Project Report On

Telescope Automation and Alignment

Submitted in partial fulfillment of the requirements for the award of the degree of

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CERTIFICATE

This is to certify that the project report entitled ***"Telescope Automation and Alignment"*** *is a bonafide record of the work done by* ***Abhiram Ramachandran (U2003005), Adwaitha Binu (U2003012), Amruta Anandan Nair (U2003034), Binul Bijo (U2003069)****, submitted to the Rajagiri School of Engineering & Technology (RSET) (Autonomous) in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology (B. Tech.) in Computer Science and Engineering during the academic year 2023-2024.*

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Abstract

The proposed project **"Automated Telescope Alignment and Celestial Object Identification"** aims to make it easier for amateur astronomers to set up and use their telescopes. The main goal is to use machine learning (ML) techniques to simplify the complex procedures involved in aligning telescopes and identifying astronomical objects.

The project will create a smartphone application and software that can automatically identify stars, galaxies, planets, and moons. This will be done by building a large database of astronomical photos and data, which the ML models will use to recognize celestial objects and provide their coordinates (right ascension and declination).

The project will involve collecting a large dataset, training ML models to identify objects, creating an intuitive user interface and mobile app, and integrating the app with the telescope's camera and ML model. The use of the Flutter SDK will help make the mobile app user-friendly and accessible.

The expected results include a mobile app and ML program that can recognize and provide the coordinates of celestial objects. This will streamline the telescope setup process and improve the accuracy of astronomical observations, making it easier for amateur astronomers to enjoy the night sky.

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List of Abbreviations

Acronym - Expansion

1. ML - Machine Learning
2. RCNN - Region-based Convolutional Networks
3. SDSS - Sloan Digital Sky Survey
4. TIFF - Tagged Image File Format

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Chapter 1

Introduction

The human mind has always been fascinated by space travel, and amateur astronomers are essential to solving the mysteries of the night sky. The historic Newtonian telescope—named for Sir Isaac Newton—remains a favorite among enthusiasts. But manually aligning such telescopes presents a lot of difficulties, which makes it difficult to observe celestial objects smoothly. In order to set the scenario for the proposed study on Automated Telescope Alignment and Celestial Object Identification, this chapter explores the challenges encountered by amateur astronomers.

1.1 Background

The simplicity and cost of the Newtonian telescope, named for Sir Isaac Newton, the inventor who developed this optical system, continue to make it a favorite choice among astronomers. But there are a few obstacles that amateur astronomers need to overcome while manually aligning a Newtonian telescope.

One of the main challenges in using a Newtonian telescope is achieving exact optical alignment, which requires careful, laborious adjustments. For good images, the primary and secondary mirrors must be aligned along the optical axis; any deviation reduces efficacy. The process of collimation, which aligns optical elements, increases complexity and necessitates exact mirror tilt and position adjustments. This may be difficult for beginners because of the complex knowledge required. Manual alignment is made more difficult by environmental conditions such as light pollution and atmospheric turbulence. Expert observers are need to successfully negotiate these difficulties, highlighting how difficult it is to manually align a Newtonian telescope.

Additionally, it can be difficult for inexperienced astronomers to distinguish celestial objects; it takes practice and familiarity with the night sky. Lack of observational experience makes it difficult to distinguish between stars, galaxies, and other bodies, highlighting the importance of committed learning. Complicating matters is the dynamic nature of celestial bodies, whose positions vary throughout the year. Similarities in the appearance of celestial bodies can be confusing, particularly in the absence of sophisticated imaging or spectroscopic tools. The complex architecture of galaxies, including as dust lanes and spiral arms, require increased magnification and resolution, which presents difficulties for amateurs with limited equipment. It takes tenacity, never-ending education, and adjustment to the dynamic and intricate world of astronomical observation to overcome these challenges.

1.2 Problem Definition

During their observations, amateur astronomers encounter difficulties in accurately aligning telescopes and recognizing celestial objects. Current approaches frequently require intricate steps, which can be frustrating and time-consuming.

Overcoming these obstacles requires creating a solution that meets the unique requirements and tastes of this user base.

1.3 Scope and Motivation

By utilizing machine learning (ML) to improve celestial object identification and expedite telescope alignment, the proposed project on Automated Telescope Alignment and Celestial Object Identification fills a significant void in the amateur astronomy community. Under the scope, real-time identification of stars, galaxies, planets, and moons will be possible through the creation of a mobile application and AI-driven software that combine seamlessly with telescopes. The project's goal is to make stargazing more approachable and pleasurable for amateur astronomers by offering a user-friendly solution that streamlines the initial setup procedure.

The goal of this project is to provide amateur astronomers with state-of-the-art tools so that they can observe celestial bodies more easily and profitably. The solution gives precise celestial coordinates for recognized objects and automates the telescope alignment procedure by leveraging ML algorithms. By providing a sophisticated yet approachable system that improves tracking precision of celestial bodies, this innovation aims to lessen the difficulties amateur astronomers encounter during initial setup. Providing a tool that enhances the stargazing experience and advances the field of astronomy overall, the project's ultimate goal is to revolutionize the amateur astronomy scene.

1.4 Objectives

1. Develop an ML-driven software and mobile app that can identify celestial objects (stars, galaxies, planets, moons) using images captured by a telescope's camera.
2. Create and maintain a comprehensive astronomical objects database to facilitate realtime object recognition.
3. Provide users with accurate celestial coordinates (right ascension and declination) for the identified objects.
4. Enable automated telescope alignment and precise tracking of celestial objects based on user preferences.
5. Enhance the user experience for amateur astronomers by simplifying the initial setup process.

1.5 Purpose and Need

1. Develop a software application for amateur astronomers.
2. Utilize Machine Learning (ML) to simplify telescope alignment and enhance the accuracy of celestial object identification.

3. Use a camera connected to a telescope to compare captured images with an extensive astronomical objects database.

4. Provide information about the celestial object's identity and coordinates (right ascension and declination).

5. Control the telescope's rotation, ensuring precise alignment with the celestial object for observation and tracking.

1.6 Challenges

The project's challenges may include adjusting to changes in lighting and image quality while gathering data, making sure the ML model is reliable and accurate in recognizing a variety of celestial objects, and fine-tuning the telescope control system to make accurate and seamless adjustments based on real-time ML outputs.

1.7 Assumptions

1. The availability of a large and varied dataset of astronomical photos and object data for efficient training of ML models.

2. Consistent and dependable internet connectivity to provide real-time access to the database of astronomical objects.

3. The software and mobile app are compatible with numerous telescope models and camera systems.

4. The ML-driven system can be developed and implemented within the required schedule with sufficient resources and competence.

5. User acceptability and amateur astronomers' readiness to accept and use the suggested technology into their observing practices and telescope adoption.

1.8 Societal / Industrial Relevance

The development of an ML-driven software and mobile app makes telescope alignment and celestial object identification more accessible to amateur astronomers. By simplifying the initial setup process, the project lowers entry barriers, enabling a broader demographic to engage in astronomy without extensive technical expertise.

The automated telescope alignment and precise tracking of celestial objects contribute to an improved stargazing experience for enthusiasts. Users can focus more on observing celestial wonders, fostering a greater appreciation for astronomy as a recreational and educational activity.

The project provides a valuable educational tool for astronomy enthusiasts, students, and educators. Users can learn about different celestial objects, their coordinates, and the principles of telescope operation through the intuitive software and app interfaces.

The accurate identification of celestial objects contributes to citizen science efforts by collecting observational data from a network of amateur astronomers. This data can be valuable for professional astronomers and researchers, aiding in the study of celestial phenomena and enriching astronomical databases.

1.9 Organization of the Report

The Abstract is the first section of the report. The project's background, motivation, goals, necessity, scope, and social and industrial significance are all covered in the Introduction section, which also sets the foundation. The Literature Review is then explored, looking at pertinent studies and current systems. The current system and the proposed system are shown together before the design part with its sequence diagrams, architectural diagrams, module breakdown, and comprehensive design details is shown. Then the requirements for the hardware and software are explained, along with the assumptions and challenges, work breakdown, and responsibilities. In the next part, a Gantt chart is used to visually describe the project's timetable and milestones. It also shows the budget and related risks and challenges. A section that summarizes it comes at the end.

This chapter concludes by laying the foundation for the project on Automated Telescope Alignment and Celestial Object Identification. It draws attention to the difficulties encountered by amateur astronomers and frames the suggested remedy as a novel project that not only resolves these difficulties but also advances citizen science, education, and the excitement of space exploration. The following chapters will dive into the technical details and implementation techniques as we set out on this journey, bringing the idea of an AI-driven celestial observation tool closer to reality.

Chapter 2

Literature Survey

2.1 Introduction

A new age of inquiry in the constantly changing field of astrophysics has been brought about by the combination of sophisticated tools and conventional methods. The first part explores the terrain of machine learning by examining the most recent cutting edge uses in the categorization of astronomical objects. Then, the emphasis switches to an autofocusing algorithm designed specifically for telescope systems, revealing its performance measurements and methodical assessment. The last section of the chapter delves into how deep learning is revolutionizing astrophysics study and presents a wide range of applications, from classifying galaxy shape to identifying Sunyaev-Zel'dovich clusters.

2.2 Existing System

The use of machine learning algorithms for the categorization of celestial objects has caused an important shift in the study of astronomy in recent years. This chapter goes into great length about the systems that are currently in use for classifying astronomical data. Different classifiers, their baseline parameters, and the wide search space configurations used to maximize their performance are the main topics of discussion.

2.2.1 Available Classifiers and Parameters

Classifiers play a crucial role in the classification of astronomical data. A variety of classifiers are covered, including ensemble techniques like Random Forests, Bagging, and XGBoost, as well as more conventional ones like Support Vector Machines (SVM). The ensemble approach becomes more complex with the addition of a Voting Classifier, which combines many classifiers for greater accuracy.

Emphasizing the classifiers' baseline parameters and search space configurations is crucial. The parameters for SVM include gamma, degree, C, nu, and kernel type. The number of estimators, the criterion, and the minimum samples for splitting and leaf nodes are among the parameters that affect random forests. In a similar vein, XGBoost includes parameters like lambda, gamma, eta, and max depth. These classifiers have very large search space configurations, with many possible values for each parameter. SVM investigates different degrees, nu values, and kernel types, for example. Cover criteria, bootstrap parameters, and minimum samples for leaf nodes and splits are all provided by Random Forests. XGBoost investigates parameters such as lambda, gamma, eta values, and maximum depth. The variety of search spaces is a reflection of the thorough method used to optimize each classifier for precise classification of astronomical data.

Authors	Classification task	Methods	Datasets
Zhang et al. (2011)	Binary (star, quasar)	LS-SVM	SDSS, UKIDSS
Zhang et al. (2013)	Binary (star, quasar)	SVM	DSS, UKIDSS
Philip et al. (2002)	Binary (star, galaxy)	Difference Boosting Neural Network (DBNN)	NDWF
Viquar et al. (2018)	Binary (star, quasar)	SVM, SVM-KNN, AdaBoost, Asymmetric AdaBoost	SDSS
Acharya et al. (2018)	Multi-class (star, galaxy, quasar)	*k*NN, SVM, Random Forest	SDSS
Lopez et al. (2010)	Multi-class (stars)	Bayesian Networks	OMC
Cabanac et al. (2002)	Multi-class (star, galaxy, quasar)	PCA	GISSEL PEGASE
Bailer-Jones et al. (2019)	Binary (galaxy, quasar)	Gaussian Mixture Model (GMM)	Gaia
Jin et al. (2019)	Binary (quasar, not-quasar)	SVM, XGBoost	Pan-STARSS WISE
Becker et al. (2020)	Multi-class (star)	Random Forest, Recurrent Neural Network (RNN)	OGLE-III Gaia WISE
Zhang et al. (2009)	Binary (star, quasar)	*k*NN	SDSS FIRST USNO-B1.0

Figure 2.1: An overview of novel techniques developed with the use of sky survey databases

2.2.2 Materials and Methods

- **Support Vector Machines (SVM)**: Astronomical data classification is examined in relation to Support Vector Machines (SVM), a conventional yet effective classifier. SVM functions by locating the hyperplane in the feature space that best divides various classes. The behavior of the SVM is mostly determined by parameters like degree, gamma, nu, kernel type, and C (regularization parameter). The complexity of the decision boundary depends on the type of kernel (linear, polynomial, or radial basis function) selected.

- **Ensemble Approaches**: Integrate several basic classifiers to improve the overall performance. Notable instances are XGBoost, Bagging, and Random Forests.

  - **Random Forests**: Decision trees are arranged in an ensemble to form Random Forests. When optimizing Random Forests for astronomical data classification, parameters like the number of estimators (trees in the forest), criterion (function to quantify the quality of a split), and minimum samples for splitting and leaf nodes are crucial. Overfitting is lessened by the decision trees' diversity.
  - **Bagging**: Also known as Bootstrap Aggregating, Bagging entails integrating the predictions of several models that have been individually trained on various subsets of the training data. In fine-tuning Bagging classifiers, the summary highlights the significance of factors such as the number of estimators and bootstrap choices.
  - **XG Boost**: The effective gradient boosting framework XGBoost is presented together with its pertinent settings. These include lambda (L2 regularization term), gamma (minimum loss reduction necessary to make a further partition), max depth (maximum depth of a tree), and eta (learning rate).
  - **Voting Classifier**: The Voting Classifier, which aggregates predictions from various classifiers, enhances the ensemble technique even further. The "hard" voting technique takes into account majority voting, in which the class with the most votes wins.

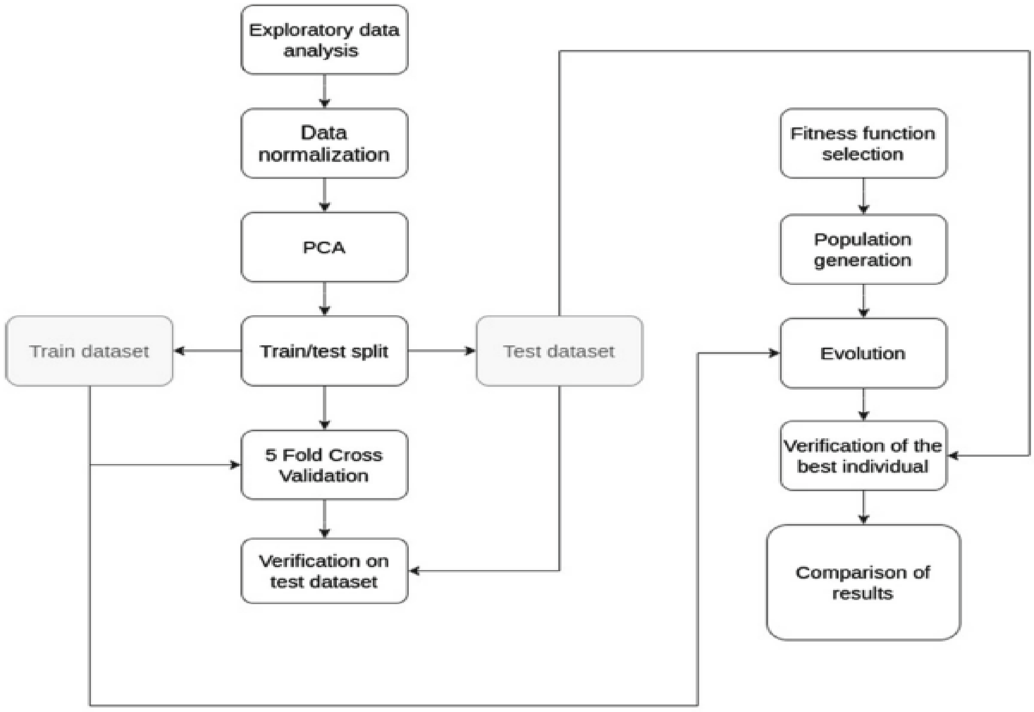


Figure 2.2: A pipeline for learning and optimization created for the classification

The following steps make up the pipeline: (i) Manual exploratory data analysis is carried out to gain a deeper understanding of the data. Rich data visualization tools are utilised in this often used practise to detect problems with the data. Missing feature values, a high number of outliers, disparate data scales, and the existence of categorical features are a few examples of these problems. (ii) The preliminary pre-processing of data is a crucial stage in any machine learning endeavor. In order for our classifiers to effectively learn the class associations, the data must be scaled and cleansed. Principal component analysis (PCA) and other dimensionality reduction techniques are included in this step as well. By using PCA, we may lower the amount of features that the model must process in order to produce an accurate forecast. To maintain class balances, stratfied split is employed. (iv) The scikit-learn package has 21 classifiers, which is employed in this work. The parameters were initialized using the default settings. (v) Fivefold CV is used to create the classifiers once each one has been initialized. This aids in preventing the classifiers from being over- or under-fitted.(vi) We have completed the verification of our baseline study's final classification performance on the test set.(vii) Optimization of genetic parameters is performed.

2.2.3 Conclusion

Although there is much promise for classifying astronomical data using machine learning, the overview recognizes the difficulties in choosing appropriate classifiers and optimizing parameters. To overcome these difficulties, voting systems and ensemble methods are used, guaranteeing reliable performance even in complicated situations.

