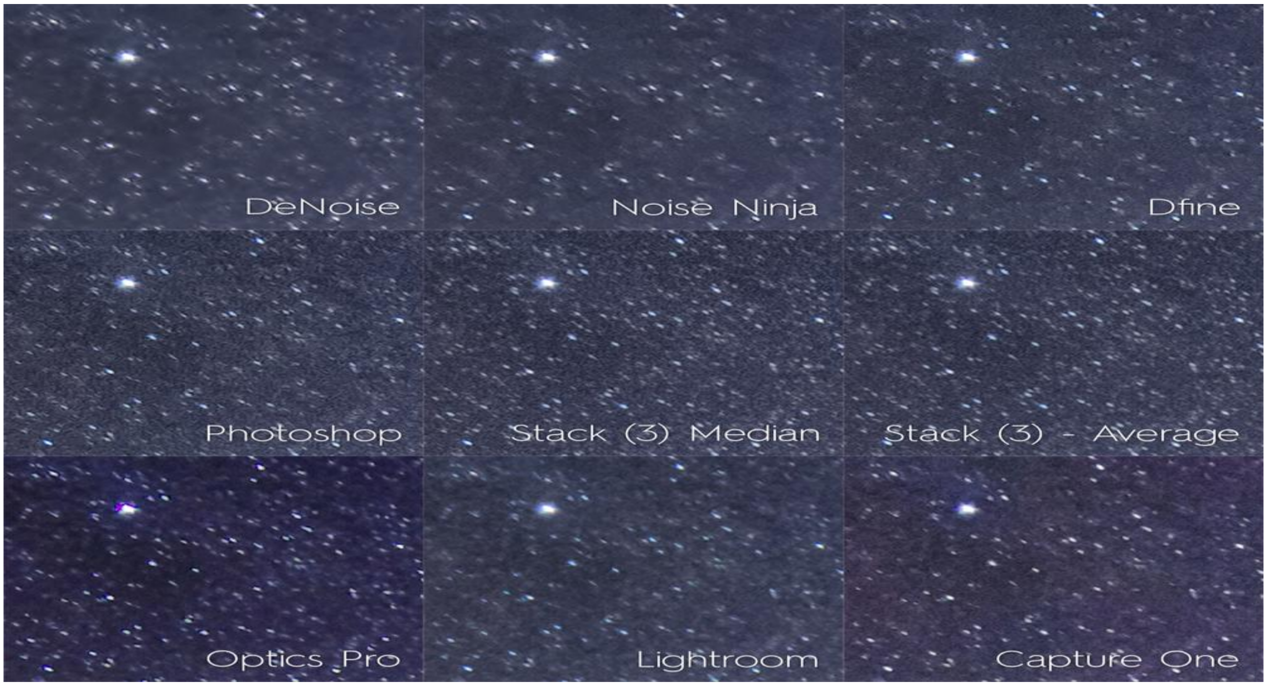

Figure 3. Example of image preprocessing including cropping, contrast enhancement, and noise reduction to improve structural visibility.

Role of AI

The AI does three main things:

1. Suggests a likely category
2. Highlights visible features in the image
3. Explains why a suggestion was made

The system never presents its output as a final answer. Students are encouraged to agree, disagree, and compare.

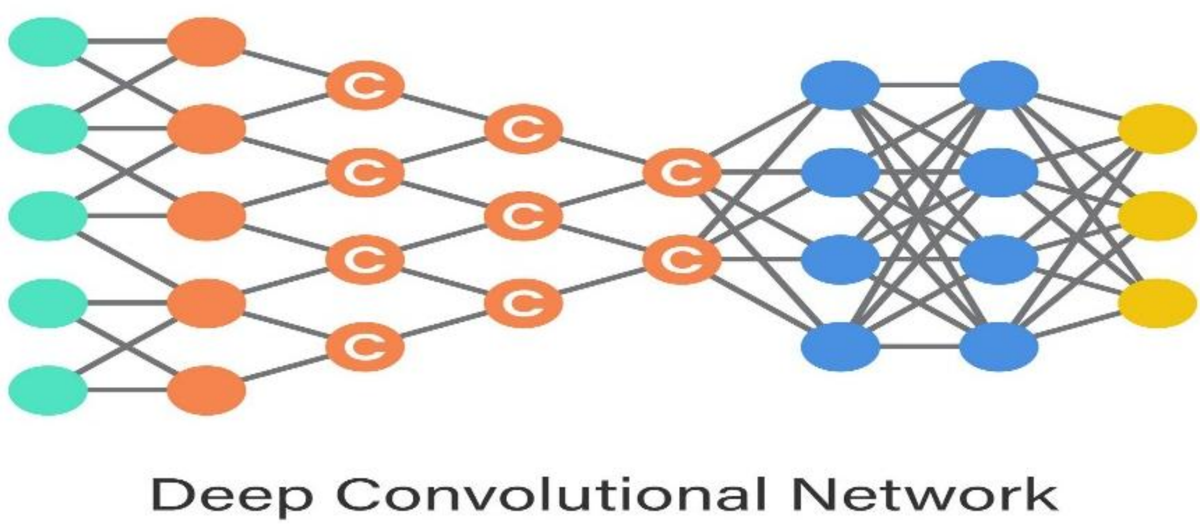

Figure 4. Example of AI-assisted feature highlighting. Brighter regions indicate structural patterns contributing to morphological suggestions.

V. EDUCATIONAL DESIGN PRINCIPLES

The system is built around the following ideas:

1. Human judgment matters: AI supports thinking, it does not replace it
2. Transparency: Students can see why a suggestion was made
3. Simplicity: Board categories are easier to learn and apply
4. Active learning: Observation and comparison are central

These principles help ensure that AI remains a learning tool.

Example Use Case

A student observed a faint galaxy using a small telescope. The image is processed to improve clarity. The system suggests that the object may be a spiral galaxy and highlights in brighter regions that could be spiral arms. It explains why these features matter.

The student then compares this suggestion with reference images and decides whether it makes sense. This process encourages reflection and builds confidence over time.

VI. IMPACT ANALYSIS

Educational Impact

This approach can help students understand galaxy structure more clearly. It encourages them to look closely at the images and think about what they see instead of accepting answers immediately.

Accessibility Impact

Because the system works with simple images, it lowers the barrier to studying galaxies. Schools without advanced equipment can still explore extragalactic astronomy.

Conceptual Impact

Students learn that AI can support scientific work without replacing human reasoning. This helps build a healthy understanding of AI as a tool rather than a shortcut.

VII. LIMITATIONS

The system has clear limits. Image quality strongly affects results. Very distant or faint galaxies may be misclassified. The system does not aim to replace professional methods or contribute to new scientific discoveries.

These limitations are intentional, given the educational focus of the work.

VIII. FUTURE WORK

Future Improvements could include larger image datasets, better visual explanations, and comparisons between student and AI classifications. Classroom testing would help evaluate how well the system supports learning over time. The framework could also be extended to study interacting galaxies or galaxy groups.

IX. CONCLUSION

This paper presents a simple, learning-based approach to identifying galaxy morphologies using AI assistance. By combining basic image processing with clear explanations, the system helps students understand what they observe while keeping human interpretation a key factor. The work shows that AI can be used to support astronomy education in a way that is accessible, transparent, and engaging, especially at learning stages.

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