THE DESIGN OF A LOW COST ALL SKY CAMERA SYSTEM WITH AUTOCLASSIFICATION

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ABSTRACT

The ability to monitor the entire sky has many useful applications in diverse fields such as Meteorology, Military Defense, Air Traffic Control, Astronomy and Ecology. The All Sky Camera (ASC) is one such device that posses this capability in the visible range. The hardware for ASC implementations can however be very costly especially for an amateur user, this is a limitation for the build out of meteor monitoring networks especially in third world areas like the Caribbean. Another limitation is that for applications such as meteor monitoring ASCs tend to suffer from a high rate of false positives as light from the moon, insects/birds, clouds and even cosmic rays may result in similar signatures to that of a meteor. This results in bottlenecks when processing data in meteor monitoring networks since additional manual oversight is required to correctly classify meteors. There have been attempts to address these problems in literature by using low cost hardware and open source software to reduce the cost of implementation of ASCs and by using computer vision techniques such as semantic segmentation and neural networks to reduce the false positive rates and improve the detection of meteors. In this paper, an ASC was built at a relatively low cost and deployed to collect data. Using this data as well as external datasets neural network models were created that are capable of doing the required classifications of meteors. The approach used is to implement detection/classification of meteors by first using motion detection and line detection techniques followed by a two stage CNN configuration for classification. The low cost Hardware of the build was found to be resilient even after 5 months of operation in various weather conditions, no hardware changes/replacements was necessary. The precision of the single station build was found to be 98.13% and 96.41% for both stage 1 and stage 2 CNN models respectively, while their accuracy is 97.33% and 89.92% respectively. To note however, the single camera (Single Station Detection) invokes certain limitations on accuracy and coverage which can be overcome in future research by building out a monitoring network using adding additional cameras.

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LIST OF ABBREVIATIONS/ACRONYMS

ASC .... All Sky Camera
ALAN .... Artificial Light at Night
AOG .... Atmospheric Optics Group
CCD .... Charge Coupled Device
CID .... Charge Injection Device
TLE .... Transient Luminous Events
UFO .... Unidentified Flying Objects
SQM .... Sky Quality Meter
SVMN .... Slovak Video Meteor Network
FRIPON ..... Fireball Recovery and Interplanetary Observation Network
AMOS .... All-sky Meteor Orbit System

1 INTRODUCTION

As suggested by its name, the All Sky Camera(ASC) is a type of camera that has a wide enough field of view to cover the entire sky. This feature enables it to have a plethora of applications for sky monitoring and detection of celestial events. They have been known to be used for light pollution monitoring, meteor and satellite detection, cloud detection and classification, aurora monitoring etc. (Santos and Ederoclite 2023). These devices however, can be very costly and furthermore both the open source and proprietary software for them usually have issues properly detecting particular classes of objects. In this paper we explore the possibility of creating a low cost ASC system that can automatically and accurately identify the meteor class of objects in the night sky. This chapter will introduce this research paper by first discussing the Historical Background to the research, followed by the Problem Statement, Research Objectives and Significance and will end with the Scope/Limitations.

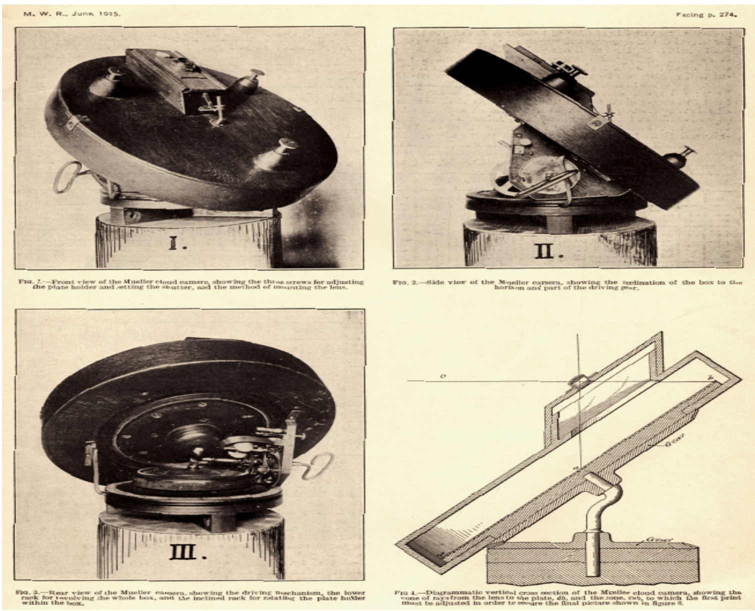


Figure 1.1: Mueller's revolving cloud camera (Fassig, Oliver L. "A REVOLVING CLOUD CAMERA." Monthly Weather Review 43, no. 6 (June 1915): 274–275. issn: 0027-0644, 1520-0493, Figure 1).

1.1 Background

The concept of a camera capable of taking pictures of large portions of the sky has existed since the early 1900's. In the paper by Fassic (1915) he mentions the concept of a 360 degree revolving camera being used to take pictures of clouds that was brought to him by a Fred Mueller some 10 years prior. This device consists of a camera that rotates on a vertical axis using a motor to make a complete rotation in about 5 to 10 seconds. The film used by this camera is unrolled at the same rate as the camera is rotated and the resulting image generated is a 360 degree view of the horizon and lower portions of the sky. Mueller went on to improve upon this to create a camera mechanism that could capture the entire sky from the horizon to the zenith in a single exposure. An image of this apparatus is shown in Figure 1.1. The way this worked was to have one large circular sheet of film 12 inches in diameter which is placed inside a circular apparatus with a slit. This is angled and placed such that the light from the zenith would be incident upon the center of this circular sheet of film at all times when rotating it about the vertical axis. The horizon would be exposed to the edges of the film. Rotating the apparatus through 360 degrees would therefore expose the whole sky to the circular film sheet. This apparatus worked, but during this time period in the early 1900's, the beginnings of other methods for cloud photography that did not require a moving camera were being discussed.

Hill (1924) discussed that R.W Wood in 1911 had taken the first photographs using a 180 degree lens as discussed in his book "Physical Optics". He goes to explain that it was not until 1922 that the application of this method of photography was used for sky/cloud recording. Hill (1924) however noted that projecting an image subtending a 180 degree field of view onto a flat plate cannot be accomplished without distorting the image. Depperman (1949) described an alternate method using a high quality camera pointed at a large silvered sphere, this achieved a similar effect as the fish eye lens where the distortion in the resultant image increased nearer to the horizon. It was only after this time that the idea to observe meteors instead of just clouds using ASC networks was brought to reality. Between 1938 and 1951 the first ASC camera meteor network was developed and operated in the United States (Colas et al. 2020), however it was only around the 1950's onwards where the first meteor recovery based on these camera systems was attempted.

Moving on to the 1960's, film based ASCs were being used by the AOG (Atmospheric Optics Group) (Shields et al. 2013), the large field of view effect was done using a large silvered spherical mirror, an image of this apparatus is shown in Figure 1.2. This spherical mirror method worked by reflecting a distorted image of the sky similar to the effect of a fisheye lens. This reflection could then be photographed allowing one to capture an image of the entire sky in one exposure, the drawback to this method is that the camera necessarily had to block out some part of the image. However, starting from about the 1970's fish-eye lens cameras were used for ASC capability. The first digital ASC systems were used in the 1980's which used Charge Injection Device (CID) technology for the camera sensors. The AOG also developed the first automated all sky imagers by combining the features of all sky cameras with scanning radio-meter measurements of sky absolute radiance. The AOG went on to develop the day/night whole sky imager in 1991, which was deployed in 1992. This system uses a cloud detection algorithm developed in 1986, this algorithm could detect opaque clouds using the red/blue spectral information ratio. A separate algorithm was developed to detect thin clouds. This day/night imager is similar to the ASCs currently in use today, consisting of a fish-eye lens projecting an image onto a CCD digital camera, this device however was thermo-electrically cooled down to -40 C to reduce thermal noise thus improving the signal to noise ratio in the resultant photographs.