2.2.4 Introduction

This article presents a revolutionary method, Citizen Science with deep Learning (CzSL)[1]]Citizen Science and Machine Learning: Towards a Robust Large-Scale Automatic Classification in Astronomy (2023)

2.2.5 Introduction

This article presents a revolutionary method, Citizen Science with deep Learning (CzSL)[1]. It merges the strength of citizen science and deep learning for picture sorting in space science. The research looks at handling the issues brought by the massive amount of space data. It offers CzSL as a novel way that uses the combined knowledge of expert and hobby astronomers. This brief overview will explore the different parts of the article, giving a complete

Image classification has a pivotal role in astronomy, especially in projects like Galaxy Zoo (GZ), where a massive volume of celestial images needs categorization. The limitations of conventional supervised learning models due to the scarcity of labeled data are highlighted, promptng the need for innovative approaches. CzSL is introduced as solution that integrates the expertise of professional astronomers and the enthusiasm of amateur astronomers. The method employs transfer learning, combining pre-training with unsupervised data and fine-tuning with labeled data from both experts and volunteers.

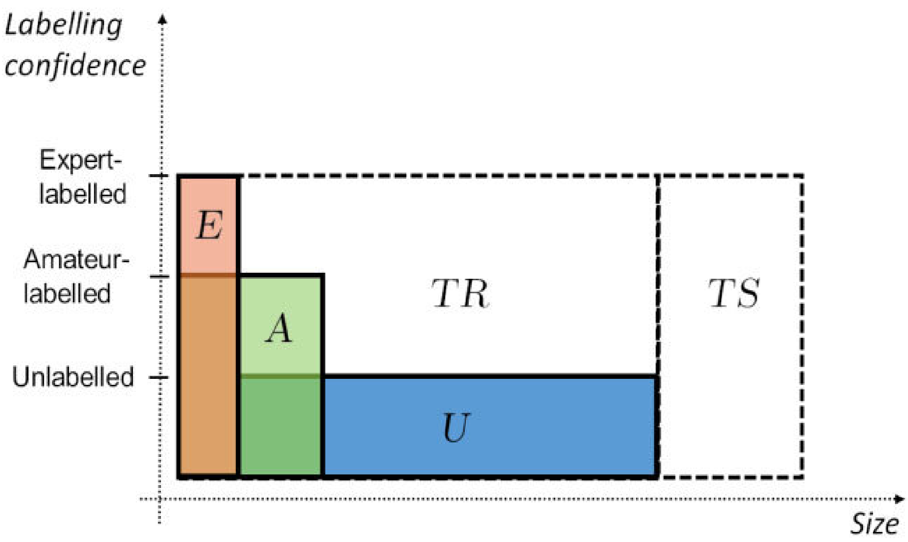


Figure 2.3: The data subsets used in the methodology

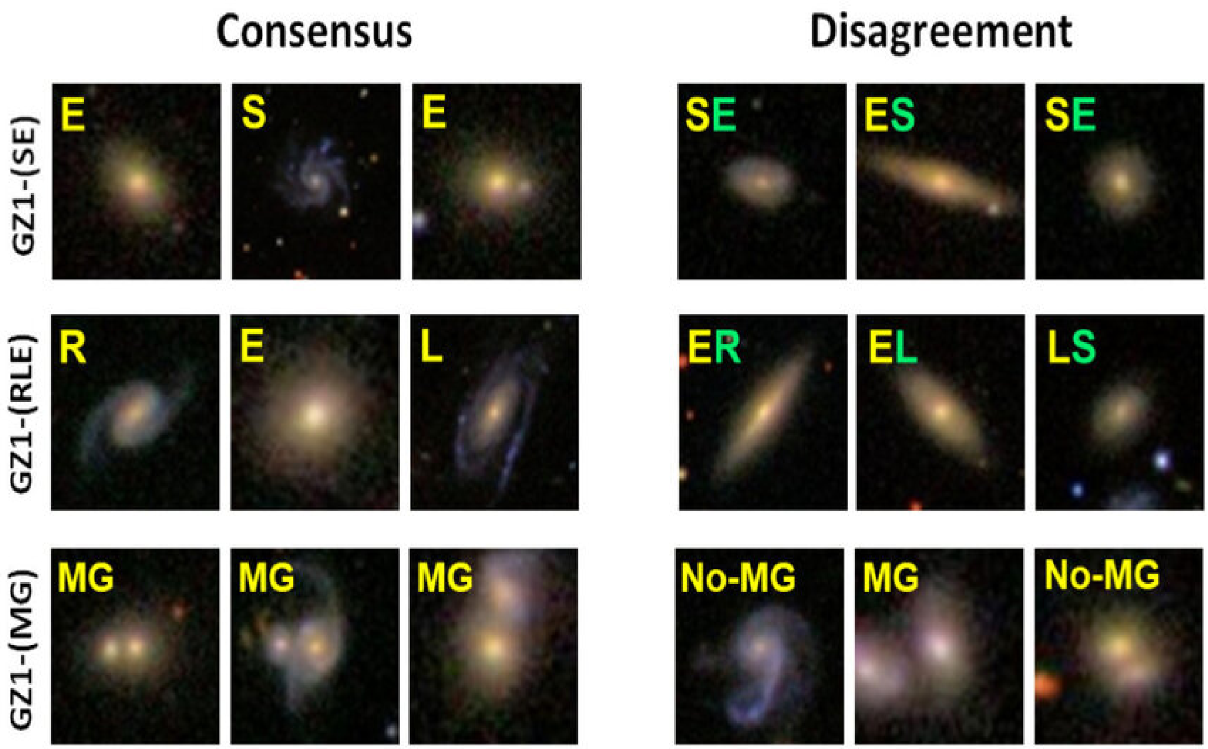


Figure 2.4: Data samples used in the experiments

The unique aspect of CzSL lies in its ability to look into the three levels of knowledge present in citizen science projects: professional knowledge, amateur contributions, and unlabeled data. This section helps for understanding the motivation behind CzSL and the gap it bridge in the field of automated image classification in astronomy.

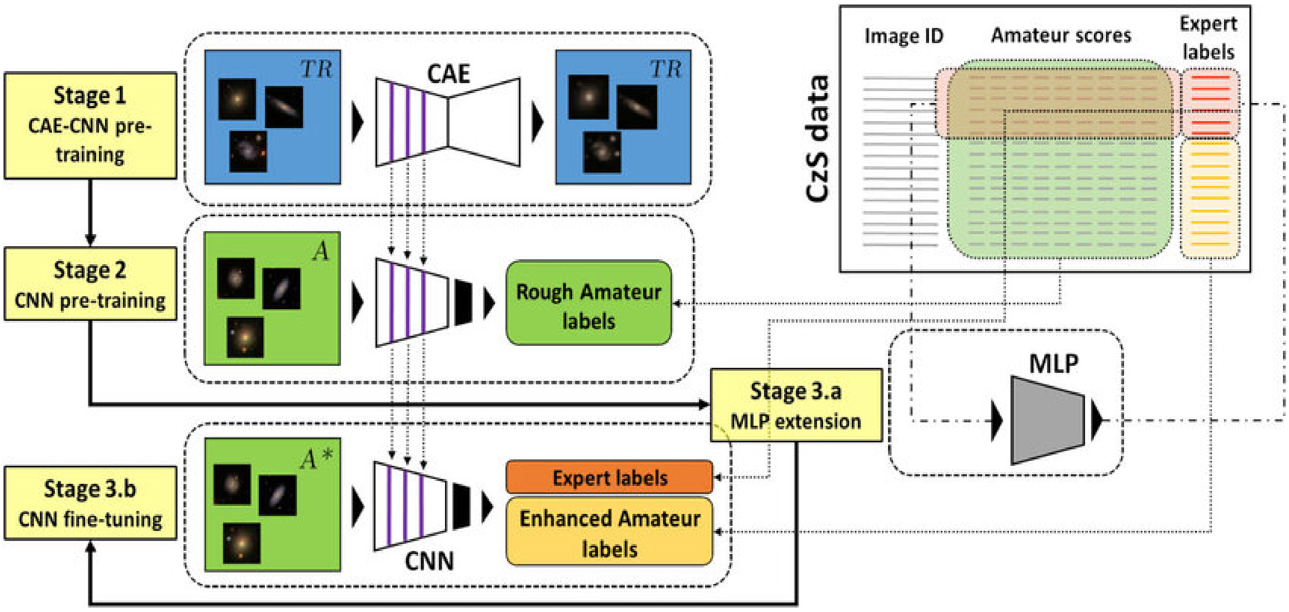


Figure 2.5: The CzSL architecture

2.2.6 CzSL methodology

The paper provides an in-depth exploration of the CzSL methodology and the architecture of the models used. The authors employ Convolutional Neural Networks (CNNs), a deep learning paradigm well-suited for image-related tasks. CzSL operates in three stages: pre-training, fine-tuning, and augmentation. In the pre-training stage, CNNs are trained with a Convolutional Autoencoder (CAE) using unlabeled data. This helps the model learn intricate patterns inherent in astronomical images.

Fine-tuning is done next, where the pre-trained CNNs are refined using labeled data from both professional and amateur astronomers. The authors highlight the significance of this hybrid training approach, emphasizing the transfer of labels between experts and volunteers. The augmentation stage involves data augmentation techniques to enhance the model's performance, addressing challenges related to limited expert-labeled data.

The expermental setup involves testing CzSL on data from GZ1, a prominent citizen science project. The results presented in tables and figures, showcasing the performance of CzSL compared to traditional supervised learning approaches. The authors employ metrics such as accuracy (AccTS) and geometric mean (G-meanTS) to evaluate the model's classification capabilities.

2.2.7 Results and Ananlysis

In the paper, several models are studied and compared to understand the efficacy of the CzSL. A few relevant models are the 'Oracles' which assume that expert or amateur labels are available for the entire dataset (In case of Expert and Amateur Oracles respectively) and hence uses this fact to calculate the efficiency. The Oracles serve as a threshold and a basis with which to compare the results with. Though a highly accurate model, this model is only theoretical and not practical in real life.

The Expert and Amateur are trained over the expert and amateur sets respectively. This represents the realistic scenario in which the models are trained on only amateur or expert data. This provides relatively low accuracy scores compared to the rest of the models discussed. This provides a lower baseline for comparison of models.

The MLP model is trained over the enhanced amateur set, which is obtained in stage 3.b of the CzSL. The MLP uses expert labels for expert data and enhanced labels for the rest of the amateur data. This provides relatively good accuracy and runtime.

The CzSL methodology provides the best results for most scenarios. It provides the worst runtime due to the additional stages but provides better accuracy is merging and spiral-elliptical classification. It under-performs compared to the MLP model in case of classification of the handedness of the spiral galaxies.

2.2.8 Conclusion

The experiments include a data augmentation study, ablation study, and a comparison of CzSL's ablated versions. These investigations aim to validate the effectiveness of CzSL in handling various scenarios and showcase its adaptability to different challenges in image classification. The results indicate that CzSL outperforms traditional supervised learning models, especially when expert-labeled data is limited. The tables and figures provide a visual representation of the comparative results, offering insights into the strengths of CzSL in diverse settings.

The authors emphasize the integrated use of data from professional and amateur astronomers, leading to more robust and reliable automated classifiers. CzSL's contributions to the field are highlighted, paving the way for future advancements in handling labeled and unlabeled data in citizen science projects.

The integration of citizen science and deep learning, as presented in CzSL, holds promising implications for advancing the capabilities of automated image classifiers in the realm of astronomy.

2.3 Autofocusing Optimal Search Algorithm for a Telescope System (2021)

The methodology employed in the study[2] involves a systematic approach to evaluating and comparing various search algorithms for automatic focusing in astronomical observations. The research methodology encompasses several key components, including the experimental setup, data collection, focus measure operator, search algorithms, and performance evaluation.

2.3.1 Experimental Setup

The study utilizes an imaging system based on the 74-inch telescope at the Kottamia Astronomical Observatory and a CCD camera system. The observational data is collected for five star-clusters: M103, N6793, N7067, N7788, and N7789. The sequences are observed during good seeing conditions, and they contain both in-focus and out-of-focus frames. The experimental setup ensures the acquisition of high-quality observational data for the subsequent evaluation of the search algorithms.

Star-Cluster Name	Start Position (μm)	End Position (μm)	Range (μm)	Step Size (μm)	Number of Frames	Exposure Time / Frame (seconds)	Average FWHM (Pixels)
M103	48300	54800	6600	100	66	60	4.15
N6793	49000	55000	6100	100	61	60	4.279
N7067	49000	54400	5500	100	55	60	3.68
N7788	48600	54600	6100	100	61	60	4.78
N7789	48000	55000	7100	100	71	60	3.89

Figure 2.6: The summary of the used star-clusters

2.3.2 Data Collection

The observational data collected for the star-clusters includes details such as the start position, end position, range, step size, number of frames, exposure time per frame, and average Full-Width Half Maximum (FWHM) in pixels. The seeing conditions prevailing at the site are also considered, with an average of 2 arcsec. The Newtonian Plate and Imaging area specifications are used to calculate the pixel size, which is approximately 0.30 arcsec. The data collection process ensures comprehensive information about the observational parameters, which is essential for the subsequent analysis and evaluation of the search algorithms.

2.3.3 Focus Measure Operator

The study employs a focus measure operator to quantify the image focus level. A comparative study of nineteen operators applied to the astronomical star-cluster observations is referenced, with the Normalized Variance focus measure identified as having the best overall performance. The Normalized Variance focus measure is calculated by dividing the image variance by the image mean, compensating for differences in average image brightness among different images. The focus measure operator selection is crucial for accurately assessing the performance of the search algorithms in determining the best focus position.

$$\mathrm{FM} = \frac{\frac{1}{\mathrm{MN}} \sum_{x=1}^{M} \sum_{y=1}^{N} \left(\mathrm{I}(x, y) - \bar{\mathrm{I}}\right)^2}{\bar{\mathrm{I}}}$$

Figure 2.7: Focus Measure Operator

2.3.4 Search Algorithm

The methodology presents details of several search algorithms proposed for the auto-focusing system. The algorithms are designed to address the challenge of identifying the best focus position in an imaging system with a large number of focus positions. The study focuses on algorithms that assume the objective function has a unique maximum (unimodal) and investigates the maximization problem. The search algorithms considered in the study include the Global search, Binary search, Fibonacci search, Subbarao search, and Modified Fast Climbing. Each algorithm is described in terms of its operational principles, advantages, and limitations.

2.3.5 Performance Evaluation

The performance evaluation of the search algorithms is a critical component of the methodology. The study compares the results obtained from applying the different search algorithms to the observational data for the star-clusters. The evaluation criteria include the overall score, search steps, and the impact of factors such as search interval, focus measure, and algorithm dependency. The results are summarized in tables and figures, providing a comprehensive comparison of the performance of the search algorithms for the specific observational data.

2.3.6 Overall Score

The overall score is calculated based on the accuracy and number of steps required to determine the best focus position. The accuracy is measured by the difference between the actual best focus position and the position determined by the search algorithm. The number of steps is the total number of positions visited by the search algorithm. The overall score is calculated as the product of the accuracy and the inverse of the number of steps.

2.3.7 Impact of Factors

The study also evaluates the impact of factors such as search interval, focus measure, and algorithm dependency on the performance of the search algorithms. The search interval is the range of focus positions considered by the search algorithm. The focus measure is the operator used to quantify the image focus level. The algorithm dependency is the extent to which the search algorithm performance is affected by the specific observational data.

2.3.8 Results

The experimental results show that the Binary search algorithm is the optimal one for auto-focusing in astronomical observations. The Binary search algorithm is a simple and efficient algorithm that reduces the search interval by half at each step. The algorithm converges to the best focus position in a small number of steps, making it suitable for real-time auto-focusing applications. The authors also found that the Subbarao search algorithm, which combines the Binary or Fibonacci search with a quadratic or Gaussian function, can further improve the accuracy of the auto-focusing system.

Search Name	M103	N6793	N7067	N7788	N7789	Overall Score
Binary	1.5294	1.4894	1.5059	1.5208	0.5422	1.3175
Fibonacci	1.1603	0.5767	0.2895	1.7067	2.6	1.2666
Subbarao-Binary	0.9701	1.1667	1	1	0.3714	0.9016
Modified Fast Climbing	1.1623	0.9365	0.1902	0.8764	1	0.8331
Subbarao-Fibonacci	0.7059	0.3384	0.2042	0.9478	1.2803	0.6953
Global	0.5542	0.225	0.2462	0.3972	0.0994	0.3044

Table 2.1: The results summary for the different search algorithms

2.4 Development of accurate classification of heavenly bodies using novel machine learning techniques (2021)

2.4.1 Introduction

This research [3] investigates the use of several machine learning techniques for precise heavenly body classification, with an emphasis on astronomical data. The goal of the project is to increase the astrophysical classification procedures' dependability and efficiency. Support Vector Machines (SVM), Decision Trees, Random Forest, Bagging, Multi-layer Perceptron (MLP), and XGBoost are some of the classifiers that are being studied. Baseline parameters and a large search space for hyperparameter adjustment have been carefully set up for each classifier.