1.1.1 Machine Learning

Convolutional Neural Networks also know as CNNs are Machine Learning algorithms often used for image classification (Cecil and Campbell-Brown 2020). CNN's are usually used in the supervised case of machine learning algorithms where labeled data is used to train the CNN. The performance of these models are evaluated by testing their predictions on labeled data not previously seen by the CNN. The use case of CNNs for meteor detection is that they can replicate the ability of traditional methods of manual meteor detection/classification. Without having to program static parameters by hand, a CNN can learn the general features of what constitutes an image of a meteor just by presenting it with enough data. The inference time or time it takes the CNN model to decide whether a single image is a meteor or not can be much smaller than what is possible manually. Add to that the fact that they can operate

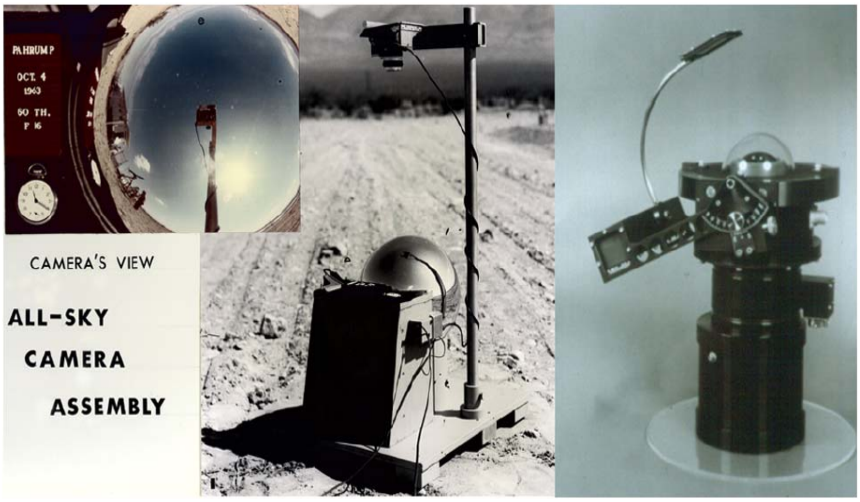


Figure 1.2: Two early WSI systems developed at MPL, the all-sky camera used in 1963(left), and the digital day/night WSI used in the 1980s(right). (Janet E. Shields et al., "Day/Night Whole Sky Imagers for 24-h Cloud and Sky Assessment: History and Overview," Applied Optics 52, no. 8 (March 6, 2013): 1605, Figure 1.)

continuously and it is obvious that they are a potential solution to the issue of the manual bottlenecks in meteor detection networks. This application of machine learning is however recent, only since the mid 2010's are papers really observed pertaining to the use of CNNs for meteor detection as evidenced by Chapter 2 of this research paper, this is also alluded to by Silva, Lorena, and Almeida (2018).

1.2 Definition of Terms

1.2.1 All Sky Camera

An ASC is a camera capable of taking an image of the entire sky in one single exposure. Current iterations usually consist of a fish-eye lens that projects an image onto a digital sensor. This enables one to keep track of objects in the sky from the zenith to the horizon.

1.2.2 Light Pollution

Excessive use of Artificial Light at Night(ALAN) is considered to be environmental pollution. This is specifically known as light pollution and affects fauna and flora in many habitats. There is also the possibility of it affecting human health. Light pollution is also a big factor the negatively affects the work of astronomers (Jechow et al. 2020).

1.2.3 Meteors/Meteoroid/Fireball/Bolide/Meteorite

A small space rock less than 1 Meter in size that came off an asteroid or a comet is called different things depending on its current status. Before entering earths atmosphere it is called a meteoroid, upon entry it is called a meteor and very bright meteors are called fireballs. If a fireball eventually explodes it is now called a bolide (Boaca et al. 2022). If a piece of that rock survives this journey and makes it to the ground it is now called a meteorite.

1.2.4 Nowcasting

A very short term forecasting of usually not more than 6 hours.

1.2.5 Line Object

This term is used in this paper to mean any line-like observation in the night sky observed from an all sky camera. It is important to note this definition includes curved lines as well.

1.2.6 Zenith

The point in the sky directly overhead an observer.

1.3 Statement of the Problem

All sky camera systems has been utilized for several use cases around the world from military applications to research and citizen applications. However, these systems are traditionally focused on usage by professional observatories, there is a lack of readily available low cost systems that can support amateur astronomers/educational institutions in astronomical or meteorological endeavors. The best option here would be to consider low cost DIY hardware/software for ASC systems. A surface level internet search easily shows that online guides exist on how to buy and assemble the hardware for a DIY ASC system, however there are limitations from a software perspective. One issue is that most software doesn't support accurate classification of similarly observed objects in the night sky. This is evident since open source software such as AllSkEyE or even proprietary software such as UFOCapture can detect lines or changes in pixels indicating the presence of a meteor, aircraft etc. but it can take manual effort in order to distinguish them accurately since these types of classifications are often riddled with false positives (Silva, Lorena and Almieda 2018; Peña-Asensio et al. 2023). A plethora of factors can cause these false positives including the presence of rain on the camera lens, lighting conditions, moon glare, insects, birds etc. Therefore robust algorithms or models are needed that can filter out unwanted detections and correctly classify wanted detections to reduce the manual effort required to classify these objects in the night sky. This manual classification requirement is also a problem in the research community where the need for classification by specialists has become a bottleneck (Peña-Asensio et al. 2023) due to the sheer volume of possible detections.

1.4 Research Objectives

Based on the observation that there is lack of ASC systems that are low cost while being capable of automated detection, classification and measurement, this research paper will aim to design, assemble and deploy the hardware for such a system. Following that, the aim is also to design and deploy software for this all sky camera system that uses computer vision to detect/classify meteors in the night sky. This research aims to deploy such a device as a proof of concept, and demonstrate its capabilities towards meteor detection. In doing so it would be proof that the capabilities can extend to creating a meteor monitoring network that would be of interest to meteor research/amateur astronomers. These general research goals can be broken down into more specific objectives shown below. The specific research objectives will be to:

- Collect and store consective 10 second exposures of the night sky for at least 1 month.
- Use data to classify observed line-like objects(meteor,aircraft,cosmic-rays) in the sky that are in motion vs other non-related events.
- Use data to classify observed meteors in the sky vs other line-like objects.
- Use sorted data to build CNN model ensemble that enables accurate classification of meteors.

1.5 Significance

Ceballos-Izquierdo (2022) discusses that Jamaica specifically does not have its own network of ASCs, there is little footage of meteors and fireballs from Jamaica and except for Puerto Rico, the wider Caribbean.

Puerto Rico has an existing ASC network and this makes up the majority of meteor and fireball detection in the Caribbean. Having such a network of cameras in Jamaica will allow the island to detect such events and further determine possible landfall areas. In Jamaica's next door neighbour Cuba there were three such major events quite recently, one in 2019 and two in 2021, these events sparked research interest in the island of Cuba (Ceballos-Izquierdo 2022). Although Cuba is very close to Jamaica only one of these events was recorded from Jamaica and it was by coincidence (dashcam footage) that it was captured by a car driver in Jamaica. This frequency suggests there may have been many more spectacular meteorite events that could be observed in the Jamaican/Caribbean sky but were missed due to a lack of ASCs or a network of them. By creating a low cost device that has the capability to detect these events automatically, this would be a proof of concept for the eventual creation of a device network to detect and log these kinds of events across the caribbean. This research could lead to the creation of a system that enables amateur astronomers in Jamaica to have similar monitoring and detection capabilities of the night sky as professional observatories without being too costly. This can also be useful to add to the Global Meteor Network which does not exist in the Caribbean (Ceballos-Izquierdo 2022).

Given enough of these systems in the hands of amateur astronomers, it can become a gold mine of data for crowd science. Improved accuracy of meteor landfalls predictions are one possible benefit in increasing the numbers of these devices, enabling quick retrieval of these scientifically precious rocks. The use could also be extended to cloud coverage monitoring that feeds into the local weather data, and this can also help in the study of TLEs (Transient Luminous Events) in the upper atmosphere. There is also a possible aspect of light pollution monitoring, which is important to astronomy especially since higher levels of light pollution means more difficulties in studying or observing fainter objects. There is a host of ecological studies associated with light pollution measurements which could be useful to the scientific community since light pollution can have an ecological impact on a diverse number of species (Jechow et al. 2020). These devices can also be used to study any Unidentified Flying Objects, or other rare/unknown phenomena in the night sky.

2 LITERATURE REVIEW

2.1 Introduction

This section will review previous literature on the subject matter of ASCs and their various use cases to understand the current status of research on using these devices and to identify any gaps in the literature. The structure of this literature review is thematic and is explored by examining the literature of ASCs from two main perspectives. First is the Basic Use Case aspect, which is concerned with the basic monitoring capabilities of these devices for various phenomena/objects in the sky. The device in this case is mainly used as a sensor and the corresponding literature discussed here is concerned with accurate detection and classification. Although auto-detection has been implemented in several different ways, there is a gap when it comes to auto-classification. The second main aspect is the Extended Use Case, this looks at the ASC as a tool beyond just mere data collection and considers them with a specific application. This is often related to the main aims of the papers in the literature review.