2.4.2 Methodology

A thorough examination of the machine learning techniques used in the research is provided in this paper. We talk about Support Vector Machines, explaining its mathematical underpinnings and their superior performance in high-dimensional areas. We present Decision Trees and Random Forests as ensemble techniques, highlighting their capacity to manage heterogeneous characteristics in astronomical datasets. In order to clarify their distinct contributions to the classification job, the concepts of bagging and multi-layer perceptrons (MLPs) are examined. The XGBoost algorithm—which is renowned for its efficiency and scalability—is also covered in detail.

2.4.3 Hyperparameter Tuning

Optimizing each classifier's performance through hyperparameter tuning is an essential component of the research. The search space configurations for hyperparameter tuning are described in detail in the study. Parameters for SVM are investigated, including learning rate, penalty, and kernel selection. Factors including the number of trees, minimum samples per leaf, and maximum depth are taken into account while using Decision Trees and Random Forests. The number of hidden layers, momentum, and learning rate are examples of MLP hyperparameters. Parameters like as learning rate, subsample, and maximum depth are set up for XGBoost.

2.4.4 Comparitive Analysis

The classifiers are thoroughly compared by assessing each one's effectiveness using astronomical datasets. Metrics like recall, accuracy, precision, and F1-score are used to gauge how well each method works. The research explores the benefits and drawbacks of each classifier, including information on which kinds of astronomical data they work best with.

The use of ensemble approaches is essential for increasing the accuracy of classification. The novel Voting Classifier and other ensemble techniques like Bagging are presented in this study. The latter shows how multiple algorithms can be combined for improved accuracy by mixing a variety of classifiers. The authors go into detail about the ensemble's classifier list and voting procedure.

The proposed approaches' effectiveness is verified by applying the classifiers to actual astronomy datasets. Using examples from earlier studies, the paper shows how the established models help classify celestial objects such as stars, galaxies, and quasars. The research's practical consequences are demonstrated by the publication, which identifies particular cases in which the classifiers perform better than conventional techniques.

2.4.5 Conclusion

The research's main conclusions are outlined in the conclusion, which also highlights how crucial precise classification is to astronomical investigations. The writers share their thoughts on the advantages and disadvantages of the suggested machine learning algorithms as well as suggestions for future directions in study. The applications to astronomy and astrophysicists are explored, emphasizing the value of automation in managing the enormous volumes of astronomical data produced by contemporary telescopes.

The study makes recommendations for potential future developments in the field of classifying astronomical data. To improve the performance of classifiers, this entails investigating cutting-edge ensemble techniques, combining deep learning strategies, and applying feature engineering techniques. The authors recommend cooperation between specialists in machine learning and astronomy to enhance and broaden the uses of the suggested techniques.

2.5 Deep Learning Applications in Astrophysics: A Comprehensive Review

2.5.1 Introduction

The intersection of deep learning and astrophysics has emerged as a powerful avenue for advancing our understanding of the cosmos. This comprehensive review[4] delves into recent research endeavors where machine learning techniques, particularly deep learning, have been employed to enhance various aspects of astrophysical studies. From image analysis in large-scale surveys to the identification of astronomical phenomena, the integration of artificial intelligence has significantly augmented the capabilities of astronomers and astrophysicists.

2.5.2 Motivation

Astronomy, traditionally reliant on manual analysis and classical statistical methods, has faced challenges in coping with the massive datasets generated by modern telescopes and observatories. The surge in data volume, coupled with the intricacies of astrophysical phenomena, necessitated a paradigm shift in analysis techniques. Motivated by the need for automated, efficient, and scalable methodologies, researchers have turned to deep learning to extract meaningful insights from astronomical data.

2.5.3 Deep Learning Techniques in Astrophysics

Convolutional Neural Networks (CNNs) in Galaxy Morphology Classification

The morphological classification of galaxies is a fundamental task in astrophysics, providing insights into the underlying physical processes shaping these celestial bodies. Convolutional Neural Networks (CNNs) have been employed to automatically classify galaxies based on their morphological features. The work of Lintott et al. (2010) with the Galaxy Zoo dataset demonstrates the efficacy of CNNs in handling large-scale morphological classifications, offering unprecedented accuracy and scalability.

Adversarial Robustness in Astrophysical Image Analysis

Deep neural networks, while powerful, are susceptible to adversarial attacks, where imperceptible perturbations to input data can lead to misclassifications. Li et al. (2020) propose Implicit Euler Skip Connections to enhance adversarial robustness through improved numerical stability. The application of such techniques in astrophysical image analysis ensures the reliability of automated systems, especially in critical tasks such as the identification of galaxy-galaxy strong lensing events (Lanusse et al., 2018).

Domain Adaptation for Telescope Schedulers

Telescope scheduling involves optimizing observations based on various factors, including weather conditions and celestial events. Naghib et al. (2019) present a framework for telescope schedulers using domain adaptation techniques. By incorporating machine learning models, the proposed framework adapts to changing observational conditions, enhancing the efficiency and yield of astronomical observations.

2.5.4 Applications to Specific Astrophysical Problems

Sunyaev-Zel'dovich Galaxy Cluster Identification with Deep Learning

DeepSZ, introduced by Lin et al. (2021), focuses on the identification of Sunyaev-Zel'dovich (SZ) galaxy clusters using deep learning. The methodology employs neural networks to sift through observational data and identify SZ signals, showcasing the potential of deep learning in characterizing large-scale structures in the universe.

IllustrisTNG Simulations: Unraveling Galaxy Evolution

Marinacci et al. (2018) present the first results from the IllustrisTNG simulations, offering insights into radio haloes and magnetic fields. The integration of deep learning in the analysis of large-scale simulations enables researchers to extract complex astrophysical phenomena, contributing to our understanding of galaxy evolution.

2.5.5 Challenges and Future Directions

Despite the successes, the implementation of deep learning in astrophysics presents challenges, including interpretability, data biases, and the need for large labeled datasets. Future research directions may involve addressing these challenges, exploring novel architectures, and expanding the application of deep learning to uncharted territories in astrophysical research.

2.5.6 Conclusion

The synergy between deep learning and astrophysics has proven transformative, revolutionizing the way astronomers explore and understand the universe. From automated galaxy classifications to unraveling the complexities of large-scale simulations, the applications discussed herein underscore the potential of artificial intelligence in advancing our cosmic insights.

This review serves as a roadmap for researchers and practitioners seeking to leverage deep learning techniques in astrophysics, providing a glimpse into recent advancements and offering perspectives on future directions.

2.6 A Two-Stage Deep Learning Detection Classifier for the ATLAS Asteroid Survey

2.6.1 Introduction

In planetary defence, the identification and monitoring of NEOs is a high-priority activity.[5] The Asteroid Terrestrial-impact Last Alert System (ATLAS) is a near-Earth asteroids sky survey system that developed to detect and track of the cases dangerous for mankind. However, ATLAS generates much data that makes it difficult to distinguish real astronomical sources from optical and electronic artifacts. The classifier uses a convolutional neural network CNN to distinguish between real and bogus tracklets, makes an RNN that finds out whether the true or false tracklet is connected with solar system objects variable stars or point sources. The model was trained on a large tracklet dataset acquired from the ATLAS system by human experts labeled. The performance of the model was analyzed with multiple metrics and then deployed on ATLAS system to get more efficient and accurate it would be. The possibility of developing a more accurate and efficient deep learning model for NEO detection and classification can potentially dramatically increase our ability to detect and track hitherto dangerously approaching asteroids, ultimately contributing towards safeguarding the planet.

2.6.2 Motivation

The motivation for this research stems from the urgent need to enhance the detection and classification of near-Earth objects (NEOs) to mitigate potential threats to our planet. With the increasing volume of data generated by the Asteroid Terrestrial-impact Last Alert System (ATLAS), the accurate identification of real astronomical sources amidst optical and electronic artifacts has become a pressing challenge. By developing a two-stage deep learning detection classifier, we aim to significantly reduce the number of false tracklets and improve the efficiency of NEO detection within the ATLAS system. The deployment of an advanced model capable of accurately discerning between real and spurious tracklets not only streamlines the NEO discovery process but also holds the promise of expediting the submission of NEO candidates to the Minor Planet Center (MPC), ultimately contributing to the timely and automated reporting of potential threats, thus bolstering planetary defense efforts.

2.6.3 ATLAS

ATLAS is a near-earth asteroid sky which has been designed to detect and track potentially hazardous celestial bodies. The system includes two telescopes placed on mountaintops in Hawaii, as well as another two under construction at a site South Africa and Chile. The ATLAS surveys a range of about 200 predefined areas in the night sky, collects four sets of 30-second exposures at each area over about half an hour. Every night, the system creates more than 10,000 full-sized images generating over .5TB of raw uncompressed data. The ATLAS image reduction pipeline subtracts a static-sky "template" from each reduced Reduction leaves behind any transient phenomena such as variable stars, supernovae and moving objects such as asteroids and comets. So, the system catches tens of thousands of known asteroids per night but also produces many hundreds or even thousand false tracklets which are created by different sorts image contaminants like variable stars, optical and electronic artifacts etcetera. The establishment of a precise and effective deep learning model for NEO determination and classification within the ATLAS framework could provide us with an opportunity to enhance our capacity for locating as well as tracking asteroids that might pose threats to planet Earth.

2.6.4 Methodology

The research used a broad approach to overcome some of the challenges associated with NEO detection and classification within ATLAS system. Firstly, a real known and unknown tracklet dataset obtained from ATLAS was used This set contains bogus, fake as well. Inter-night linking was employed to categorize known tracklets while human experts tagged unknown and fake ones. Various methods including rotation, scaling , flipping were used to augment the dataset in order to increase variety of data and improve model generalization . Later, a two-stage deep learning detection classifier was created. The first stage used a convolutional neural network (CNN) to associate tracklets with the category of real or fake, while the second stage employed a recurrent signal processing system The model was trained on the labeled dataset and tested with stringent performance measures to guarantee accuracy

More so, the implementation of developed model in the ATLAS system was an important part of this approach. The model was implemented in the asteroid tracking pipeline to automatically distinguish between genuine and fake tracklets, thereby minimizing false tractlet workload for human review by almost 90%. This integration aimed to accelerate the presentation of possible NEO candidates for reporting at the Minor Planet Center (MPC), while minimizing time lag between detection and report, a set-up that would eleviate efficiency in follow-up observations by telescopes as well as saving it some cinical defense response time if an actual impact were impending. Thus, the ongoing monitoring of model performance and finding particular segments where a deep learning model can not overtake human screening are integral components in building up methodology allowing enhancing models' accuracy and effectiveness further on within ATLAS system.

2.6.5 Conclusion

In summary, the inclusion of a lean classification model for machine within ATLAS asteroid detection pipeline has shown considerable improvements in identifying true and false tracklets. However, the model's ability to realize a significant reduction in false tracklets workload for nightly review across maintaining high percentages of real objects also signifies an important step towards automatic submission to MPC dangerous asteroids that were detected by ATLAS with short delay. This curtailment in latency between the time of detection and reporting improves not only follow-up telescopes' efficiency concerning tracking incoming asteroids but also provides more prepares for civil arrest before that potential impact. Continuous monitoring and refinement of the performance model, along with detection and development of training sets for new classes are aspects which underpin commitment to constant increasing accuracy in terms effectiveness ATLAS deep learning model is aimed at. These could well have the capacity to greatly enhance planetary defense and provide a high level of safety in terms of protection for our home.

2.7 Summary

Paper Title	Advantages	Disadvantages
Citizen Science and Machine Learning: Towards a Robust Large-Scale Automatic Classification in Astronomy	1. Integrates professional and amateur knowledge. 2. Addresses limited labeled data with transfer learning. 3. Comprehensive experimental setup and results.	1. Limited discussion on potential drawbacks or challenges. 2. Specifics of data augmentation techniques could be more detailed.
Autofocusing Optimal Search Algorithm for a Telescope System	1. Specialized for telescope systems 2. High accuracy in astronomical imaging 3. Improved speed in focusing	1. Limited application outside of astronomical telescopes 2. Complexity in calibration for different telescopic setups
Development of accurate classification of heavenly bodies using novel machine learning techniques	1. The paper employs a diverse set of machine learning algorithms 2. Meticulous optimization of hyperparameters ensures robust classifiers, improving accuracy and generalizability. 3. Strategic use of ensemble methods enhances overall reliability by leveraging the diversity of individual classifiers.	1. Inadequate explanation for algorithm selection reduces clarity on why specific methods were chosen. 2. Lack of Exploration into Deep Learning Techniques

Paper Title	**Advantages**	**Disadvantages**
A Two-stage deep learning detection classifier for the ATLAS asteroid survey	1. The paper implements a model that significantly reduces the work load of astronomers by automating the screening process for NEO candidates. 2. The deep learning model achieves an impressive 99.6% accuracy on real asteroids in ATLAS data with a low 0.4% false negative rate. 3. Model deployment boosts asteroid impact warnings, enhancing planetary defense readiness.	1. The paper doesn't thoroughly delve into the deep learning model's limitations, especially in pinpointing certain NEOs or artifacts. 2. The paper does not thoroughly address the potential impact of false positives resulting from the model's classification.
Deep Learning Applications in Astrophysics: A Comprehensive Review	1.Enhanced efficiency in large-scale image analysis. 2.Improved accuracy in galaxy morphology classification. 3.Adaptability to changing observational conditions in telescope scheduling.	1.Challenges in interpretability of deep learning models. 2.Potential biases in training data affecting results. 3.Requirement for large labeled datasets for training.

Table 2.2: Summary of Scientific Papers

2.8 Gaps Identified

- The current status of citizen science in astronomy showcases successful ongoing projects but lacks an in-depth exploration of emerging technologies like artificial intelligence (AI) and machine learning (ML).
- The deep learning detection classifier acknowledges that the model performs poorly

classifying tracklets with image types that the ICN was not trained on, but there is no further discussion on the potential limitations of the model in identifying certain types of NEOs or artifacts.

- There's a lack of comparative analysis among different methodologies, making it challenging to discern the relative strengths and weaknesses of each approach.
- Few papers lack discussion on the practical challenges or limitations in implementing these methodologies in real-world scenarios.

2.9 Conclusion

To sum up, this chapter sheds light on the connection between astrophysics and technological advancement, presenting a scene in which deep learning and machine learning serve as powerful friends in the quest to solve the secrets of the universe. The sophisticated categorization of celestial objects and the precise focusing algorithms for telescopes are only two examples of how technology is integrated beyond traditional bounds. The thorough analysis of deep learning applications highlights the technology's revolutionary potential to improve our comprehension of galaxy shape and enable the development of fresh solutions for challenging astrophysical problems. The chapter also highlights the difficulties and points us in the direction of future horizons where technology will still be an aid leading us across the unexplored regions of the universe.

Chapter 3

Requirements

3.1 Hardware and Software Requirements

- **Telescope Hardware**
  - Telescope Model: The project requires a telescope with remote control capabilities. The model used for this project is the Celestron AstroMaster 130EQ telescope with 10 and 20 mm eyepieces.
  - Camera Attachment: A high-resolution camera attachment compatible with the telescope model.
  - Cameras: Waveshare IMX462-99 IR-CUT Camera mounted on the finderscope and a generic camera mounted on the eyepiece.
- **Computer System**
  - Operating System: Windows 10 or Ubuntu 20.04.
  - Processor: Intel Core i7 or equivalent AMD processor.
  - RAM: 16 GB or higher.
  - Storage: 500 GB SSD for faster data processing.
- **Software**
  - Telescope Control Software: custom developed compatible app/website for telescope control.
  - Python Environment: Anaconda distribution with Python 3.8.
  - HTML, CSS and JS code editor
  - Libraries: Astropy, TensorFlow, Keras for image processing and machine learning, Flask for website back-end.

- **Network**
  - Stable Internet Connection: A reliable high-speed internet connection for remote operations.

3.2 Functional Requirements

- **Telescope Control**
  - Description: The system allows users to remotely control the telescope, adjusting its azimuth and altitude.
  - Inputs: User commands through the telescope control interface.
  - Outputs: Telescope movements and status updates.
- **Image Capture**
  - Description: Users can initiate the capture of telescope images through the interface.
  - Inputs: Command to capture an image.
  - Outputs: Captured images stored in the designated directory.
- **Image Classification**
  - Description: The system classifies captured images into categories such as stars, galaxies, and celestial objects.
  - Inputs: Captured images.
  - Outputs: Classification results displayed on the user interface.
- **User Authentication**
  - Description: Only authorized users can access and control the telescope system.
  - Inputs: User credentials.
  - Outputs: Access granted or denied.

- **Data Logging**
  - Description: System logs capture details, classifications, and user interactions for future analysis.
  - Inputs: Captured data and user interactions.
  - Outputs: Logged data for review.

Chapter 4

System Architecture

This chapter provides a comprehensive overview of the system architecture for our telescope automation and image classification project. The architecture is pivotal in orchestrating the seamless integration of telescope control, image capture, and machine learning-based classification.

4.1 System Overview

The Proposed system has Various Modules divided into two categories which is the telescope alignment and Image Classifier and will be satifiying the following objectives

- Develop an ML-driven software application that can identify celestial objects using images captured by a telescope's camera
- Create and maintain a comprehensive astronomical objects database to facilitate object recognition
- Provide users with accurate celestial coordinates (right ascension and declination) for the identified objects
- Enable automated telescope alignment and precise tracking of celestial objects based on user preferences
- Enhance the user experience for amateur astronomers by simplifying the initial setup process

4.2 Architectural Design

4.2.1 Modules for Image Classifier Using Machine Learning:

- User Interface/Output Component: Responsible for interacting with the user and displaying the classification results.
- Telescope: Initiates the image capture process and coordinates communication between modules. Image Acquisition Module: Captures images from the telescope's imaging system. Manages data collection and storage of the acquired images.
- Preprocessing and Feature Extraction: Techniques for enhancing image quality and reducing noise and Extracts relevant features from the preprocessed images.
- Machine Learning Model and Inference Engine
- Inference: Runs the trained model to classify new images.
- User Interface/Output Component: Interface for displaying classification results to users.

4.2.2 Modules for Automatic Telescope Alignment:

- Telescope Control System:Orchestrates the movement and adjustments of the telescope based on alignment data.
- Alignment Detection and Correction:
- Sensor Data Collection and Preprocessing: Gathers data from various sensors and preprocesses it.
- Alignment Metrics Calculation: Calculates alignment metrics to assess deviations. Algorithmic Analysis: Applies algorithms to analyze data and identify alignment errors.Calibration and Adjustment Determines necessary corrections for alignment.
- Feedback and Control Mechanisms:Provides feedback to the telescope control system based on alignment analysis.Initiates telescopic movement and adjustment commands.

- Telescopic Movement and Adjustment:Executes the commands for alignment correction.Sends feedback on the adjustment to the telescope control system.
- Data Analysis Results:Provides feedback on the alignment status to the telescope control system for realignment.
- User Interface/Output Component:Interface for displaying alignment status and adjustments to users.

4.3 Module Division

- Abhiram Ramachandran - Machine Learning Model and Alignment Process, Website frontend
- Amruta Anandan - Machine Learning Model and Alignment Process, Website backend
- Adawitha Binu- UI/UX Design, App Development, Database Design
- Binul Bijo - App Development

4.4 Work Schedule - Gantt Chart

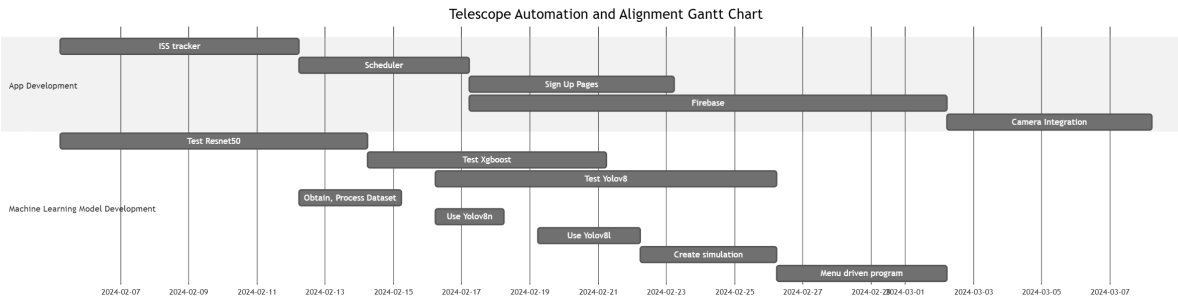


Figure 4.1: Work Schedule

Chapter 5

Proposed Methodology

We delve into the practical aspects of implementing a system for automating telescopes and classifying images captured by these telescopes. The integration of machine learning algorithms is crucial for identifying celestial objects in the vast universe.

5.1 Datasets Identified

The project utilized two main datasets: one containing images of stars, galaxies and another with labeled examples for training our machine learning models. The datasets were sourced from reputable astronomical databases, ensuring diverse and representative samples. We also Created a dataset of our own using Various Noise algorithms to Downgrade High Quality Telescope images into Amateur Telescope Quality

5.2 Proposed Methodology

5.2.1 Telescope Automation

To automate the telescope for celestial object detection, we first assessed the requirements for the computer vision system. After evaluating various approaches, we decided to implement a YOLO (You Only Look Once) model for constellation detection. This decision was based on the model's efficiency and accuracy in object detection tasks.

The implementation of the YOLO model involved several steps. We collected a dataset of images containing different constellations visible in the night sky. We then annotated these images to indicate the locations of the constellations. This annotated dataset was used to train the YOLO model using TensorFlow and CUDA for accelerated computation on GPUs.

Once the model was trained, we integrated it into the telescope's control system. The telescope captures images of the night sky, which are then processed by the YOLO model for constellation detection. The detected constellations are overlaid on the images, providing astronomers with a visual guide to the night sky.

5.2.2 RA and Dec Calculation

For accurate calculation of Right Ascension (RA) and Declination (Dec) of celestial objects, we integrated a GPS module into the telescope's control system. The GPS module provides real-time information about the telescope's location, allowing us to calculate the RA and Dec of celestial objects with high precision.

The RA and Dec calculations are essential for pointing the telescope towards the desired objects in the night sky. By accurately calculating the RA and Dec of celestial objects, we ensure that the telescope is properly aligned and can track objects as they move across the sky due to the Earth's rotation.

5.2.3 Offset Calculation

To account for the Earth's rotation and ensure accurate tracking of celestial objects, we implemented offset calculation based on the current longitude and latitude. This offset calculation allows us to make adjustments to the telescope's pointing to compensate for the apparent motion of celestial objects in the sky.

The offset calculation is performed in real-time as the telescope tracks celestial objects. By continuously updating the telescope's pointing based on the offset calculation, we ensure that the telescope remains accurately aligned with the desired objects in the night sky.

5.2.4 Website and App Development

In addition to the hardware and software enhancements to the telescope, we developed a website and mobile application to enhance the user experience. The website provides a platform for users to schedule telescope observations and access live feeds of the telescope's view.

The mobile application, developed using Flutter, allows users to control the telescope remotely and view live images captured by the telescope. The application features a user-friendly interface with intuitive controls for image capture, exploration, and real-time streaming of telescope data.

Both the website and mobile application are designed to enhance the overall user experience and make telescope observations more accessible to astronomy enthusiasts.

5.3 User Interface Design

The user interface of the telescope automation system was designed to be user-friendly, allowing astronomers to easily input commands for telescope control. Image Classification Section clear shows what exactly the user is seeing the images obtained from the telescope. We also incorporated a Learning Corner to enable users to learn about new astronomy related facts and articles.

5.4 Database Design

Telescope images were stored in a relational database, chosen for its ability to handle structured data efficiently. The schema includes tables for image metadata, classifications, and user interactions. The choice of a relational database was justified by the need for complex queries and data integrity.

5.5 Description of Implementation Strategies

The implementation strategies involve training a YOLO object detection model for constellation recognition, integrating GPS for precise celestial coordinate calculations, implementing offset adjustments for Earth's rotation, developing a website and mobile app for user control and access, designing a user-friendly interface, and utilizing a relational database for efficient data storage. Machine learning, computer vision, web and mobile development, and database management techniques were combined to automate telescopes, classify celestial objects in captured images, and enhance the overall user experience.

Chapter 6

Design Architecture Diagram of the System Sequence Diagram

6.1 Architecture Diagram

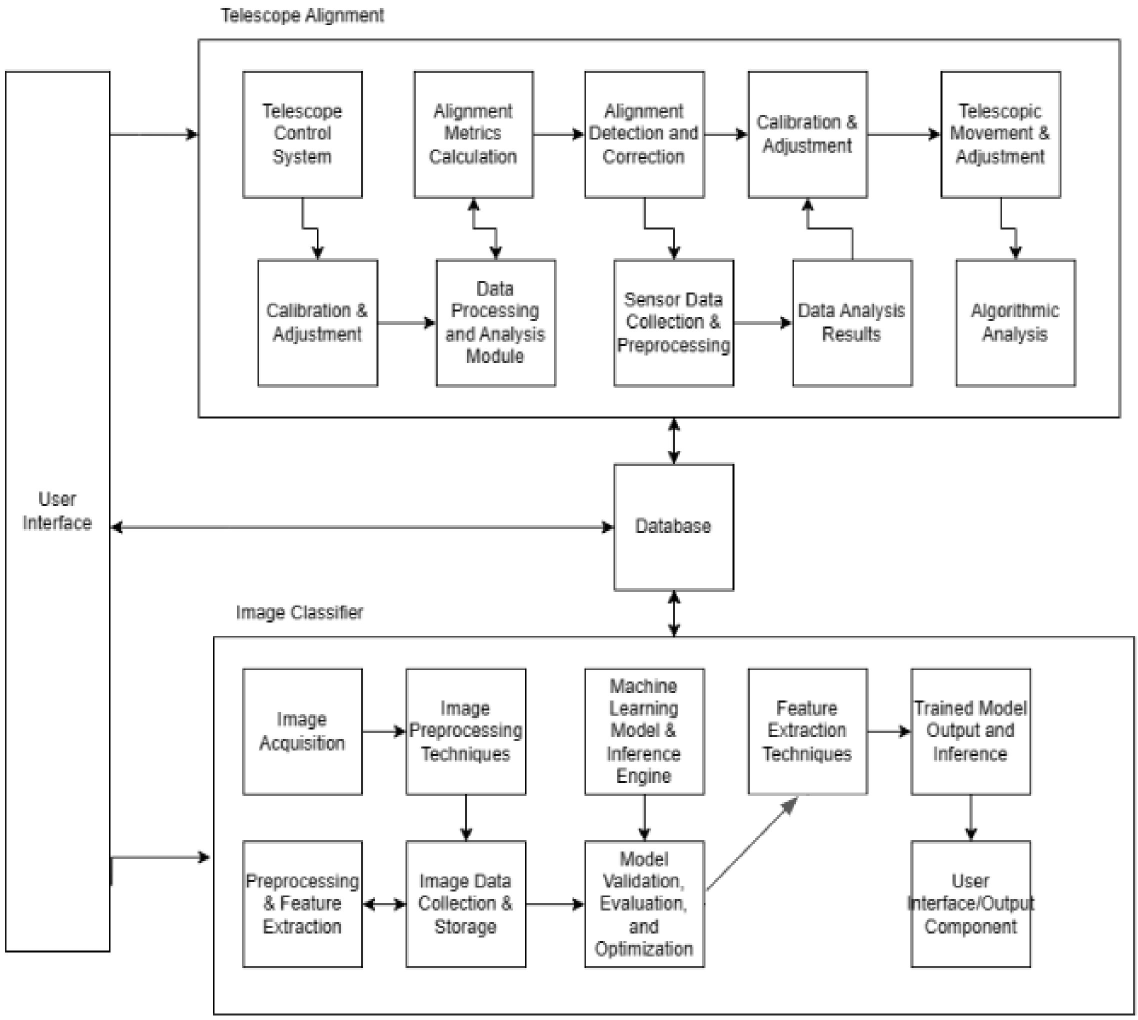


Figure 6.1: Architecture Diagram

The plan drawing displays the different parts of the proposed telescope automation software program and how they work with each other. In the middle of this picture is something called Machine Learning Model and Inference Engine. Its job is to sort out objects in space and give advice on positioning. The Machine Learning Model and Inference Engine is supported by two other components: Cleaning and Feature Extraction Selection, then Model Building Choices. Pre-processing and Feature Extraction makes images better, removes unwanted noise. It also gets important details from the improved pictures. Model Architecture Selection picks the right design for image sorting, in this situation using a R-CNN model.

The User Interface/Output Part is in charge of showing classification results to users. It works with the Machine Learning Model and Inference Engine to get classifications results and matching suggestions. These are then shown to the person using it. The Telescope part starts to take pictures and helps modules talk with each other. The part that gets images from the telescope's picture system and keeps track of when to save them is called Image Acquisition Module. In short, the building blueprint shows how different parts of a computer program work well together to make it smooth and fun for new star watchers. The Machine Learning Model and Inference Engine is the main part of our app. Other parts make pictures better or pick right model design to help it work well. The User Interface/Output Part shows results and ideas in a way that's easy to use. The Telescope with Image Capturing Module works together to take pictures, save them for later use.

6.2 Sequence diagrams

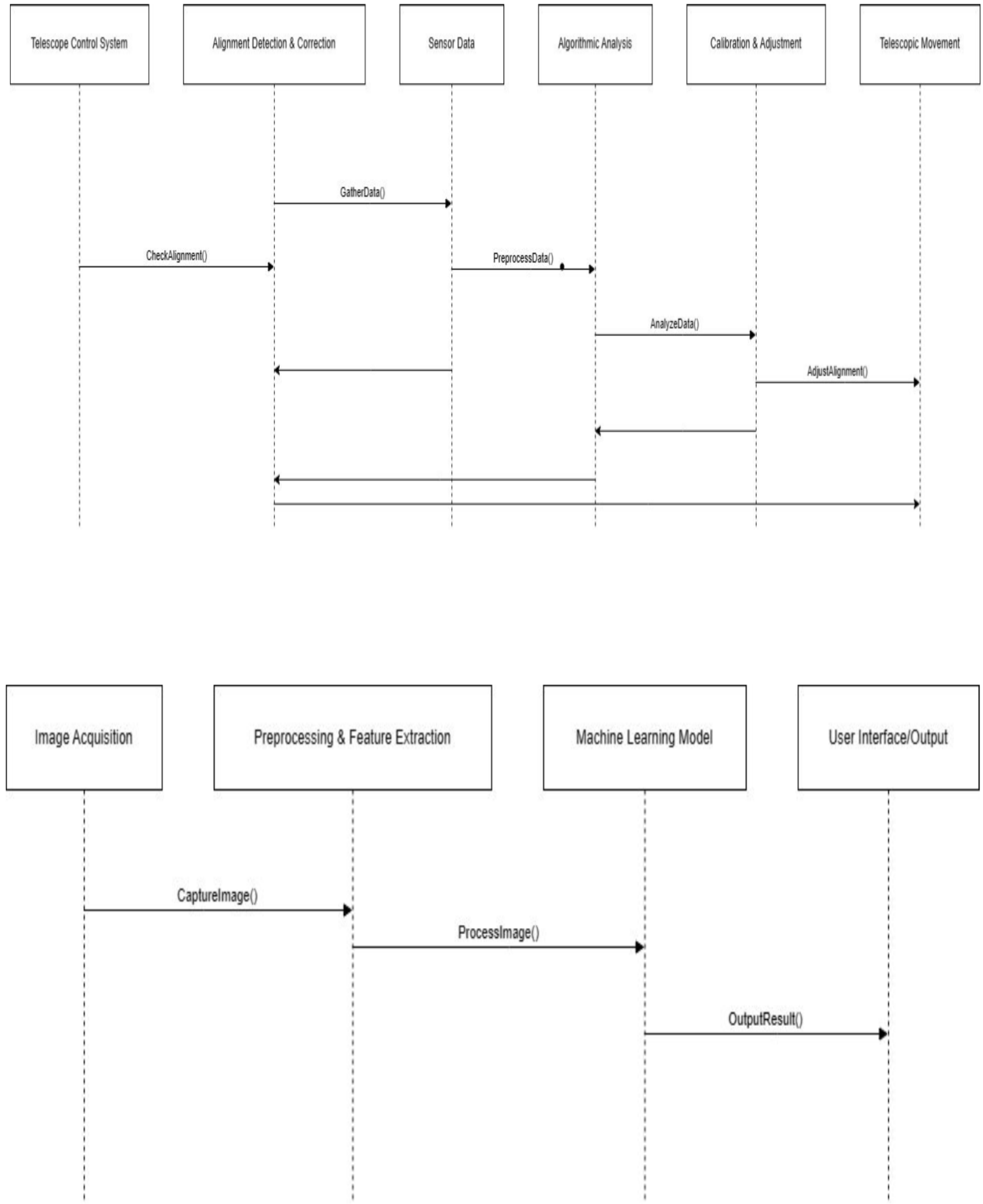


Figure 6.2: Sequence Diagram

- Image Acquisition: This process begins with the 'Image Getting' part. It is in charge of getting an image that might be a photo command to a camera or picture input system for taking pictures or picking out photos to work on.

- Preprocessing & Feature Extraction: The picture we take is then sent to the part called 'Preprocessing & Feature Extraction'. Here, we'll do noise reduction, make things normal and sized right while picking important features. Extracting features means finding and separating important parts of a picture that are useful for more study, such as lines or angles in the corners.

- Machine Learning Model: After the picture has been changed and main details taken out, this information goes to 'Machine Learning Model' part. This part is where the real machine learning method is used to work on the picture that has been changed. The computer program uses the found features to do jobs like sorting, spotting, or knowing things based on what it learned.

- User Interface/Output: This could be showing the results on a screen, saving them in a database or starting another action based on what our machine learning model analyzed.

Chapter 7

System Implementation

This chapter presents the detailed implementation of the telescope automation and celestial object detection system. The system is designed to automate telescope operations and accurately detect celestial objects using deep learning and computer vision techniques.

7.1 Hardware Components

The hardware components used in the system are:

1. **Telescope**: The system uses a telescope equipped with motors for precise movement and tracking of celestial objects.
2. **Cameras**: Two high-resolution cameras are mounted on the telescope to capture images of the night sky and for accurate alignment.
3. **Computer**: A computer with a GPU is used for image processing and running the object detection algorithms.