2.2 Basic Use Case Aspect

2.2.1 Hardware

It is important to note that the many use cases of all sky cameras are only possible due to capable hardware. As such, many researchers have taken to designing reliable, sensitive and adaptable systems that while being able to detect faint signals accurately, can operate with minimal maintenance in various harsh environments. To detect faint light signals it is often a requirement to operate in harsher environments where light pollution is minimized. From the perspective of weather proofing some papers take varying levels of effort in ensuring the cameras can withstand the elements. The level of effort to weatherproof ASCs are observed to be strongly correlated to the expense of the ASC build. Low cost ASC builds tend to use very cheap weatherproofing enclosures as shown by

Santos and Ederoclite (2023) who use a basic project box as the camera container. The ASC system used by Santos and Ederoclite (2023) suffered from water leakage but this was luckily caught before the internal components were damaged, this however goes to show that weatherproofing should be a central consideration due to the similarly low cost nature of this research. More expensive systems such as the Alcor System ASC (Fernández and Rodríguez 2023) are pre-fabricated and come with a pre-built housing that contains an anti-condensation system, temperature and humidity sensor and an automatic aperture. For the even more expensive setups, cost is usually not a focus of their papers and not mentioned per se, however one of the likely most expensive ASC systems is the AMOS system discussed by Tóth et al. (2015). This system was designed with weather proofing as a focus, since it is meant to operate in very harsh, windy and cold locations in Slovakia. The enclosure for AMOS was tested in a wind tunnel up to 52 m/s in its closed configuration and up to 32 m/s during operation. The AMOS research had sufficient funding and there were even future plans set in stone to deploy further AMOS ASCs in the Canary Islands and Chile. Walker et al. (2006), went as far as using a dedicated 3 meter tower as the housing for the all sky camera on their TMT and LSST observation sites. They used a research grade camera costing around US$8000. As mentioned before, this research is of the low cost nature therefore special attention needs to be taken in water/weatherproofing to ensure the device can operate while withstanding the outside elements. Heating elements should be used in conjunction with a temperature and/or humidity sensors to remove or prevent moisture build up on the lens or dome. The enclosure needs not be wind tested to the extent of the AMOS camera system since it is low cost and the conditions/location in Jamaica where it will be deployed is not especially harsh.

In terms of the camera hardware, Santos and Ederoclite (2023) explored low cost but capable camera units to be used as an ASC. To that end, they considered the lower tier ZWO cameras such as the ASI120MC, ASI224MC and ASI178MC cameras which are all under US$300 and are the lowest cost astronomy cameras offered by ZWO. The 120 and 224 models have a 1.2 MP resolution while the 178 comes with a 6.4 MP resolution. The AMOS system uses a specially built enclosure and includes a rather expensive component which is its image intensifier (Tóth et al. 2015), therefore the AMOS ASC system is likely not cheap however the camera itself is mid range in cost at around US$500 for a used camera on eBay. The camera used in the ASC design of Mandat et al. (2013) costs around US$800 which is about a mid-range cost as well albeit with a lower cost enclosure as mentioned above. Some ASC builds use more expensive ZWO cameras such as the pre-built Alcor System that uses a ASI-294 Pro (Fernández and Rodríguez 2023) with an 11.7 MP resolution, this camera comes with its own internal cooling system to prevent overheating and to reduce thermal noise and costs around US$1100. Walker et al. (2006) uses a much more expensive research grade camera costing US$8000 today, but this is a much lower cost option than the specialized TIR(Thermal-Infra-Red) camera they considered as an alternative which would have cost them $100,000 USD ($152,000 USD adjusted for inflation) at the time. Although we can see there are pretty large price differences, the performances of the low cost cameras are not too different from those of mid-range cost for this application of detection. By varying the exposure time it is possible for the lower cost cameras to detect fainter stars with similar detection magnitudes to that the mid-range cameras at higher FPS. Although the lower cost cameras are still capable of detection, their main drawback is that they cant be used to calculate the velocity of a meteorite/aircraft as the FPS at longer exposures would be too low. The low cost ASI224 used by Santos and Ederoclite (2023) could detect stars up to magnitude 6 with 60 seconds exposure compared to the magnitude 6.3 detection capability of the more expensive camera used by Mandat et al. (2013) and the magnitude 5 detection by the AMOS system, both of which operate at higher FPS of at least 15FPS. For the application of pure detection it is ok but to be fair, the AMOS system attempts to determine meteor landfalls as well and as stated before this requires higher FPS which lowers the exposure time of the camera. This means that although the faintness of background stars that can be detected by both systems during operation is comparable, the AMOS system can actually perform much better, they are only comparable if we constrain the AMOS camera use case to meteor velocity/trajectory determination.

2.2.2 Auto-Detection

We can subdivide this topic into two approaches, auto-detection considering the entire frame and auto-detection considering objects visible inside a frame. In the case of the entire frame, it is possible to do cloud cover and light pollution measurements, this could even be done at varying angular elevations with respect to the camera. For objects in frame i.e. meteors and aircraft we would define an area of interest based on various detection criteria such as changed pixels and extract that for detection. Auto-detection of objects in the night sky is fairly easy to do especially with already available software (Peña-Asensio et al. 2023), the difficulty is in auto-classification which will be discussed later. Some papers employ the use of proprietary software like UFOCapture and ASGARD to do auto-detection (Silva, Lorena and Almieda 2018; Tóth et al. 2015). UFOCapture operates similarly to motion capture (Silva, Lorena and Almieda 2018) and detects if there are differences in the current vs previous frame, it then saves that frame and creates a thumbnail image of the area of interest (Silva, Lorena and Almieda 2018). The proprietary softwares works well for detection, however there are known open source alternatives that are also capable such as Freeture and AllSkEye (Audureau et al. 2014; Santos and Ederoclite 2023; Colas et al. 2020). AllSkEye uses a line detection algorithm to identify possible meteor trails (AllSkEye – AllSkEye.) and is very popular in the amateur astronomy community, it is often used for home-made ASC builds. UFOCapture is popular with meteor researchers using ASCs although it wasn't intentionally built for that, while ASGARD was built for meteor detection specifically (Blaauw and Cruse 2012) but it is somehow not as popular for this application. Based on papers read, most research involving meteor detection use the proprietary software UFOCapture (Tóth et al. 2015; Suk and Šimberová 2017; Silva, Lorena and Almieda 2018), two papers read use open source software, one is Santos and Ederoclite (2023) that used AllSkEye and another is Colas et al. 2020 that uses Freeture. Freeture is mostly used within the Fripon global network of cameras.

Light pollution can be measured by using a SQM(Sky Quality Meter). Shown in figure 2.1., this is a standard way to do this kind of measurement. This however, only measures light pollution around the zenith and would miss light domes closer to the horizon (Kolláth and Dömény 2017). Mandat et al. (2013) suggests one way to calibrate an ASC to measure light pollution is to leave the SQM and ASC recording overnight, and calibrate the light flux observed in the ASC to the SQM measurements. In contrast Kolláth and Dömény (2017) took a more scientifically precise approach in which they created a toolkit called DiCaLum that could convert raw camera images to arrays of luminance or radiance in units such as mags per arcsec squared. However they noted that due to vignetting effects of the camera sensor and the lens they would need to calibrate for that as well. They suggested they could use a method of astrometric calibration but preferred the lab method where they had access to high quality luminance meters. In the lab method, Kolláth and Dömény (2017) rotated the camera at various angles at each of various cross-sections relative to a fixed light source and measured the Luminance at each angle, since the light source is fixed any decrease in luminance would be because of vignetting effects. Therefore when luminance is measured in the field with the same vignetting calibrated ASC, they can account for losses from vignetting to get a more precise measurement. Jechow, Kyba and Hölker (2020) in contrast did not calibrate or create their own tools, they just used a commercially available pre-calibrated ASC that had its own corresponding software, this setup already accounts for vignetting effects and provides a luminance value for each pixel. Jechow, Kyba and Hölker (2020) then proceeded to do a light pollution characterization of the city of Berlin by taking light pollution measurements at 12 stops along a transect of the city from the city center to the rural areas. They accounted for cloud amplification which was not mentioned by Kolláth and Dömény (2017) and Mandat et al. (2013) as a factor influencing luminance measurement. This is noted due to the required precision of measurements Kolláth and Dömény (2017) use in their research they should likely have included this factor in their paper. By reviewing the methods of Kolláth and Dömény (2017) and Jechow, Kyba and Hölker (2020) it is evident that the method used by Mandat et al. (2013) is insufficient to get an accurate light pollution measurement as Mandat et al. (2013) did not account for vignetting or account for cloud amplification. Measuring sky quality is a prominent use case of all sky camera's especially as it related to astrnomical observations. Good sky quality correlates with good observation conditions however high precision is required to get accurate results.