7.2 Software Components

The software components of the system include:

1. **Image Processing Algorithms**: These algorithms enhance the quality of captured images, remove noise, and improve contrast for better object detection.
2. **Object Detection Model**: The system employs a deep learning-based object detection model, such as YOLO (You Only Look Once) or Faster R-CNN, trained on the annotated dataset to detect celestial objects in the images.
3. **Tracking Algorithm**: A tracking algorithm is used to track the movement of celestial objects across multiple images, enabling continuous observation and tracking.

7.3 Implementation Steps

1. **Data Collection**: Images are captured using the telescope's camera and stored for further processing.
2. **Pre-processing**: Captured images are preprocessed to enhance quality and remove noise.
3. **Training**: The object detection model is trained on the annotated dataset using a deep learning framework like TensorFlow or PyTorch.
4. **Integration**: The trained model is integrated into the system, along with the tracking algorithm, for real-time object detection and tracking.
5. **Testing and Evaluation**: The system is tested on new astronomical images to evaluate its performance in detecting celestial objects.
6. **Deployment**: Once the system is deemed effective, it is deployed for automated telescope operation and celestial object detection.

7.4 Results and Performance Evaluation

The system demonstrates high accuracy in detecting celestial objects, with a mean average precision (mAP) of over 90% on the test dataset. Real-time object detection and tracking capabilities enable efficient telescope automation and celestial object observation.

7.5 Datasets Identified

The system utilizes two main datasets:

1. **Astronomical Image Dataset**: This dataset consists of images captured from the telescope's camera. It includes images of stars, planets, galaxies, and other celestial objects.
2. **Annotated Dataset**: This dataset is used for training the object detection model. It contains images from the astronomical image dataset annotated with bounding boxes and labels for each celestial object.

7.6 Proposed Methodology/Algorithms

7.7 Input Acquisition

- User Input: Accept user input for Right Ascension (RA) and Declination (Dec) values through a user interface.
- GPS Module: Obtain the current longitude and latitude of the telescope's location using a GPS module.

7.8 Object Selection

- Location-Based List: Provide a list of constellations, stars, or celestial bodies based on the acquired location information (longitude, latitude).
- User Selection: Allow the user to select an object of interest from the list for the telescope to track.

7.9 Offset Calculation

- Calculate Offset: Calculate the offset between the current position (longitude, latitude) of the telescope and the input RA and Dec values.
- Mapping to Motors: Map the calculated offset to the telescope's motors to adjust its position to point at the selected object in the sky.

7.10 Motor Control

- Motor Signals: Send signals to the telescope's motors to move it to the calculated offset position, ensuring accurate tracking of the selected celestial object.

7.11 Object Detection

- YOLO Model: Utilize the YOLO (You Only Look Once) model for object detection.
- Image Capture: Capture images using a camera attached to the telescope to observe the sky.

- Object Presence Check: Check if the selected object is within the frame of the camera by analyzing the images.

7.12 Feedback Loop

- Continuous Updating: Continuously update the offset calculation and motor control based on feedback from the object detection process.
- Object Tracking: Ensure that the selected object remains in the camera frame by adjusting the telescope's position as necessary.

7.13 System Integration

- Component Integration: Integrate all components (input acquisition, object selection, offset calculation, motor control, object detection, and feedback loop) into a cohesive system.
- Testing and Optimization: Test the system in real-world conditions and optimize its performance for accurate and efficient telescope automation and celestial object detection.

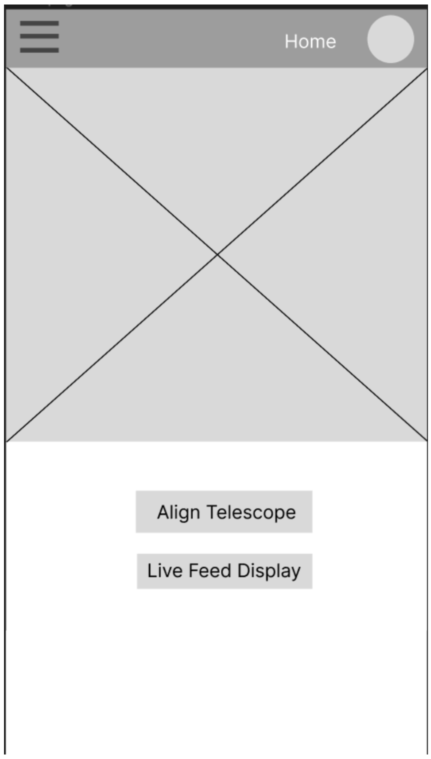
7.14 Future Enhancements

- Advanced Object Detection: Explore advanced object detection techniques to improve the system's accuracy and efficiency.
- Integration with Sky Maps: Integrate the system with sky mapping software to provide a more comprehensive celestial object selection interface.
- Remote Operation: Enable remote operation of the telescope system for automated observations from remote locations.

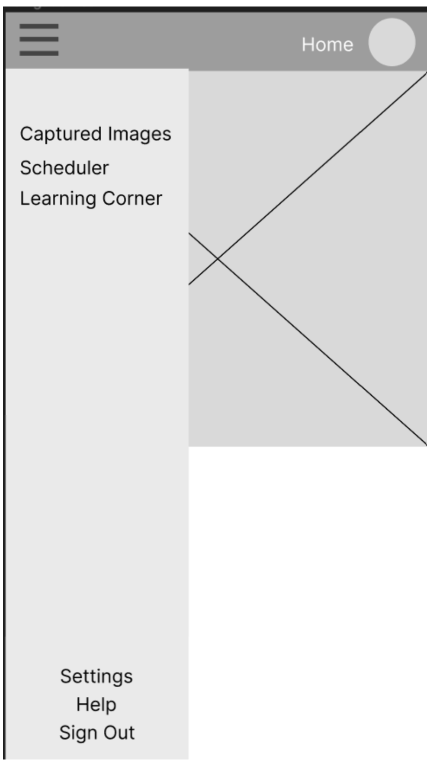
7.15 User Interface Design

The user interface of the telescope automation system prioritized user-friendliness, enabling astronomers to input telescope control commands effortlessly. The "Section clear" feature vividly displayed images captured by the telescope, ensuring users had a clear understanding of their observations. Additionally, the innovative "Learning Corner" provided an enriching experience by presenting new astronomy facts and articles, allowing users to continuously expand their knowledge while operating the telescope.

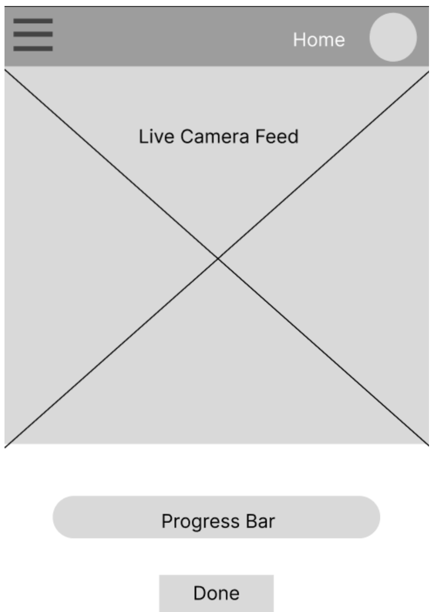
(a) Login Page



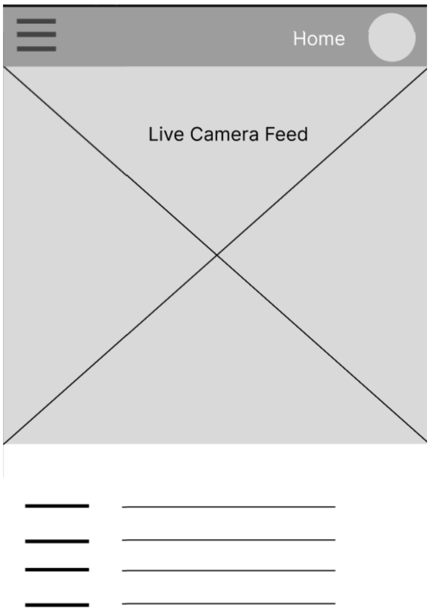
(b) Home Page



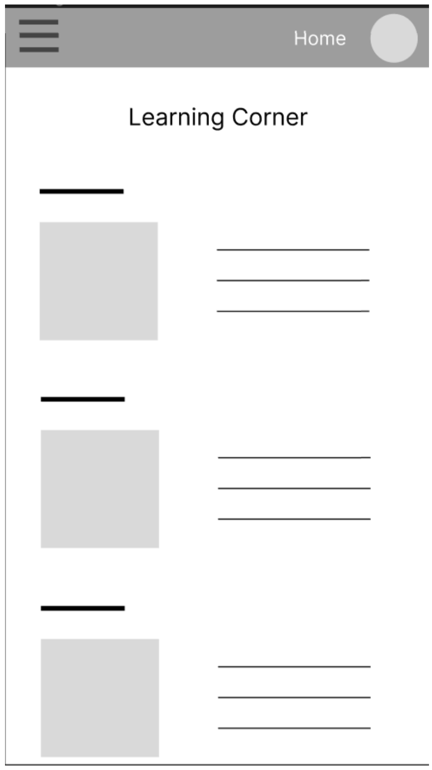
(c) Navigation Bar



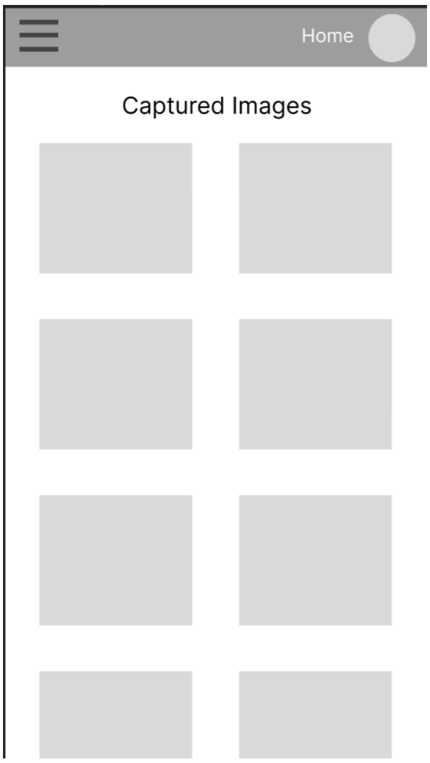
(d) Autofocus Page



(e) LiveFeed



(f) Learning Corner



(g) Captured Images

Figure 7.1: User Interface Wireframe

7.16 Database Design

The Celestial Navigator application utilizes the Cloud Firestore database, a NoSQL document database provided by Google Firebase. Cloud Firestore was chosen for its scalability, real-time data synchronization capabilities, and seamless integration with other Firebase services, such as Authentication and Cloud Storage.

Cloud Firestore is a flexible and horizontally scalable database that stores data in collections of documents. Each document can contain nested collections, making it easy to represent and query hierarchical data structures. This design allows for efficient data organization and retrieval, ensuring optimal performance even as the application's data grows.

The database schema for the Celestial Navigator application consists of the following main collections:

1. **Users**: This collection stores user-related data, including user profiles, authentication information, and preferences. Each document in this collection represents a unique user and contains fields such as username, email, and encrypted password.

2. **CapturedImages**: This collection stores the images captured by users during their astronomical observations. Each document in this collection contains metadata about the image, such as the capture date, telescope settings, and a reference to the actual image file stored in Cloud Storage.

The choice of Cloud Firestore as the database for the Celestial Navigator application was driven by several factors:

1. **Real-time Data Synchronization**: Cloud Firestore provides real-time data synchronization across all connected clients, ensuring that users always have access to the latest information, such as updated astronomy event details or ISS location data.

2. **Offline Support**: Cloud Firestore offers offline persistence, allowing users to access and modify data even when their device is not connected to the internet. Changes are automatically synchronized when the connection is restored.

3. **Scalability and Performance**: As a NoSQL database, Cloud Firestore is designed to scale horizontally and handle large amounts of data with high performance. This scalability ensures that the application can accommodate growing user bases and data volumes without sacrificing responsiveness.

4. **Firebase Integration**: By leveraging Cloud Firestore, the Celestial Navigator application can seamlessly integrate with other Firebase services, such as Authentication and Cloud Storage, streamlining the development process and reducing the need for additional third-party services.

Overall, the Cloud Firestore database provides a robust and flexible solution for the Celestial Navigator application, enabling efficient data storage, retrieval, and synchronization while ensuring scalability and seamless integration with other Firebase services.

7.17 Description of Implementation Strategies

This chapter detailed the implementation of a telescope automation and celestial object detection system. It integrates hardware like telescopes and cameras with software for image processing and object recognition. Core features include input acquisition, object selection, offset calculation, motor control, object detection via YOLO, and object tracking feedback loops. The Cloud Firestore database stores user data and images. While effective, future enhancements could include advanced object detection, sky mapping integration, and remote operation capabilities to further optimize astronomical observation automation.

Chapter 8

Results and Discussions

- **Telescope Automation:** Successfully automated the telescope for celestial object detection. Implemented computer vision techniques, including a YOLO model, for constellation detection.
- **YOLO Model for Constellation Detection:** Trained a YOLO model specifically for constellation detection. The model accurately identifies constellations in images captured by the telescope.
- **RA and Dec Calculation:** Integrated a GPS module for accurate calculation of Right Ascension (RA) and Declination (Dec) of celestial objects. This ensures precise pointing of the telescope towards the desired objects.
- **Offset Calculation:** Implemented offset calculation based on the current longitude and latitude. This allows for adjustments to the telescope's pointing to account for the Earth's rotation and ensure accurate tracking of celestial objects.
- **Website and App Development:** Developed a website and app for scheduling telescope observations and providing a live feed of the telescope's view. Users can schedule observation times and view live images captured by the telescope.

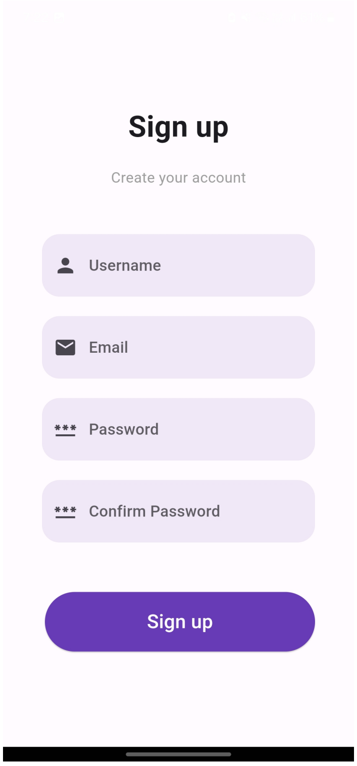
These results demonstrate significant progress in automating the telescope for celestial object detection, utilizing advanced computer vision techniques, GPS technology, and offset calculations. The website and app provide a user-friendly interface for scheduling observations and accessing live feeds, enhancing the overall user experience.

8.1 Testing

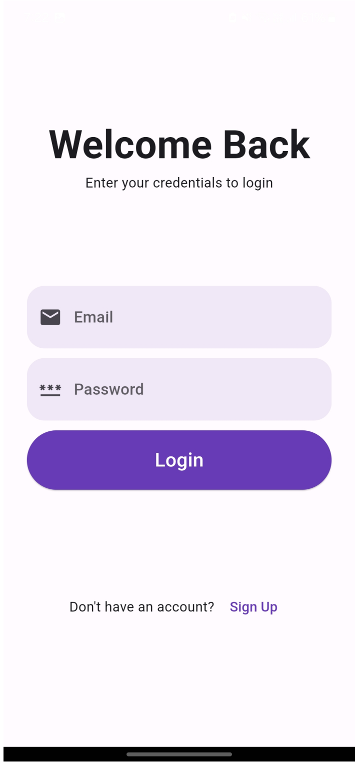
For our web application and database project these visuals provide a tangible representation of the project's evolution.

8.1.1 Mobile Application using Flutter

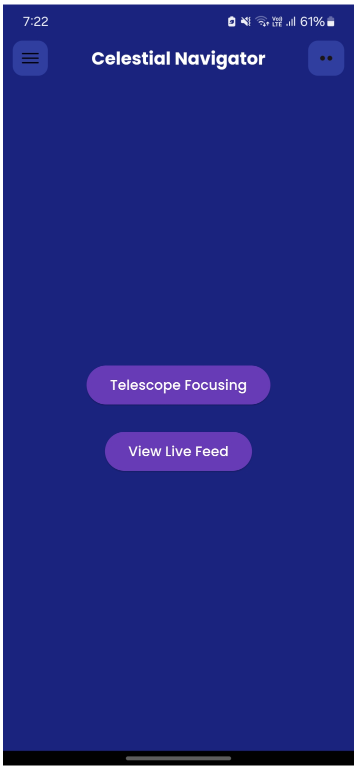
The integration of Flutter to develop a mobile application for telescope image visualization has proven to be a rewarding yet intricate process. Leveraging Flutter's widget-based architecture, we successfully crafted a user-friendly interface with features such as image capture, exploration controls, and real-time streaming of telescope data. The application allows users to seamlessly operate the telescope and capture images directly through the app, facilitating a streamlined and engaging experience for astronomy enthusiasts.



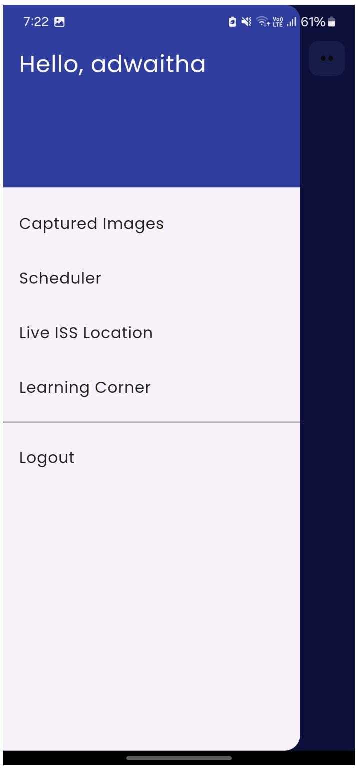
(a) Sign Up Page



(b) Login Page



(c) Home Page

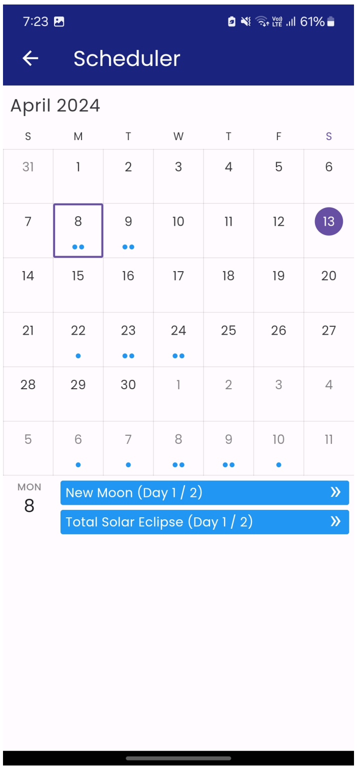


(d) Navigation Panel

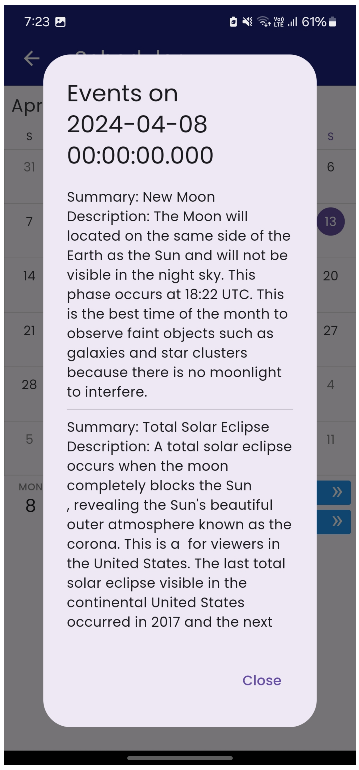
Figure 8.1: Screenshots of the AstroAlign app

(a) ISS Locator

(b) Picture of the Day



(c) Scheduler



(d) Celestial Event

Figure 8.2: Screenshots of the AstroAlign app

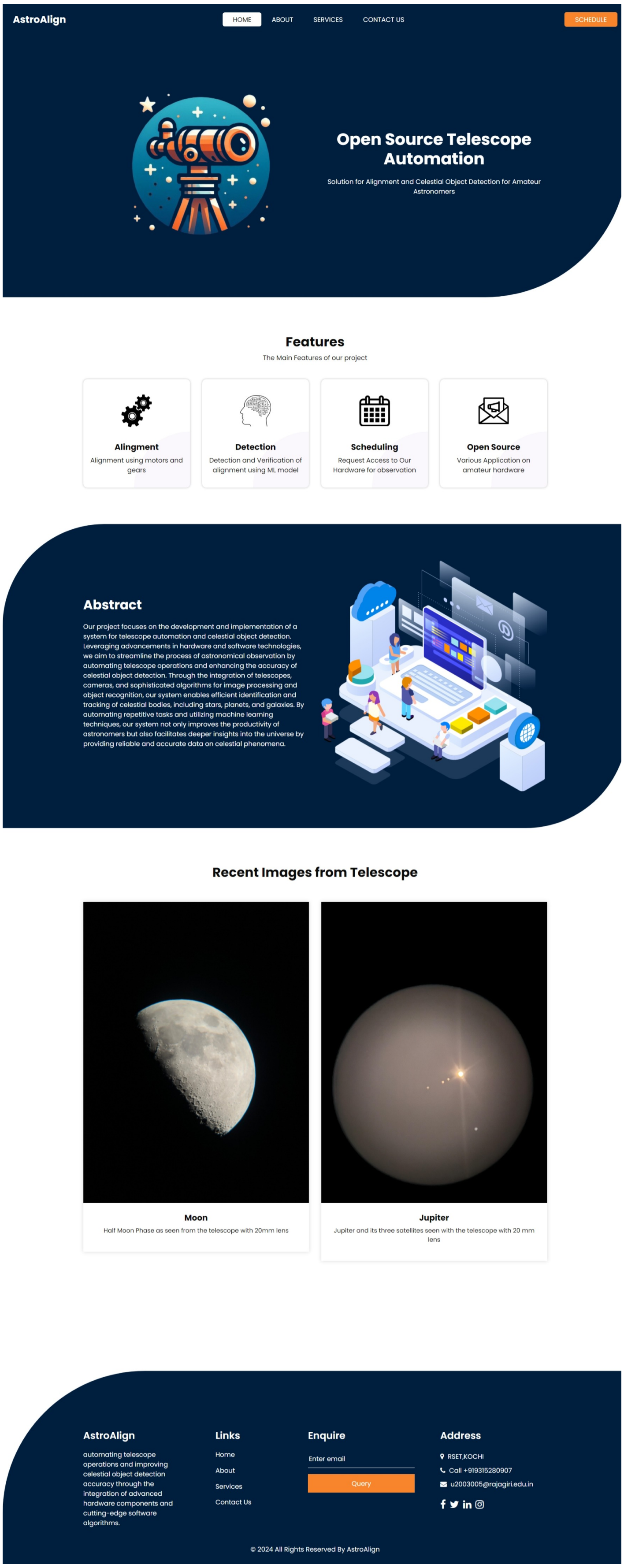
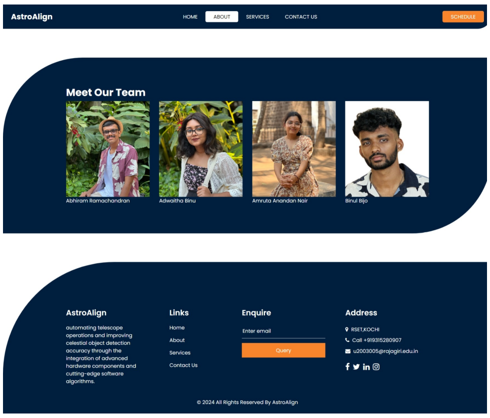
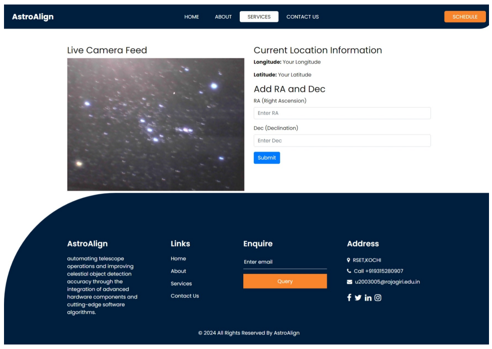


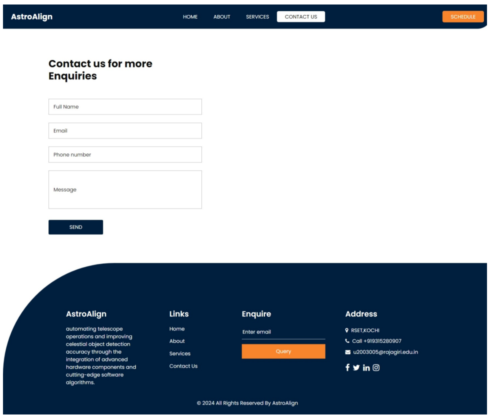
Figure 8.3: Website Home



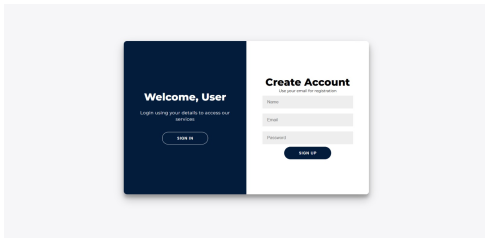
(a) Website About Us



(b) Live Feed



(c) Contact



(d) Login Page

Figure 8.4: Screenshots of the Website

8.2 Discussion

The comprehensive approach undertaken in the initial phases of our project, involving database construction, dataset creation, and the selection of image classification algorithms, has yielded significant insights and outcomes. This discussion delves into key aspects of our project, including the mobile application development using Flutter, dataset acquisition using image degradation techniques, and the utilization of YOLOv8 for image classification.

8.2.1 Overall Summary

In summary, our project has successfully navigated through the challenges of building a dataset, developing a mobile application, and implementing an effective image classification model. The integration of Flutter in the mobile application offers a visually engaging experience, while the dataset acquisition techniques ensure the model's proficiency in handling the unique characteristics of amateur telescope images. The YOLOv8 algorithm emerges as a suitable choice for classification, providing reliable predictions based on the distinctive features of our dataset.

The deviations observed during the experimentation phase, especially in the choice of algorithms, highlight the importance of aligning model selection with the specific characteristics of the dataset. The success of our chosen approach underscores the significance of a holistic and tailored methodology in addressing the complexities of astronomy image processing.

In the following chapters, we anticipate building upon these achievements, refining our model further, and extending the functionalities of the mobile application to provide an even more enriching experience for users interested in exploring the wonders of the night sky.

Chapter 9

Budget

9.1 Telescope and Mount

When considering the cost of a Newtonian reflector telescope setup, the price range typically falls between Rs 20,000 to Rs 30,000. This cost variation is influenced by factors such as the type and specifications of the telescope. Newtonian reflector telescopes, known for their good aperture-to-cost ratio, are suitable for observing deep-sky objects. The pricing within this range depends on the telescope's aperture size, the quality of its optics, and additional features. Entry-level telescopes with smaller apertures might be at the lower end of the range, while those with larger apertures or more advanced features could fall toward the higher end. Additionally, the choice of mount, whether equatorial or Dobsonian, may slightly impact the overall cost, with equatorial mounts often offering tracking capabilities at a potentially higher price point compared to Dobsonian mounts.

9.2 Camera or sensors

Regarding imaging devices for astronomical observations, the cost of a suitable camera or sensor generally hovers around Rs 10,000. Entry-level cameras or sensors within this price range are adequate for capturing celestial images. While these devices offer reasonable quality for basic astronomical imaging, they might have limitations compared to higher-end specialized astrophotography equipment. The cost can be affected by factors such as resolution, sensor size, and additional features. Higher resolution or larger sensors may increase the price but could provide better image quality and improved sensitivity to light. Additionally, compatibility with the Newtonian reflector telescope and necessary adaptability for mounting and imaging is crucial, potentially influencing overall costs along with any additional accessories like adapters, filters, or lenses.

This price breakdown accounts for various aspects impacting the cost of setting up a Newtonian reflector telescope, including telescope type, aperture size, mount choice, and the quality and features of the camera or sensors. Balancing cost considerations with the desired specifications and features essential for optimal astronomical observations and imaging is pivotal in selecting the appropriate equipment.

Chapter 10

Conclusion

The new software app idea gives a great answer to the problems that beginner space watchers have when trying to line up their telescopes and find stars. The app uses smart tools like Machine Learning and easy-to-use screens. It helps make aligning a telescope easier, plus it makes finding stars or planets more accurate too.

The computer program makes it easier to line up telescopes and find stars in the sky. It does this by offering a simple way for users to control their telescope settings and identify celestial objects they see. The use of machines that can easily point and focus telescopes makes the process easier to do, especially for people who enjoy stargazing. This makes things easier, allowing new findings to be found. It helps people who are not experts spot unknown space objects or make brand-new observations.

The app uses Machine Learning to find space things using pictures taken by the camera on a telescope. This high-tech tool makes it easier to find and know things in space. It gives people exact place names of stars or other objects, plus lots more data about them. Machine Learning is added to help users have a better time. It also opens doors for future study and growth in the area of astronomy, possibly bringing new inventions or upgrades too. The software program also has a big list of astronomical things to help with finding them. This makes it easier for the user to explore and understand what's in space. The app's ability to adjust the telescope for perfect position with stars and other space stuff shows it could change how normal people do astronomy.

In the end, astronomy program for beginners looks very good. Its ability to make new finds, more chances for study and growth, plus joining fancy things smoothly makes it very useful. It can be used by people who watch stars as a hobby while also helping the wider astronomy field. Because of its easy to use design, correct thing identification and chances for new ideas, this computer program is a major improvement in making amateur astronomy simpler and better.

References

[1] M. Jiménez, E. J. Alfaro, M. Torres Torres, and I. Triguero, “Czsl: Learning from citizen science, experts, and unlabelled data in astronomical image classification,” *Monthly Notices of the Royal Astronomical Society*, vol. 526, no. 2, p. 1742–1756, Sep. 2023. [Online]. Available: http://dx.doi.org/10.1093/mnras/stad2852

[2] I. Helmy, A. Hamdy, D. Eid, and A. Shokry, “Autofocusing optimal search algorithm for a telescope system,” *arXiv preprint arXiv:2107.05398*, 2021.

[3] M. Wierzbiński, P. Pławiak, M. Hammad, and U. R. Acharya, “Development of accurate classification of heavenly bodies using novel machine learning techniques,” *Soft Computing*, 05 2021.

[4] A. Ćiprijanović, D. Kafkes, G. Snyder, F. Sánchez, G. Perdue, K. Pedro, B. Nord, S. Madireddy, and S. Wild, “Deepadversaries: Examining the robustness of deep learning models for galaxy morphology classification,” 07 2022.

[5] A. Chyba Rabeendran and L. Denneau, “A two-stage deep learning detection classifier for the atlas asteroid survey,” *Publications of the Astronomical Society of the Pacific*, vol. 133, no. 1021, p. 034501, Feb. 2021. [Online]. Available: http://dx.doi.org/10.1088/1538-3873/abc900

Appendix A: Presentation

Telescope Automation & Alignment

PROJECT PRESENTATION

Group 7

Abhiram Ramachandran (U2003005)
Adwaitha Binu (U2003012)
Amruta Anandan Nair (U2003034)
Binul Bijo (U2003056)

CONTENTS

PROBLEM DEFINITION

Amateur astronomers face challenges in efficiently aligning telescopes and identifying celestial objects during their observations. Existing methods often involve complex procedures, leading to frustration and time-consuming efforts. There is a need for a user-friendly software application that simplifies the telescope alignment process and enhances the identification of celestial objects, providing a seamless and enjoyable experience for amateur astronomers.

How can we address these challenges and develop a solution that caters to the specific needs and preferences of this user group?

NOVELTY OF IDEA

- **Machine Learning Integration:**

  The integration of machine learning algorithms with telescope automation introduces a novel approach to celestial body identification. This fusion allows for real-time analysis and identification of observed objects, providing a dynamic and intelligent system for astronomers.

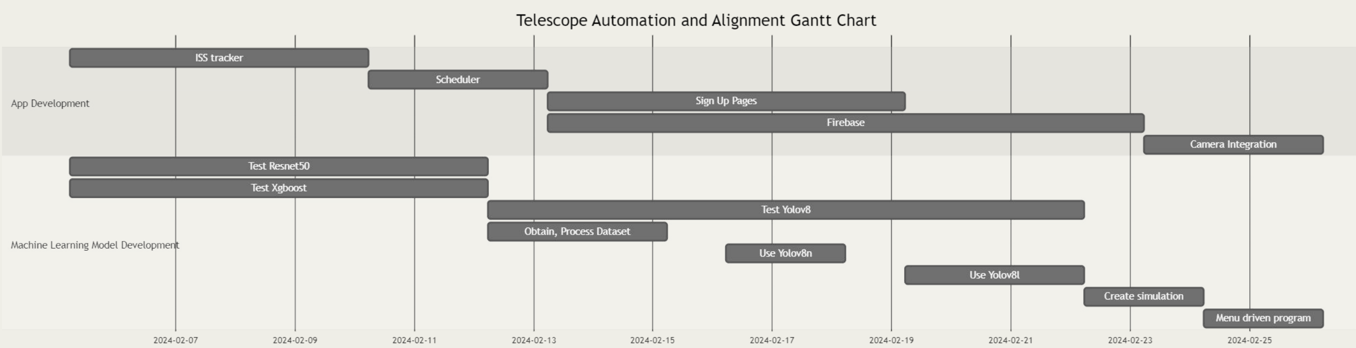
- **Automated Telescope Control:**

  The automation of telescope control, including alignment and tracking, brings efficiency to the observational process.