Another prominent use case of sky cameras is cloud cover measurements. The cloud cover measurement method explored by Mandat et al. (2013) is rather novel compared to the other papers read and determines cloud cover by splitting the sky into 70 segments. For each segment observed, bright stars in that segment are compared to a star catalog. Where any fainter star is found within 1 degree of a matched bright catalog star, it is considered paired. The final cloudiness value is found after consid-

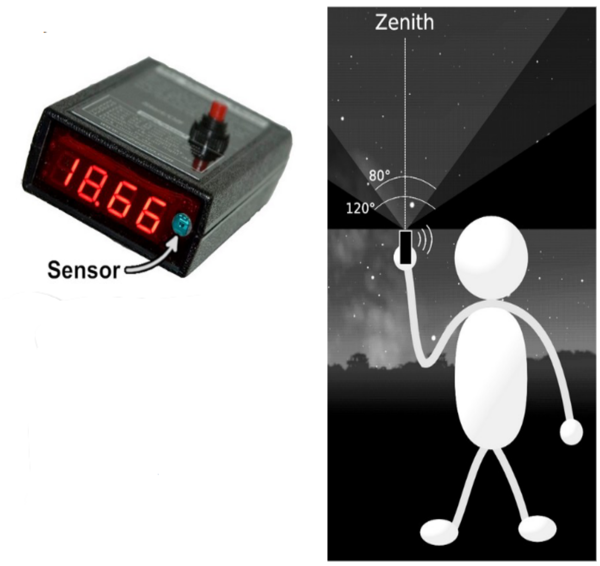


Figure 2.1: Sky Quality Meter (Doug Welch, Anthony Tekatch. "Sky Quality Meter." http://unihedron.com/projects/darksky/).

ering all segments and is a measure of the ratio of paired vs unpaired stars, where the paired stars represent an area that is clear and unpaired stars represent an area obscured by clouds. In contrast to this method of cloud cover measurement, the more common method of cloud cover measurement is the use of a pixel wise red-blue ratio which works by distinguishing cloud and cloud free pixels (Voronych et al. 2019; Dev et al. 2017; Lothon et al. 2019; Shields et al. 2013; Haputhanthri et al. 2021). This method involves taking the ratio of red and blue pixels on a pixel by pixel basis over the entire image to get a 2D array of these ratio values, then a threshold is used to create a binary image of cloud vs sky (Haputhanthri et al. 2021). This method was developed primarily for daytime cloud cover measurements but can be used for night time cloud cover measurements. However at night the sky can take on a reddish tinge due to light pollution thus making the task of distinguishing cloud and sky with this method more difficult (Dev et al. 2017). Dev et al. (2017) tested 14 different color channels and was able to use ROC curves to determine that instead of the red-blue ratio (R/B) color channel, the R-B color channel is the best discriminator of clouds vs sky for night time images. They go on to use the SLIC algorithm on the resulting R-B image to generate pixel clusters, this however results in getting an over-segmented image. Unsupervised k-means clustering can be used to join these over-segmented sections into one to get the final binary cloud vs sky image. Compared to the method used by Dev et al. (2017)

or the red vs blue ratio method, the approach by Mandat et al. (2013) although novel, does not appear to be reliable. This is discussed in their paper (Mandat et al. 2013) where their algorithm fails when the moon is in the sky which is a regular and common occurrence. The moon increases the brightness of the background sky which reduces the ability of the ASC to see stars. Based on the literature read, there is a gap in paper's covering ASC cloud cover measurements at night, most papers focus on day time images and neglect night time cloud measurements (Dev et al. 2017).

2.2.3 Auto-Classification

In general auto-detection of objects within a frame is relatively easy to do (Peña-Asensio et al. 2023), but auto-classification is the more challenging task. This requires one to first detect that a possibly desired object is in frame and either develop an algorithm that ensures the object is the desired one or use previously trained machine learning models to classify the object correctly. Auto-classification will be required for meteor detection since it is very common to get false positives using both open source and proprietary software like UFOCapture, AllSkye or Freeture etc (Silva, Lorena and Almieda 2018; Peña-Asensio et al. 2023). The first stage detection will only imply that it has possibly seen one of the desired objects and the next stage must determine with a level of certainty that detected objects is a meteor. Without this type of classification capability, researchers usually have to include a manual step after initial detection where a specialist would classify images as meteors or non-meteors (Silva, Lorena and Almieda 2018; Peña-Asensio et al. 2023), this is a bottleneck when there are large volumes of classifications and represents a gap in the process slowing down the processing capability of meteor networks. Silva, Lorena and Almieda (2018) attempt to solve this issue but employing the use of supervised learning techniques to train an ML model capable of distinguishing meteors from non-meteors. Fernández and Rodríguez (2023) on the other hand used a similar method of supervised learning but instead used it to distinguish between Aircraft and non-aircraft.

The methods of Silva, Lorena and Almieda (2018) involved collecting a small dataset of images of meteors and non-meteors and having experts classify them. They were able to extract an impressive 3451 features from 21 feature sets for each picture in their dataset. Using these features, several classification models were then created using basic sci-kit learn tools such as SVM, AdaBoost, KNN, DT etc. these were compared to one of the best performing models from their Kaggle competition. In this Kaggle competition they split their dataset into public and private subsets, competitors could then use the public set to train their models and the private set was used to decide the winner based on the f1-score metric. The second place winner's method was discussed and compared to their own implementations in their paper. This method trains on all the features from the 21 feature sets and generates 21 ML models using logistic regression, the predictions of which creates a 21 length feature vector that is used to make the final prediction. Fernández and Rodríguez (2023) in contrast did not rely on external parties, they used a deep neural network model called ResNet which is type of a convolutional neural network(CNN) to do their classifications, their data was also small however they used data augmentation techniques that generated new images by making slight changes to the original images such as zooms, shifts and rotations. What they found was that they could make relatively good predictions above a twenty degree elevation with respect to the ASC, but below that there were too many false positives due to light pollution and artificial lights. Another possible reason for these false detections is the use of improper masks, their semantic segmentation masks were basically only lines and did not account for the small details in structure of the aircraft line signature. One drawback of Silva, Lorena and Almieda (2018) was that although their dataset was very small, they did not use a data augmentation technique to effectively increase their dataset size, they only used oversampling which is also a drawback as it increases the chances of overfitting. They also did not deploy their model therefore data from the real world performance of their model is non-existent. As such it cannot be said whether their model works well or not for actual detections. In general it can be said that Fernández and Rodríguez (2023) has a better and more robust methodology to train their classification model compared to Silva, Lorena and Almieda (2018).

2.3 Extended Use Case Aspect

In the previous section we looked at the ASC being used to collect data, most papers however, have a particular use case for an ASC beyond just designing good hardware and collecting images. This is what is discussed in this section.

Toth et al. (2015) uses their Slovakian SVMN network of ASCs to determine the trajectory of meteors, which enabled them to successfully recover a meteorite. The Fripon network (Audureau et al. 2014; Colas et al. 2020) originating in France is very similar to the SVMN network of Toth et al. (2015) and is also intended to recover meteorites, the similarities don't end there however. Both Fripon and SVMN networks go beyond just meteor recovery and use relatively high FPS ASCs to calculate the trajectories and velocities of observed meteors, enabling them to extrapolate the probable orbital parameters of the parent asteroid or comet. With this information they can determine if there are any possible future impacts of these parent asteroids or comets with Earth. Essentially their ASC networks becomes a sort of asteroid impact warning system which is a use case that extends well beyond simple meteor monitoring or detection.

Kolláth and Dömény (2017) and Mandat et al. (2013) monitor light pollution for similar reasons, they want to know the long term trends of light pollution in a particular area. In contrast Jechow, Kyba and Hölker (2020) were only interested in the current status of light pollution in Berlin and not long term measurements, therefore they only took measurements of light pollution for two nights. This was done along a transverse of the city of Berlin to map how light pollution declines going from the city center to rural areas. Going back to Mandat et al. (2013), their main purpose for long term monitoring was to select the best location for a Gamma Ray Observatory from four locations in the Northern Hemisphere and another location from 5 locations in the Southern Hemisphere. Characterizing the long term cloudiness and sky quality(light pollution) was a metric they devised to help them decide what location is best to deploy their observatory, which means their research has a finite end. The long term monitoring of light pollution done by Kolláth and Dömény (2017) is more of a continuous monitoring without a definite end as they would continuously monitor International Dark Sky Parks to ensure they fit the threshold for low light pollution and can be certified as such.

Voronych et al. (2019) talks about how cloud cover and cloud motion estimation data can aid in nowcasting of solar irradiance. This can be used to predict fluctuations in photovoltaic systems output which is challenging to solar photovoltaic system operators (Haputhanthri et al. 2021) who have to constantly match the imbalance between power generation and power consumption in real time. This use case of ASCs extends beyond just cloud monitoring and applies it to help manage the health of the energy grid by giving operators time to adjust for fluctuations in power output of their solar farms. The paper by Voronych et al. (2019) is more concerned with improving the accuracy of these solar irradiance predictions instead of the creating algorithms for the predictions themselves by providing a quality metric for data collection when there is rain, since the rain drops on the camera lens could be detected as clouds or otherwise obscure the images causing inaccurate measurements. Haputhanthri et al. (2021) on the other hand look to directly create a novel algorithm that predicts irradiance using data from an ASC.