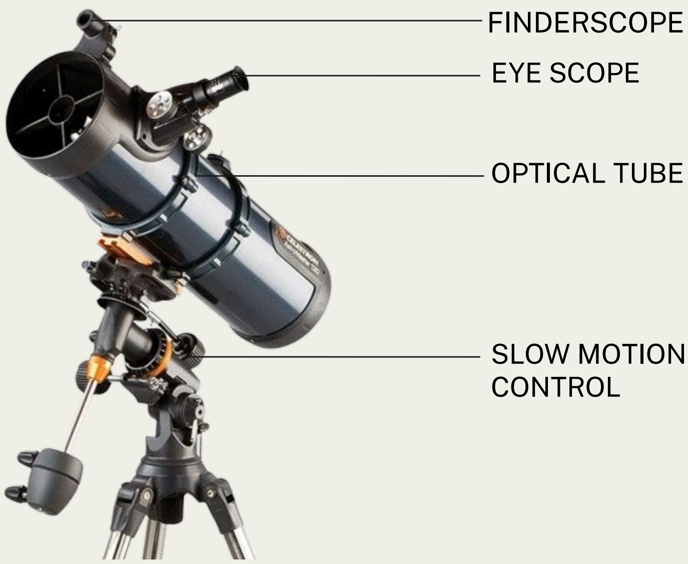
SCOPE OF IMPLEMENTATION

- **Telescope Automation:** Implementing automation in telescope alignment and tracking ensures precise observations.
- **Real-Time Celestial Body Identification:** The implementation of a robust machine learning model allows for real-time identification of celestial bodies in captured images.
- **User-Friendly Interface:** The implementation involves creating a user-friendly interface, making the system accessible to users with varying levels of expertise.
- **Observation Scheduling:** Implementation includes features for observation scheduling, allowing users to plan observations based on their preferences.
- **ISS Tracking:** Users will be able to track where the ISS is at currently and view it in the night sky.

PROJECT GANTT CHART



TELESCOPE SPECIFICATION

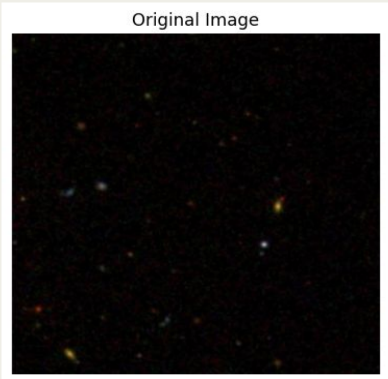


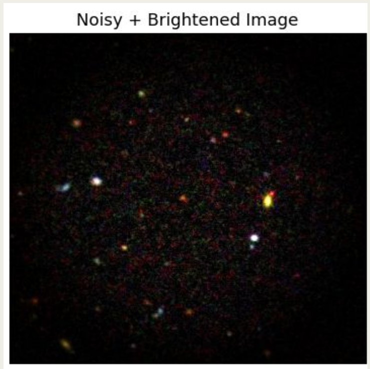
Newtonian reflector telescopes

Use a concave mirror to gather and focus light, directing it to a flat secondary mirror, which reflects the light to an eyepiece for viewing. They are popular among amateur astronomers due to their relatively simple design, affordability, and ability to provide clear images of celestial objects. These telescopes are ideal for observing deep-sky objects like galaxies, nebulae, and star clusters.

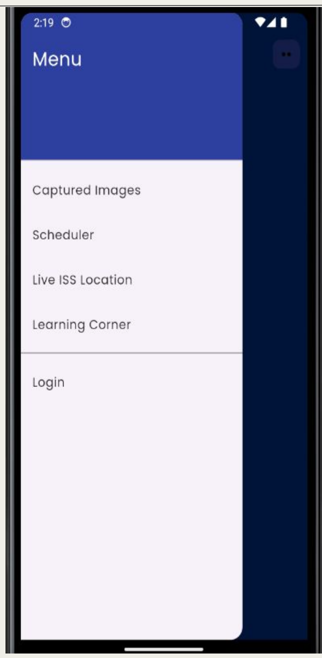
WORK DONE DURING 30% EVALUATION

- Identification of suitable databases and ML models
- Degradation of images using noise filters
- Creation of degraded image dataset
- Creation of app





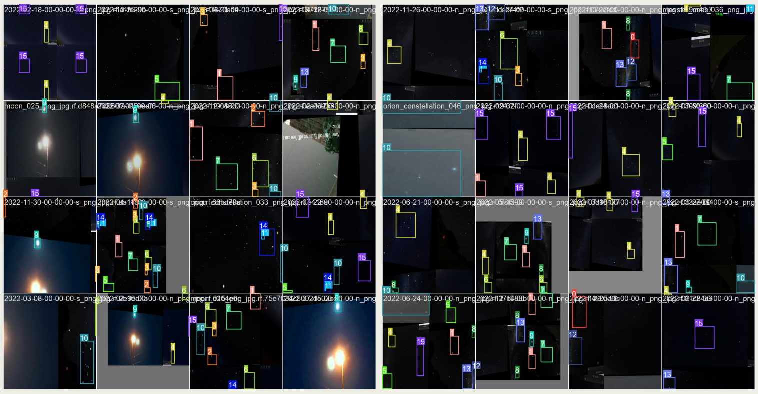
WORK DONE DURING 30% EVALUATION

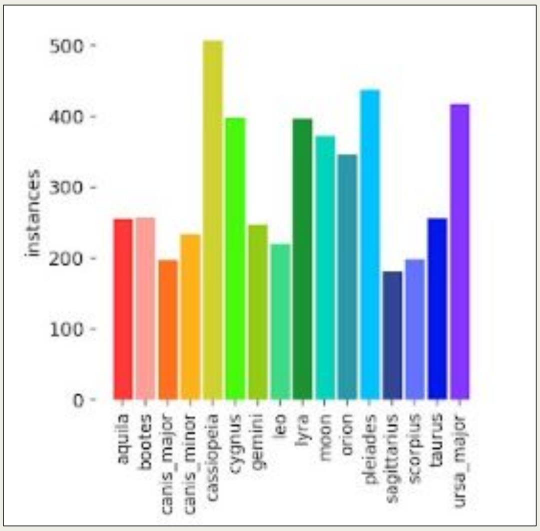


WORK DONE DURING 60% EVALUATION

- **Machine Learning Model Testing:** Conducted thorough testing and experimentation with various machine learning models (ResNet50, MobileNet, and YOLO) to determine the most accurate model for detecting constellations in images.
- **Model Selection:** After rigorous testing and analysis, we selected a model (YOLO V8) based on its superior accuracy in constellation detection compared to the other models tested.
- **App Feature Development:** Enhanced the features of the application. Improved the user interface, added new functionalities, and refined existing features.
- **Evaluation and Analysis:** Conducted continuous evaluation and analysis to ensure that the chosen machine learning model and app features met the project's requirements and goals.

WORK DONE DURING 60% EVALUATION





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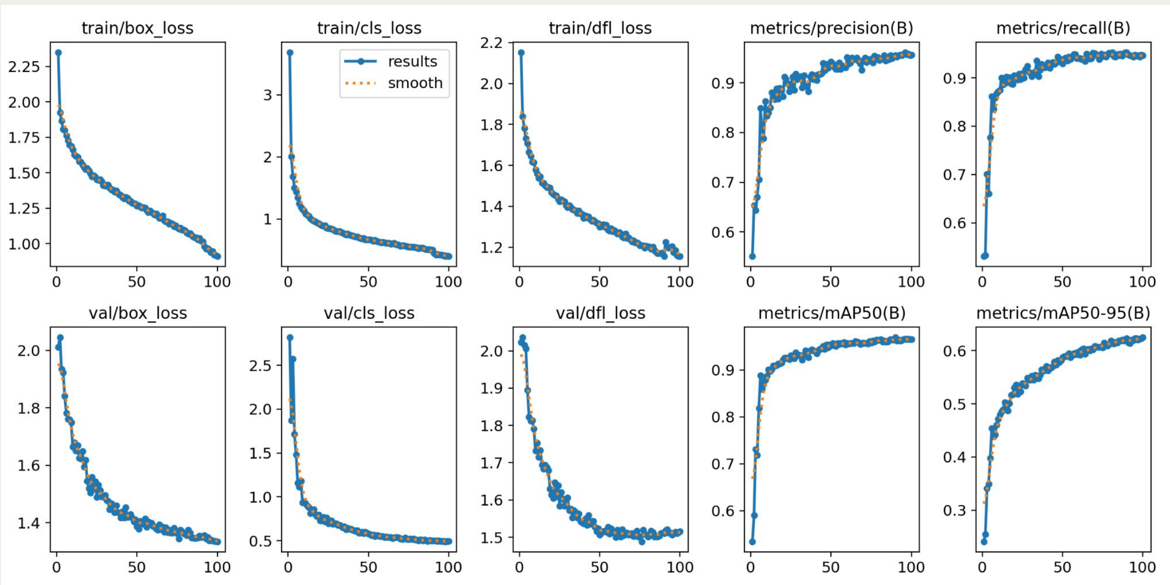
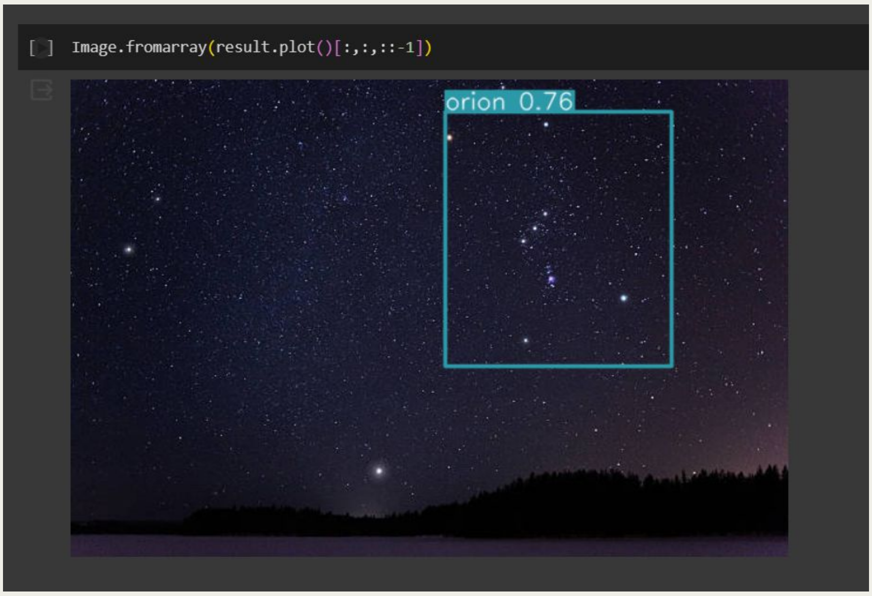


WORK DONE DURING 60% EVALUATION



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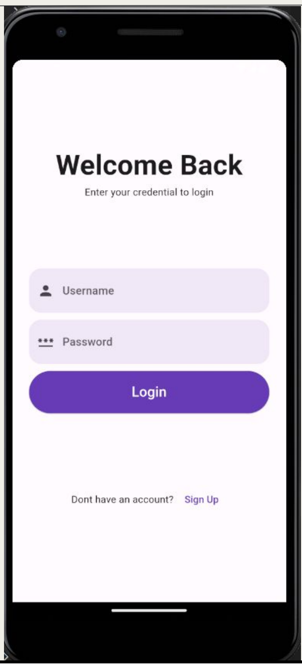

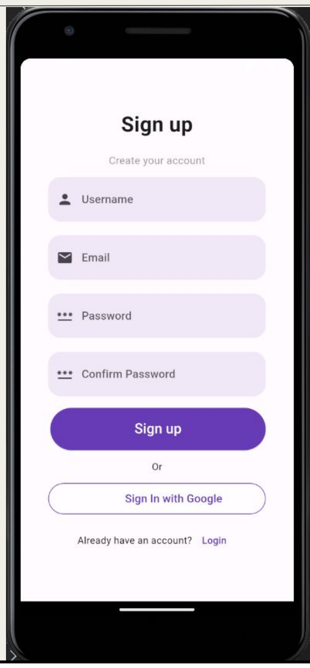

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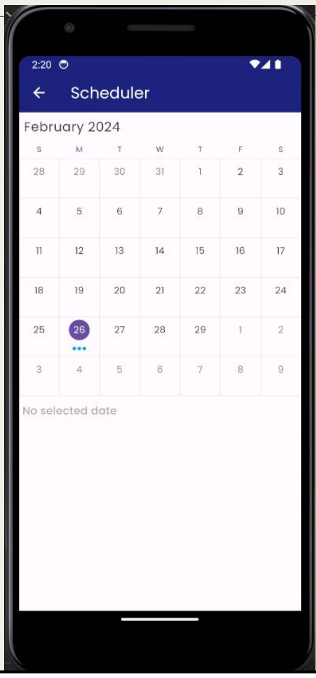
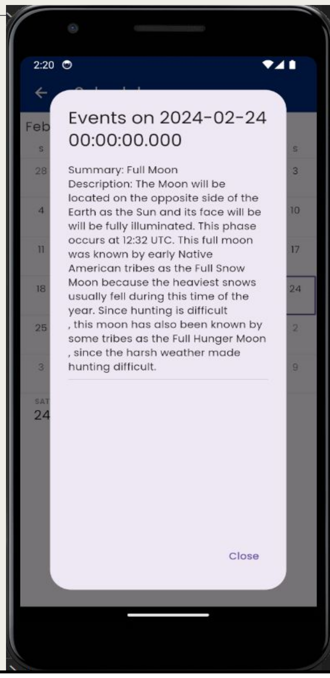
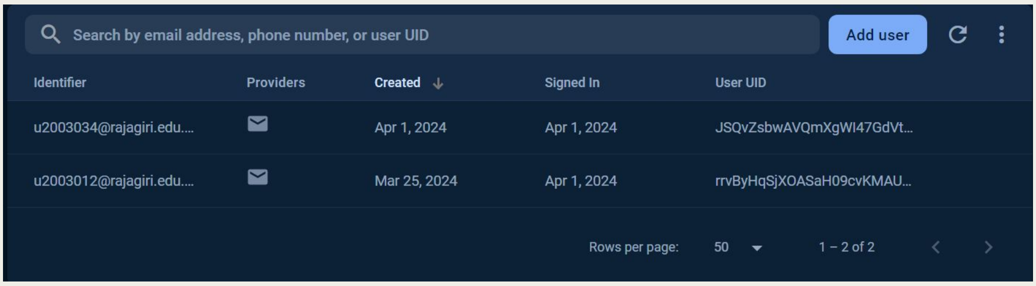
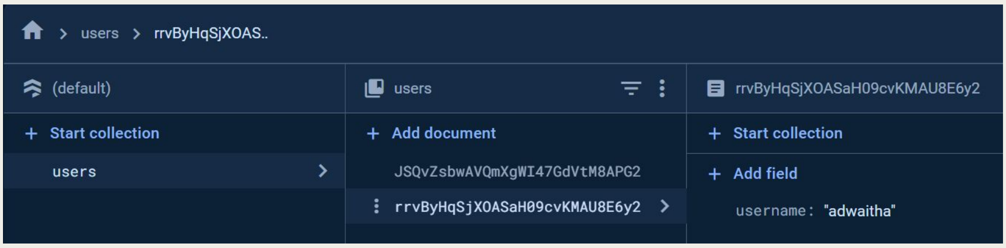