2.4 Summary

In summary, one of the biggest issues being faced in researching meteors is the bottleneck in detecting them as this requires manual oversight. Attempts were made at creating automated systems using pre-defined algorithms, however these are often riddled with false detections. The machine learning route is a more recent endeavour for this particular application and has shown promise of reducing false detections for both aircraft and meteors. Cloud cover is often done using a pixelwise red/blue ratio however most papers covering ASC cloud cover are focused on daytime measurements, only one paper was found that detailed methods specifically for night time cloud cover measurements with an ASC. In terms of sky quality it is difficult to get an accurate reading without proper photometric and vignetting calibrations of the ASC used. ASCs have also found uses in solar irrradiance prediction allowing them to help manage solar farms by predicting incident light levels using cloud motion estimation. Networks of these camera have become a sort of asteroid collision warning system and can even be used to help improve aircraft safety. ASCs can also be used to certify or recertify dark sky parks.

3 METHODOLOGY

3.1 Methodological Approach

This paper takes a quantitative and design science approach to the methodology, an all sky camera system was built and data gathered, analyzed and implemented. There already exists similar professional solutions at both the software and hardware level for this kind of application however based on a review of literature there are still issues with classification and most of the existing solutions are very costly devices. This methodological approach entails the collection of images and doing the classifications manually at first. This manual process along with external datasets was used as a base to create a program that can automate the detection process. In doing this, the manual classifications was used as ground truth and the error between the automated method and the manual method can be found which reveals how well the ASC system performs, allowing for it to be evaluated on its usefulness in the field.

3.2 Hardware and Acquisition

The all sky camera system, shown in Figure 3.1 and Figure 3.2, uses the ZWO ASI120MC which is a 1.2MP astronomy camera capable of exposure times between 64 microseconds and 2000 seconds. For this use-case, this camera is equipped with a 180 degree fish eye lens to cover the entire sky in a single exposure. All frames collected are 10 second exposures with Gain in the range 70-100. Based on early testing, this allows enough exposure time for the camera to distinguish clouds at night and to also see fainter stars which can help to give context of the location and direction of an observed meteor. To protect the data acquisition components from the outside elements, they are be placed inside a 150x150x70 mm water and dust proof project box, a 3.1 inch clear acryllic camera dome protects the camera itself while allowing it to collect data. The camera is both powered and connected to the Raspberry Pi 4 via its usb 3.0 port. To power the Raspberry Pi itself however, a PoE Hat solution was used, this board plugs directly onto the Raspberry Pi and powers it via its ethernet connection. The ethernet connection is connected/powered via a TP-Link TL-SF1005P power over ethernet(PoE) switch. This switch can handle up to 30 Watts on a port however the Waveshare PoE hat limits this to about 20 Watts. Based on the power budget, 20 watts is enough to operate the Raspberry Pi, ZWO Camera and the two fans inside the enclosure. The switch is plugged into a LAN WiFi router which allows the all sky camera to communicate on the local network. Originally the plan was to have heating elements inside the enclosure to prevent condensation buildup on the dome, however it turned out that the Waveshare PoE hat for the raspberry pi gives off a lot of heat during operation, so much that the extra fan was deemed necessary, this fan pulls in the cooler outside air during operation at night to help cool down the system thus reducing noise in the camera. Some measures were taken to remove terrestrial light sources in the field of view of the camera. Since the lens is 180 degrees, terrestrial light sources introduced constant glare into the images at night, by placing objects around the camera to obstruct this, these glares were greatly reduced which improved visibility of the sky.

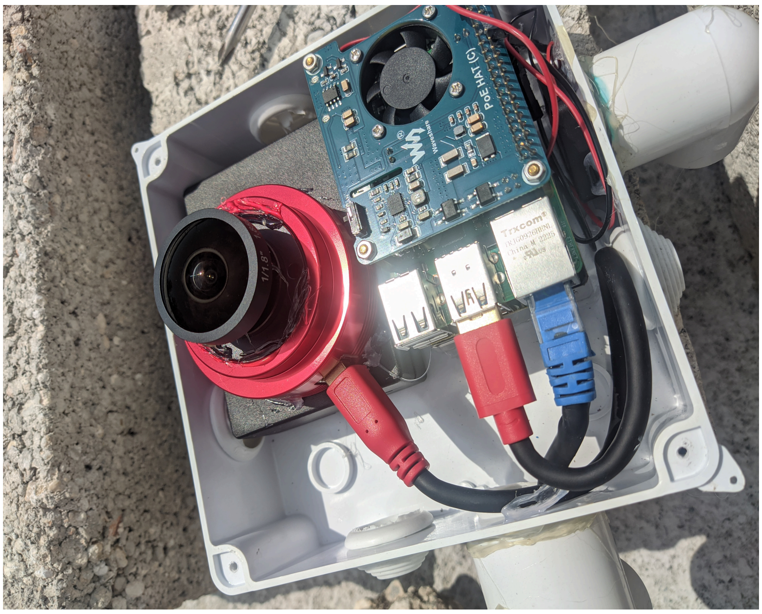


Figure 3.1: All Sky Camera showing internals

In order for the all sky camera to have continuous autonomous operation several bash scripts and cron jobs were created on the Raspberry pi. Firstly there is a python script called ‘acquisition.py’, this sets up the camera parameters such as exposure time and gain and tells the camera

Figure 3.2: All Sky Camera in Operation

to take images. It also collects the image data and saves them locally to the Raspberry Pi. This allows the ASC device to collect data even in the absence of a network connection to the server. The script is also responsible naming each file in such as way as to ensure no conflicts and data is not overwritten via the use of timestamps. Other important information is transferred via this file naming convention such as exposure, gain and temperature parameters. This script however, only collects images during the night between 7pm and 6am everyday therefore daytime meteors are not taken into account. To ensure more stable operation and reduce loss of data the python script is automatically restarted if the program crashes for any reason. This is achieved by using a service. This service automatically restarts the python script if for any reason it crashes during operation. Using a cron job this service is set to start each time the raspberry pi boots up, in this way if there is a power outage for example, upon the power returning the all sky camera will automatically continue to take images without the need to manually start the acquisition script. Since there is limited space on the raspberry pi for storing images, a cron job for a script called 'housekeeping.sh' was created that runs every hour. This script deletes every image saved by the acquisition script older than 3 days which prevents the local storage from filling up. On the server/pc side another script runs every 5 minutes called 'pullfromcam.sh' that uses the rsync protocol to get images stored on the raspberry pi. This does not delete images on the server side but copies any new images it sees onto the server/pc.

All cameras inherently have noise, howevver cheaper cameras usually have worse noise characteristics (Santos and Ederoclite 2023), this noise increases with temperature therefore depending on the temperature, the noise characteristic in an image changes. There is however, a method to reduce noise in the images called dark frame subtraction. This can be achieved by subtracting the corresponding dark frames from the images. A dark frame is a picture taken with the lens covered, such that no external light reaches the sensor. The resulting image would therefore only contain the noise in the image. Stemming from this, a library of stacked dark frames was made at various temperatures observed during operation. This forgoes the need to have a special iris/lid apparatus in the ASC system and has the added advantage of preventing the need for taking dark frames at regular intervals which would result in the ASC system losing data. To create a stacked dark frame, the camera lens was completely covered for at least 10 frames at 10 second exposures at a particular temperature, then using a python script, a single stacked image was created from those 10 or more frames that represents the noise in the camera at a particular temperature. Since the images generated contain the temperature at the time they are taken in the filename, this is used to reference the corresponding stacked dark frame which as explained above can be used to reduce noise in each image. This is useful when displaying the image since most of the noise is removed revealing details in the image.

It was originally intended to do this dark frame subtraction before doing a consecutive subtraction of frames in the data processing pipeline, however it was observed that this had the effect of lowering the chances of line detection, likely due to reduced pixel values which would go very low after a second subtraction for the motion detection step. Therefore instead, consecutive original frames are subtracted directly when checking for signs of meteors since along with highlighting changes the immediate previous frame would approximate the noise in the current image the best. Considering the low cost and therefore lesser capability of the camera sensor, high FPS operation was not as feasible if the background stars are to be visible in the images. Longer exposures allows for a camera to see fainter objects if they are relatively stationary with respect to the camera. On a 10 second exposure the stars in the sky are effectively stationary with respect to the camera therefore, this allows even a cheap camera to see faint stars. This does not apply to meteors however, since they are fast moving and their bright flight is ephemeral. This means that increasing the exposure has no bearing on the camera's ability to observe meteors, however the background stars are a useful reference, this is why each frame was set to 10 second exposures. Another benefit of long exposures is that they also help to simplify the detection pipeline since the detection algorithm need only work using one frame instead of attempting to track the meteor over multiple frames from a video. The drawback however is that it is harder to distinguish an aircraft or other objects from a meteor in the final image especially near the edges of the fish-eye lens image. It was possible to do exposures longer than 10 seconds for this application however since the detection process involves image subtraction, longer exposures would make the images more prone to subtraction artifacts. These subtraction artifacts shown in Figure 3.3 usually results from cloud or tree motion and can form line-like structures that can be similar to that of a meteor making the detection system more prone to false positives.

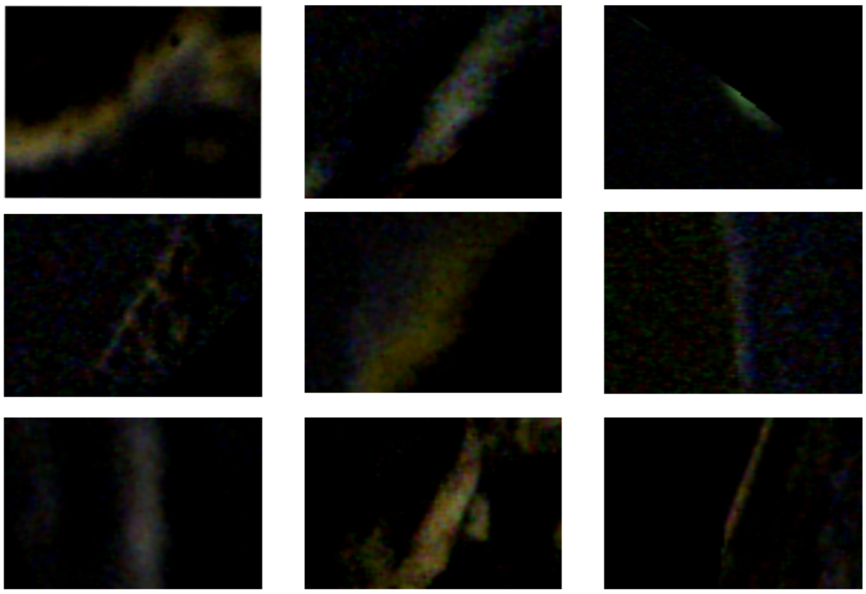


Figure 3.3: Subtraction and Edge Artifacts

The final hardware topology is shown in Figure 3.4. The ASC system consists of two main components, one is the ASC device itself and the other is the server. The ASC device is consisted of the main image acquisition components which are the ASI ZWO camera and the Raspberry Pi 4. It is connected to the Local Area Network via a PoE switch, this PoE switch is connected to a Gigabit port on the LAN Wifi router. The PC is also connected to this same Local Area Network via WiFi enabling the camera to communicate with it. The image acquisition components such as the Raspberry Pi and ZWO Camera are located inside the project box enclosure for protection allowing them to collect data without too much worry of the weather conditions. The job of the PC is to act as a storage and processing center, it stores images sent to it and it is used to do the computer vision heavy lifting during the creation of the models. The resultant CNN models can however be used directly on the ASC camera as well by running the adapted code on the Raspberry Pi 4.

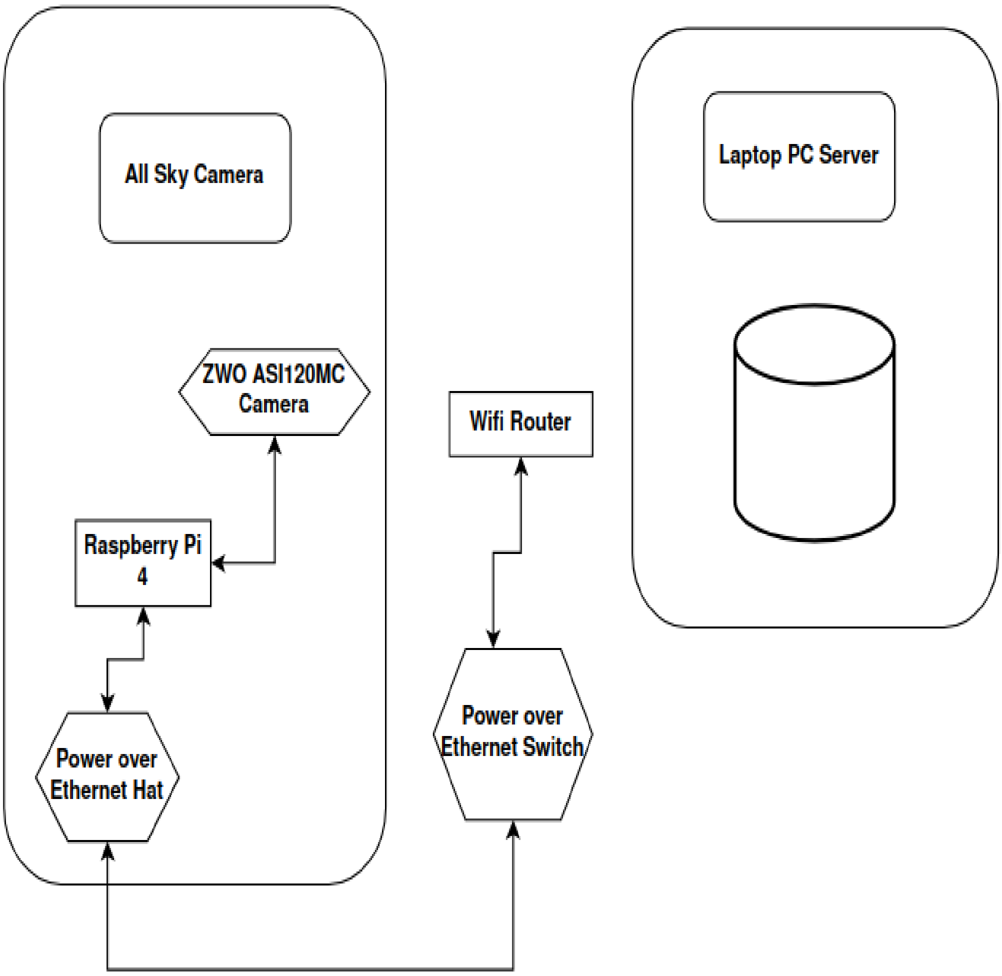


Figure 3.4: ASC System hardware topology

3.3 Data Collection

To give a computer the ability to distinguish between an aircraft/other line objects and a meteor, one approach is to detect lines in the image and collect enough data to train a neural network model as a classifier between the two. To collect the data however, several pre-requisite steps were done as shown in Figure 3.5 and 3.6. Firstly motion detection via subtraction of consecutive frames is done using the OpenCV library, this is followed by line detection using the Hough Transform which is also implemented using the OpenCV library. The image subtraction serves to highlight changes in the new frame since the previous frame, which in the event of a meteor appearing would highlight it while effectively removing the background. This helps to eliminate any potentially similar but static instances of line-like objects in the image, the drawback here however is shown in Figure 3.3 where due to processes like cloud/tree motion, line like subtraction artifacts can be created from the consecutive frame subtraction. Reducing the length of the exposure to 10 seconds can help to limit this however since there would be less time for changes to take place between images. The line detection parameters were set to detect lines a minimum length of 10 pixels with a max breakage of 5 pixels and a minimum of 1 pixel. The thought process here was to allow for detection of faint meteors that could only excite single pixels in a short line. These thresholds would allow for their detection. The Hough Lines algorithm outputs detected lines as a pair of coordinates for each pair of points that define the line. To these points a buffer of 40 pixels is added or subtracted as necessary to get the coordinates for a rectangular bounding box for the detected line. This bounding box also defines where to crop the image to get a region of interest with the detected line. These cropped-in images are saved to a folder along with the original image but with the bounding boxes painted on. To do the classification manually the cropped images are manually copied to their respective folder for each class. The original with the bounding boxes painted on is used as a reference to help in the manual classification process. Oftentimes context can help to determine if the line detected is a meteor, aircraft, cloud, insect etc. In this manner, data is collected for each night and manually sorted as required.

Initially there were thousands of line like images coming out of the line detection, these were mostly due to cloud and tree motion and other artifacts. To help accelerate the data collection process, a preliminary model was created using transfer learning from the inceptionv3 model. Imbalanced data was used of line-like objects (meteor, aircraft, cosmic ray, satellites etc.) vs false positives (noise, glares, insects etc), the so called, interesting vs not-interesting dataset. After training, this preliminary model had a 99% accuracy and a good precision and recall at 98%.

This means that although the training data is imbalanced this model is essentially very good at distinguishing between objects that are found to be interesting(meteors, aircraft, satellites, cosmic rays etc.) from objects that are not interesting (clouds, trees, insects, edge artifacts, moon glares, subtraction artifacts etc.). With this model, the data could be filtered much faster as its inference time is only 20ms, therefore all outputs from the line detection were fed to this model and only ones below the threshold of 0.23 which represents objects that closely resemble airplanes or meteors were saved primarily, any false positives such as clouds artifacts that got past this initial filter were saved as well to be fed back into the model as not-interesting when it was retrained. After this step the images are manually classified as meteor, aircraft, cosmic ray or not-interesting. The data is classified like this instead of just meteor vs other to enable to creation of multiple models for an ensemble approach. The first model acts as a barrier to image artifacts and terrestrial objects such as insects, birds, trees, moon glares etc, that got past or were created from the image subtraction and line detection processes. These are classified as 'not-interesting' and objects such as meteors, aircraft, satellites, cosmic rays are classified as interesting. This is because these objects can be considered distinct line-like object and a model more specialised in telling meteors apart from these objects would likely perform better instead of a more generalized model.