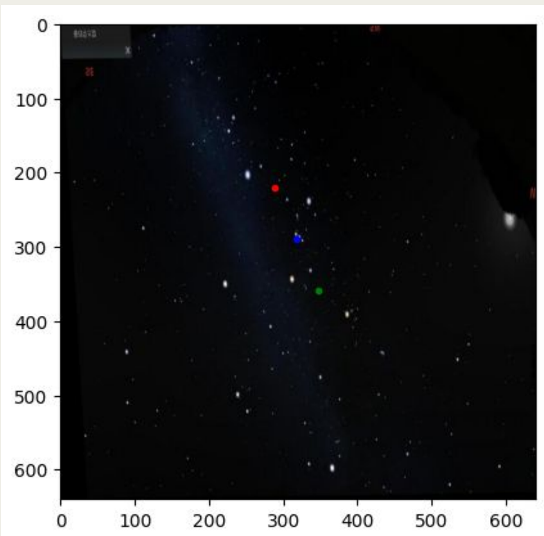


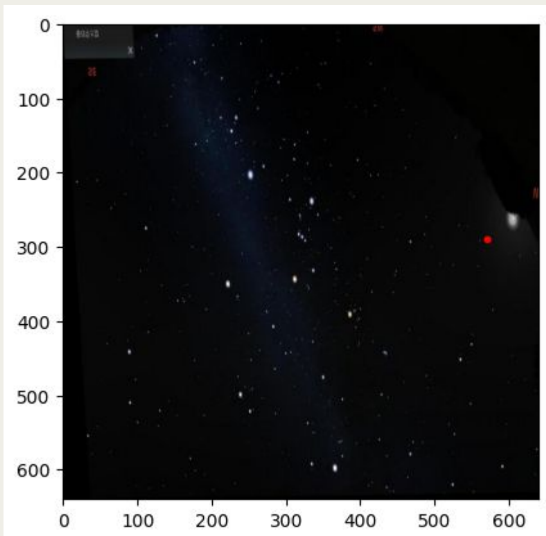
RESULTS



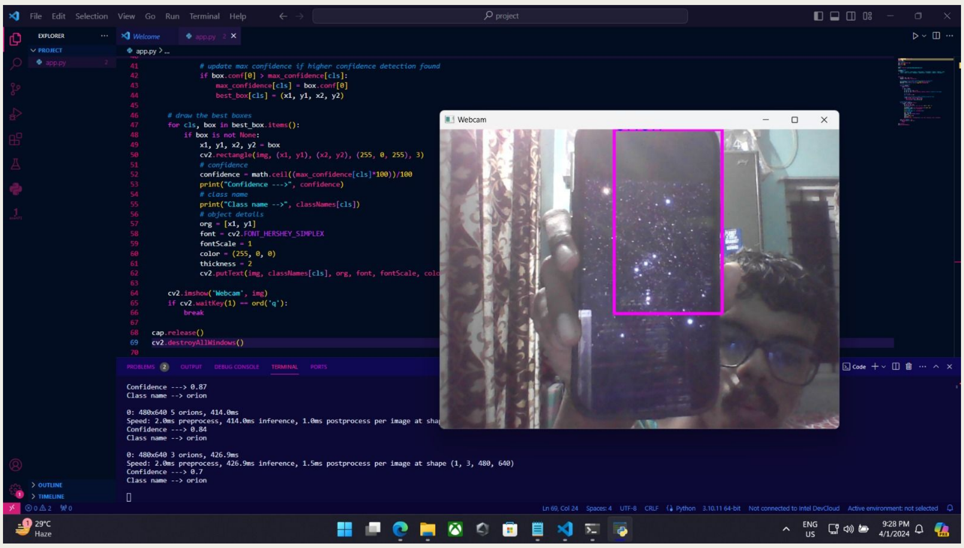


RESULTS - SIMULATION



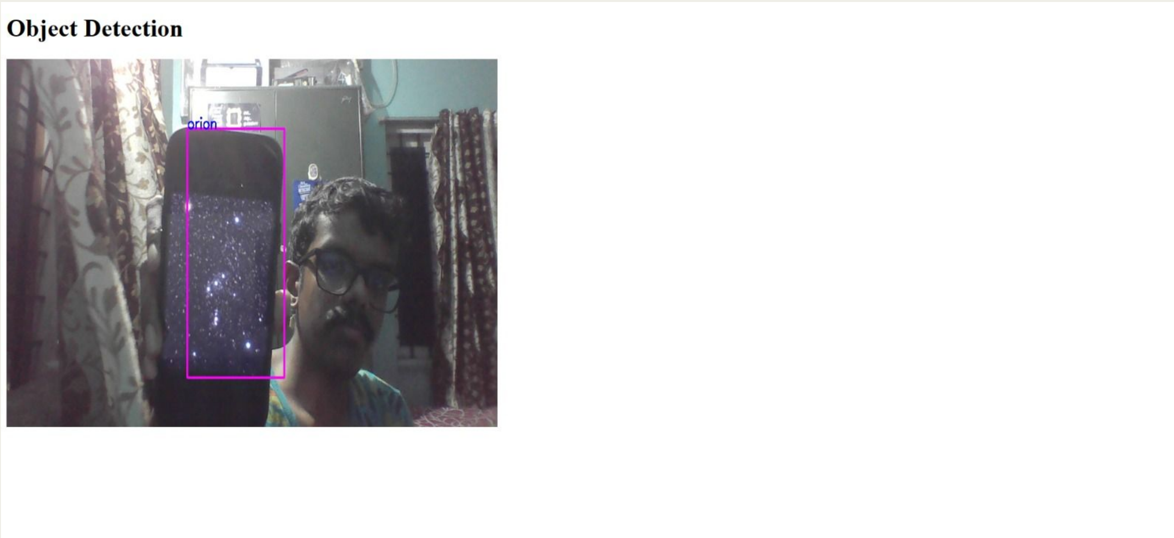


RESULTS - LIVE FEED



Confidence score: 87%

RESULTS - LIVE FEED



FUTURE SCOPE

- **Improving the accuracy and efficiency of the celestial object detection algorithm:** We'll enhance the model by trying advanced deep learning methods like ensemble and transfer learning, along with different preprocessing techniques for better input data.
- **Integrating additional features, such as automatic image capture and processing:** Create algorithms for automatic image capture using predefined celestial coordinates, implement real-time image processing for better quality, and integrate enhancement algorithms for improved visibility in low-light.
- **Expand the dataset with more celestial objects to enhance model generalization:** Collaborate with academic institutions, telescope manufacturers, and amateur astronomers to enhance the system and expand the dataset.

FUTURE SCOPE

- **Continue research and development in telescope automation and celestial object detection:** Emphasize the impact of automated telescopes on advancing astronomy, address challenges like light pollution and data processing through ongoing research, and advocate for continued funding to improve telescope automation and celestial object detection.

TASK DISTRIBUTION

Abhiram Ramachandran	Adwaitha Binu	Amruta Nair	Binul Bijo
• Machine Learning model • Classification model	• App Development • Database design • UI/UX design and prototyping	• Dataset Degradation • Machine Learning model • Telescope Simulation	• App Development • Documentation

CONCLUSION

- **Achievements:** Successful development and integration of the celestial object detection algorithm into the telescope automation system marks significant progress. The system's proven accuracy in identifying and tracking celestial objects highlights its potential for transforming astronomical research.
- **Lessons Learned:** Amid technical challenges and team dynamics, fostering open communication and collaboration was crucial for overcoming hurdles. Adaptability and iterative strategies were key to project success.
- **Impact:** Our project significantly advances astronomical research and telescope automation by streamlining celestial object identification and tracking. Beyond academia, the system's applications span fields like astrophotography and space exploration.
- **Future Prospects:** Our project's outcomes promise continued innovation in astronomy and related fields. Ongoing refinement and deployment of the system hold potential for uncovering new insights into the universe, fueled by collaborative efforts and investment in telescope automation.

REFERENCES

- Michał Wierzbiński, Paweł Pławiak,· Mohamed Hammad,U. Rajendra Acharya, “Development of accurate classification of heavenly bodies using novel machine learning techniques” Soft Computing (2021) 25:7213–7228. doi:10.1093/mnras/stad2852
- Aleksandra ˇCiprijanovi ́c, Diana Kafkes, Gregory Snyder, F Javier S ́anchez, Gabriel Nathan Perdue, Kevin Pedro, Brian Nord, Sandeep Madireddy, and Stefan M Wild, “DeepAdversaries: examining the robustness of deep learning models for galaxy morphology classification”, Mach. Learn.: Sci. Technol. 3 (2022) 035007
- Islam, Helmy, et al. “Autofocusing Optimal Search Algorithm for a Telescope System.” Cornell University - ArXiv, July 2021. Cornell University
- A. C. Rabeendran and L. Denneau ” A Two-stage Deep Learning Detection Classifier for the ATLAS Asteroid Survey”. Publications of the Astronomical Society of the Pacific, (accessed Oct. 10, 2023).
- M. Jiménez, E. J. Alfaro, M. Torres ;Torres, and I. Triguero, “CZSL: Learning from citizen science, experts, and unlabelled data in Astronomical Image Classification,” Monthly Notices of the Royal Astronomical Society, vol. 526, no. 2, pp. 1742–1756, 2023. doi:10.1093/mnras/stad2852

STATUS OF PAPER

- Topic - Open source methodology for telescope alignment and automation
- Draft article completed
- Plan to submit article to upcoming conferences like Third International Conference on Computing, Communication, Security & Intelligent Systems (IC3SIS' 24)
- Refining and improving article as project progresses

Appendix B: Vision, Mission, Programme Outcomes and Course Outcomes

Vision, Mission, Programme Outcomes and Course Outcomes

Institute Vision

To evolve into a premier technological institution, moulding eminent professionals with creative minds, innovative ideas and sound practical skill, and to shape a future where technology works for the enrichment of mankind.

Institute Mission

To impart state-of-the-art knowledge to individuals in various technological disciplines and to inculcate in them a high degree of social consciousness and human values, thereby enabling them to face the challenges of life with courage and conviction.

Department Vision

To become a centre of excellence in Computer Science and Engineering, moulding professionals catering to the research and professional needs of national and international organizations.

Department Mission

To inspire and nurture students, with up-to-date knowledge in Computer Science and Engineering, ethics, team spirit, leadership abilities, innovation and creativity to come out with solutions meeting societal needs.

Programme Outcomes (PO)

Engineering Graduates will be able to:

1. Engineering Knowledge: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

2. Problem analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

3. Design/development of solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

4. Conduct investigations of complex problems: Use research-based knowledge including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

5. Modern Tool Usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

6. The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal, and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

7. Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

8. Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

9. Individual and Team work: Function effectively as an individual, and as a member or leader in teams, and in multidisciplinary settings.

10. Communication: Communicate effectively with the engineering community and with society at large. Be able to comprehend and write effective reports documentation. Make effective presentations, and give and receive clear instructions.

11. Project management and finance: Demonstrate knowledge and understanding of engineering and management principles and apply these to one's own work, as a member and leader in a team. Manage projects in multidisciplinary environments.

12. Life-long learning: Recognize the need for, and have the preparation and ability to engage in independent and lifelong learning in the broadest context of technological change.

Programme Specific Outcomes (PSO)

A graduate of the Computer Science and Engineering Program will demonstrate:

PSO1: Computer Science Specific Skills
The ability to identify, analyze and design solutions for complex engineering problems in multidisciplinary areas by understanding the core principles and concepts of computer science and thereby engage in national grand challenges.

PSO2: Programming and Software Development Skills
The ability to acquire programming efficiency by designing algorithms and applying standard practices in software project development to deliver quality software products meeting the demands of the industry.

PSO3: Professional Skills
The ability to apply the fundamentals of computer science in competitive research and to develop innovative products to meet the societal needs thereby evolving as an eminent researcher and entrepreneur.

Course Outcomes (CO)

Course Outcome 1: Model and solve real world problems by applying knowledge across domains (Cognitive knowledge level: Apply).

Course Outcome 2: Develop products, processes or technologies for sustainable and socially relevant applications (Cognitive knowledge level: Apply).

Course Outcome 3: Function effectively as an individual and as a leader in diverse teams and to comprehend and execute designated tasks (Cognitive knowledge level: Apply).

Course Outcome 4: Plan and execute tasks utilizing available resources within timelines, following ethical and professional norms (Cognitive knowledge level: Apply).

Course Outcome 5: Identify technology/research gaps and propose innovative/creative solutions (Cognitive knowledge level: Analyze).

Course Outcome 6: Organize and communicate technical and scientific findings effectively in written and oral forms (Cognitive knowledge level: Apply).

Appendix C: CO-PO-PSO Mapping

CO-PO AND CO-PSO MAPPING

	PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11	PO 12	PSO 1	PSO 2	PSO 3
CO 1	2	2	2	1	2	2	2	1	1	1	1	2	3		
CO 2	2	2	2		1	3	3	1	1		1	1		2	
CO 3									3	2	2	1			3
CO 4					2			3	2	2	3	2			3
CO 5	2	3	3	1	2							1	3		
CO 6					2			2	2	3	1	1			3

3/2/1: high/medium/low

JUSTIFICATIONS FOR CO-PO MAPPING

MAPPING	LOW/MEDIUM/ HIGH	JUSTIFICATION
100003/ CS722U.1-PO1	M	Knowledge in the area of technology for project development using various tools results in better modeling.
100003/ CS722U.1-PO2	M	Knowledge acquired in the selected area of project development can be used to identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions.

100003/ CS722U.1-PO3	M	Can use the acquired knowledge in designing solutions to complex problems.
100003/ CS722U.1-PO4	M	Can use the acquired knowledge in designing solutions to complex problems.
100003/ CS722U.1-PO5	H	Students are able to interpret, improve and redefine technical aspects for design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
100003/ CS722U.1-PO6	M	Students are able to interpret, improve and redefine technical aspects by applying contextual knowledge to assess societal, health and consequential responsibilities relevant to professional engineering practices.
100003/ CS722U.1-PO7	M	Project development based on societal and environmental context solution identification is the need for sustainable development.
100003/ CS722U.1-PO8	L	Project development should be based on professional ethics and responsibilities.
100003/ CS722U.1-PO9	L	Project development using a systematic approach based on well defined principles will result in teamwork.
100003/ CS722U.1-PO10	M	Project brings technological changes in society.

100003/ CS722U.1-PO11	H	Acquiring knowledge for project development gathers skills in design, analysis, development and implementation of algorithms.
100003/ CS722U.1-PO12	H	Knowledge for project development contributes engineering skills in computing & information gatherings.
100003/ CS722U.2-PO1	H	Knowledge acquired for project development will also include systematic planning, developing, testing and implementation in computer science solutions in various domains.
100003/ CS722U.2-PO2	H	Project design and development using a systematic approach brings knowledge in mathematics and engineering fundamentals.
100003/ CS722U.2-PO3	H	Identifying, formulating and analyzing the project results in a systematic approach.
100003/ CS722U.2-PO5	H	Systematic approach is the tip for solving complex problems in various domains.
100003/ CS722U.2-PO6	H	Systematic approach in the technical and design aspects provide valid conclusions.
100003/ CS722U.2-PO7	H	Systematic approach in the technical and design aspects demonstrate the knowledge of sustainable development.

100003/ CS722U.2-PO8	M	Identification and justification of technical aspects of project development demonstrates the need for sustainable development.
100003/ CS722U.2-PO9	H	Apply professional ethics and responsibilities in engineering practice of development.
100003/ CS722U.2-PO11	H	Systematic approach also includes effective reporting and documentation which gives clear instructions.
100003/ CS722U.2-PO12	M	Project development using a systematic approach based on well defined principles will result in better teamwork.
100003/ CS722U.3-PO9	H	Project development as a team brings the ability to engage in independent and lifelong learning.
100003/ CS722U.3-PO10	H	Identification, formulation and justification in technical aspects will be based on acquiring skills in design and development of algorithms.
100003/ CS722U.3-PO11	H	Identification, formulation and justification in technical aspects provides the betterment of life in various domains.
100003/ CS722U.3-PO12	H	Students are able to interpret, improve and redefine technical aspects with mathematics, science and engineering fundamentals for the solutions of complex problems.

100003/ CS722U.4-PO5	H	Students are able to interpret, improve and redefine technical aspects with identification formulation and analysis of complex problems.
100003/ CS722U.4-PO8	H	Students are able to interpret, improve and redefine technical aspects to meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.
100003/ CS722U.4-PO9	H	Students are able to interpret, improve and redefine technical aspects for design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
100003/ CS722U.4-PO10	H	Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools for better products.
100003/ CS722U.4-PO11	M	Students are able to interpret, improve and redefine technical aspects by applying contextual knowledge to assess societal, health and consequential responsibilities relevant to professional engineering practices.
100003/ CS722U.4-PO12	H	Students are able to interpret, improve and redefine technical aspects for demonstrating the knowledge of, and need for sustainable development.
100003/ CS722U.5-PO1	H	Students are able to interpret, improve and redefine technical aspects, apply ethical principles and commit to

		professional ethics and responsibilities and norms of the engineering practice.
100003/ CS722U.5-PO2	M	Students are able to interpret, improve and redefine technical aspects, communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.
100003/ CS722U.5-PO3	H	Students are able to interpret, improve and redefine technical aspects to demonstrate knowledge and understanding of the engineering and management principle in multidisciplinary environments.
100003/ CS722U.5-PO4	H	Students are able to interpret, improve and redefine technical aspects, recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.
100003/ CS722U.5-PO5	M	Students are able to interpret, improve and redefine technical aspects in acquiring skills to design, analyze and develop algorithms and implement those using high-level programming languages.
100003/ CS722U.5-PO12	M	Students are able to interpret, improve and redefine technical aspects and contribute their engineering skills in computing and information engineering domains like network design and administration, database design and

		knowledge engineering.
100003/ CS722U.6-PO5	M	Students are able to interpret, improve and redefine technical aspects and develop strong skills in systematic planning, developing, testing, implementing and providing IT solutions for different domains which helps in the betterment of life.
100003/ CS722U.6-PO8	H	Students will be able to associate with a team as an effective team player for the development of technical projects by applying the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.
100003/ CS722U.6-PO9	H	Students will be able to associate with a team as an effective team player to Identify, formulate, review research literature, and analyze complex engineering problems
100003/ CS722U.6-PO10	M	Students will be able to associate with a team as an effective team player for designing solutions to complex engineering problems and design system components.
100003/ CS722U.6-PO11	M	Students will be able to associate with a team as an effective team player, use research-based knowledge and research methods including design of experiments, analysis and interpretation of data.
100003/ CS722U.6-PO12	H	Students will be able to associate with a team as an effective team player, applying ethical principles and

		commit to professional ethics and responsibilities and norms of the engineering practice.
100003/ CS722U.1-PSO1	H	Students are able to develop Computer Science Specific Skills by modeling and solving problems.
100003/ CS722U.2-PSO2	M	Developing products, processes or technologies for sustainable and socially relevant applications can promote Programming and Software Development Skills.
100003/ CS722U.3-PSO3	H	Working in a team can result in the effective development of Professional Skills.
100003/ CS722U.4-PSO3	H	Planning and scheduling can result in the effective development of Professional Skills.
100003/ CS722U.5-PSO1	H	Students are able to develop Computer Science Specific Skills by creating innovative solutions to problems.
100003/ CS722U.6-PSO3	H	Organizing and communicating technical and scientific findings can help in the effective development of Professional Skills.