The time to collect data is limited and the final dataset is small, therefore data augmentation techniques were used. This process essentially creates 'new' data from existing data by applying image transformations such as flips, rotations, shifts, zooms etc. This is help to generalize what the model detects as well as providing more examples to train on. Another method that was used to help solve the small dataset issue was to add images from an online dataset. Data specifically from the Shirasuna and Gradvohl (2023) and the Sennlaub et al. (2022) datasets for meteors was used to increase the size of the meteor dataset. The images of meteors from the Sennlaub et al. (2022) were already in a similar format in that they were cropped in to the meteor and its background removed, so those could be added directly. The images from the Shirasuna and Gradvohl (2023) dataset were passed through the pre-equisitee step of line detection to obtain the ROI. Motion detection could not be used since this dataset is not a sequence of images. Adding external data can greatly help to generalize the model by providing examples from various different

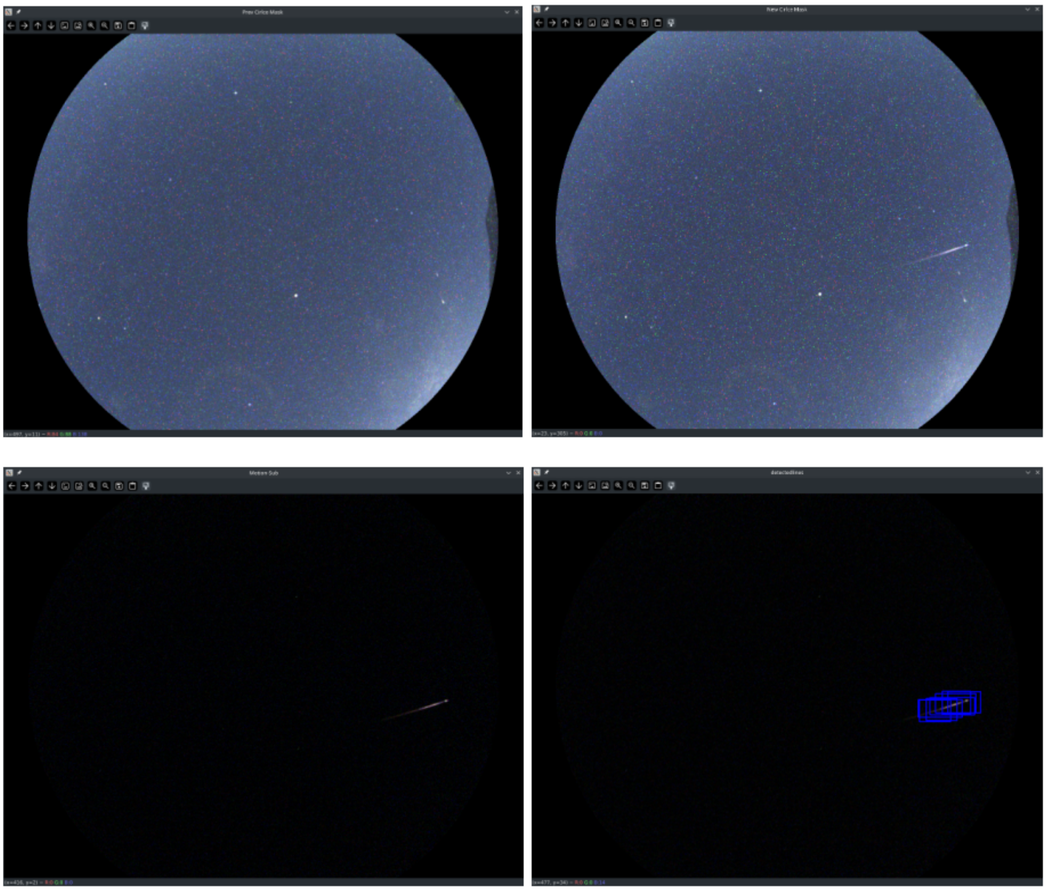


Figure 3.5: Image Subtraction and Line Detection Highlighting Meteor: Top Left Image is subtracted from Top Right Image Yielding Lower Left Image, Lower Right Image shows meteor detected after Line Detection Step

cameras at various different lighting conditions etc.

3.4 Data Analysis

After the data collection phase is over the performance of the all sky camera was analyzed, this was done by manually doing the various measurements/classifications on the collected data and comparing them with the results of the automated measurements/classifications. All methods of evaluation is therefore quantitative.

For the analysis supervised learning is used to train an ML model on this dataset and its performance evaluated. Using inceptionv3 as the base, Transfer learning was used to create two models which are used in an ensemble for classification. The first model is the finished version of what was used during data collection. After using that model, any false positives were used to retrain it in the 'not-interesting' category. Such that after each round of training it would be better at filtering out what is deemed 'not-interesting'. To ensure good convergence of the model, a hyperparameter search was performed to determine the optimal hyperparameters such as learning rate, batch size etc.

One of the best distinguishing characteristic of an aircraft is that it has intermittent blinking lights that appear as bright points at regular intervals along its path, another is that it can appear in more than two frames. This is in contrast to a meteor that has an average visible lifespan of 0.8s (Audureau et al. 2014; Colas et al. 2020). A meteor was seen as one single line that wont persist past two frames in a 10 second exposure time frame. The way a single meteor could exist in two frames is that it could occur at the end of one frame and the beginning of the following frame. Therefore, to manually distinguish between an airplane and a meteor can oftentimes be trivial. There are however times when it is much more difficult, sometimes the intermittent lights are not distinct perhaps due to a combination of altitude of the airplane and vignetting from the camera. Other objects that could be mistaken for a meteor are falling space debris, and orbiting satellites, and sometimes perhaps due to the high altitude at early morning an aircraft reflects sunlight briefly when it is at the correct angle relative to the camera. Therefore it could be visible then a bright flash occurs that fades out along its path, this is almost identical to the signature of a meteor but can be discerned manually by carefully inspecting the pixels in the line, which should alternate red and blue consistently. Another way that one could distinguish this from a meteor could be the fact that this could last more than 2 frames.

3.5 Justification

There are multiple methods of achieving the research goals however in this section the reasons for using the specific methods stated above was discussed, justified and compared to alternate methods. First the hardware perspective is discussed, then the algorithmic techniques used for detection at the pre-CNN stage are discussed. Finally the justification for using CNNs are discussed.

In terms of the camera, the exposure time of 10 seconds was used because from early testing, this exposure time is observed to be sufficient to distinguish clouds in the sky, observe background stars for reference and

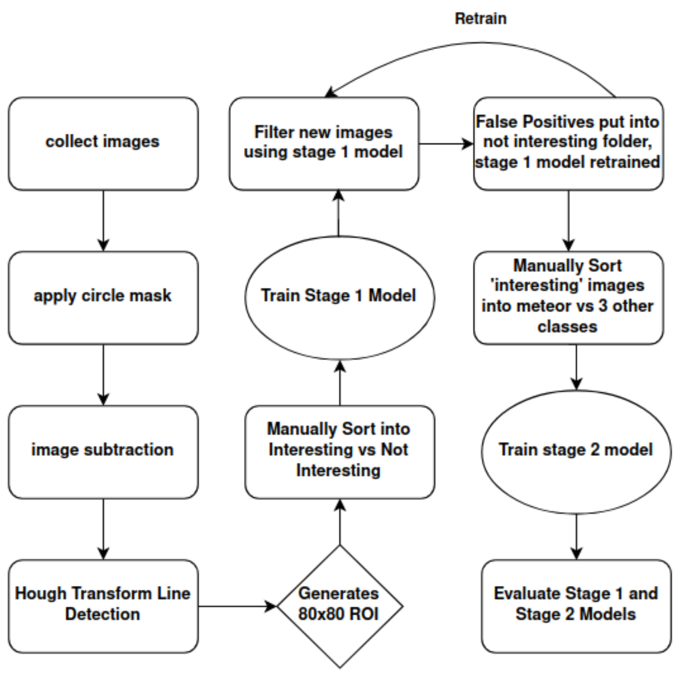


Figure 3.6: Data Collection and CNN Model Training Flow

to see meteors. It is possible to do exposures longer than 10 seconds for this application however since the detection process involves image subtraction, longer exposures would make the images more prone to subtraction artifacts. These subtraction artifacts shown in Figure 3.2 usually results from cloud or tree motion and can form line-like structures that can be similar to that of a meteor making the detection system more prone to false positives. At 180 degrees the lens of the camera was able to cover the entire sky and horizon, a lens with greater viewing angle than this would include unnecessary terrestrial objects and less than this wont capture the entire sky and horizon. No heating element was needed since the PoE hat outputs a lot of heat during operation. This helps to prevent any condensation build up inside the dome of the all sky camera which could obscure measurements.

There are a few ways we can detect meteors, one of these rely on the Hough transform line detection technique (AllSkEye – AllSkEye.). This method simply detects when a line broken or not is observed in the image. This method works but it is easy to see how it would incur a lot of false detections, since meteors and other objects in the night sky can have a similar line like signature. Therefore, if you were looking for meteor, an aircraft or satellite may trigger a detection using that method alone. False detections may also be due to line like signatures generated in the 10 second exposure images from flying animals such as birds/insects/bats or even static line like objects on the horizon in the frame. For static objects, false detections can be avoided by using a method similar to Audureau et al. (2014) and UFOCapture. This method works by subtracting successive frames to remove stationary features, this basically only highlights moving objects in the image. This helps to avoid false detections as it removes any line like aspects of buildings or other terrestrial infrastructure nearby that could trigger line detection. After subtraction Audureau et al. (2014) proceeds to extract regions of interest (ROI) from this subtracted frame to create what they call Local Events. This method defines a 10 pixel zone around the LE that if another LE intersects, they are grouped together. Audureau et al. (2014) then goes on to define Global Events (GE), which are the same LE object across multiple frames. Without this, regardless of the base detection method, the ASC system would count each new frame detection as a new separate object which isn't necessarily true, one object can persist across multiple frames and it would be redundant to count it as a new object for each new frame. This frame subtraction method by itself however, is likely worse than the Hough Transform line detection method by itself as it doesn't specifically look for lines but looks for any pixel changes. It would therefore be more likely to suffer from a wider range of false detections including those that are not even similar to the aircraft or meteor line objects. However, since meteors are short duration, any Global Event lasting beyond a set number of frames can be considered an aircraft which is useful for distinguishing between them, but otherwise it cannot intrinsically distinguish between aircraft and meteor and would still require a specialist to do manual classifications between these two objects (Peña-Asensio et al. 2023).

In order to automatically reduce false detections and reliably distinguish between these two types of objects an additional filter in the form of an image classification machine learning model is used. A similar method was employed by Fernández and Rodríguez (2023), but they used semantic segmentation for both the initial detection and classification. The way the semantic segmentation is used is that masks of the outline of an aircraft are manually generated from known images of aircraft and these along with the original images are used to train a machine learning model that learns how to pick out the specific pixels in an image corresponding to aircraft. This paper employs aspects from the various methods discussed above to filter out false detections and improve classification performance, first frame subtraction + line detection + CNN classification was used. The frame subtraction removes static elements and the line detection pulls out line objects, finally the classifier is taught how to distinguish between each class, this ensures only line objects in motion are detected and what is detected are classified as a meteor or not. The reason for not using semantic segmentation is that for this application the semantic segmentation method used by Fernández and Rodŕiguez (2023) is basically just detecting lines therefore it is redundant when already using line detection. In this paper, after the frame subtraction and line detection pre-filters the regions of interest in the image, the neural network was used to classify the objects detected as a meteor or not, this should take into account all the color and spatial information to improve the chances of a correct classification.

4 Results

4.1 Hardware

The hardware was able to withstand direct sunlight, rain and winds for over 5 months continuously. Even after torrential rains no moisture was observed inside the system, this is likely in part due to the high output heat from the PoE Hat board, which would prevent condensation build up inside the system. This can also be attributed to the fact that the enclosure used has a rubber seal around its rim and the acrylic dome was fixed to the enclosure using PVC cement and a layer of hot glue. The entry points for the Ethernet cable and intake fan are covered by elbow pipes sealed with hot glue with their opening pointed down, such that air or cables can go in but water will not be able to enter.

The system was able to reboot itself after power outages however there were times the image acquisition service failed to start on boot and had to be started manually. On the rare occasionally images acquired had artifacts subtending the entire width of the image likely due to bugs in the ZWO camera itself. The artifacts are usually missing exposure on the top part of the image resulting in that area being much darker, this usually occurs in random images among normal ones and there is usually a line separation between these two regions. Therefore it may be picked up in the line detection, however by including these images in the dataset set as the unwanted set, they are rejected by the Stage 1 CNN model.

4.2 Motion Detection

The motion detection step works very well in highlighting meteors against the background especially during a clear night. Along with removing the background it also removes noise from the image. Normally removing noise is done by subtracting an average of dark frames however since the frames being subtracted are consecutive the previous frame would be the best performing sub-tractor to remove noise.

The motion detection step can introduce artifacts in the image as shown in Figure 3.5. These line-like artifacts can have a negative effect on the performance of the system. Using higher FPS effectively eliminates that issue but comes with another set of challenges.

4.3 Line Detection

The Line Detection performed worse when there was a dark frame subtraction followed by a consecutive frame subtraction. Thus the dark frame subtraction step was removed. The parameters of the line detection are set such that the smallest and thinnest of lines would be detected, this is what was observed when detecting for e.g. faint cosmic rays.

4.4 Post Stage 1 Detection Classes

After the stage 1 model filters out the ‘not-interesting‘ images, there are 4 main classifications of line objects observed in the remaining ’interesting’ images, namely: meteors, aircraft, cosmic rays and ’Other’, see Figure 4.1.

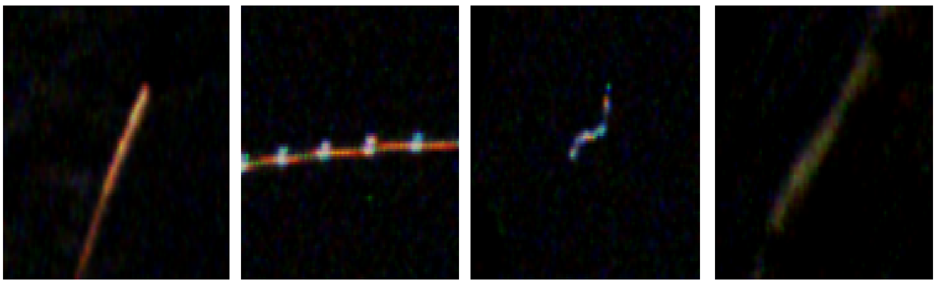


Figure 4.1: Four Main Image Classifications Observed after the First Stage, From Left: Meteor, Aircraft, Cosmic Ray and Image Artifact

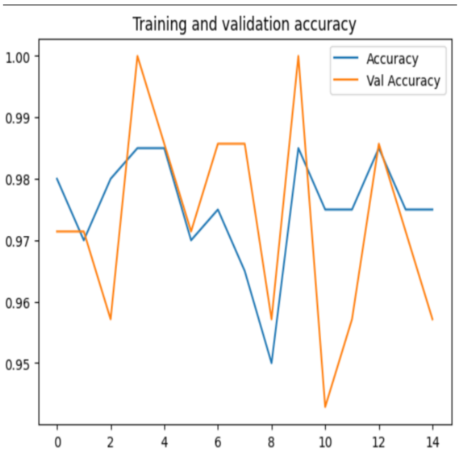
Meteors are the rarest observed of these classes. Airplanes and ’Other’ are understandably much more common. Cosmic ray artifacts are also much more commonly observed than meteors. The last class called ’other’ represents any false positive image that should have been filtered out by the stage 1 model.These include the subtraction artifacts, edge artifacts, camera artifacts, glares, insects, birds etc.

4.5 CNN Models

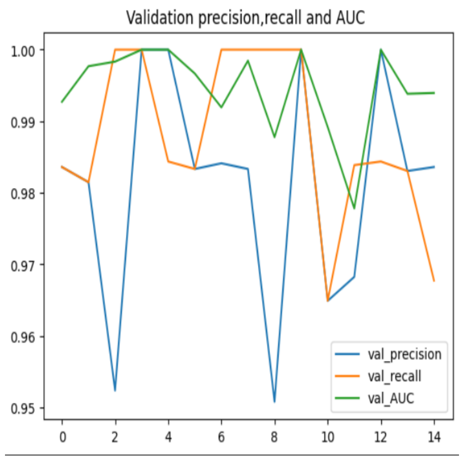
The focus is on the validation metrics instead of the training metrics since this is represents the performance of the model on data it has not seen in its training. This gives us a good idea of what to expect when it is deployed. The Precision metric measures how much of the positives the model identifies are actually correct, it is also know as the True Positive Rate. The Recall metric measures the rate of positives identified out of all actual positives. The F1 Score metric is the harmonic mean between the Precision and Recall, it is useful for dealing with imbalanced datasets. Its formula is shown below:

$$f1 = 2 * \frac{(precision * recall)}{(precision + recall)}$$

The Stage 1 model performs very well, its validation Recall and Precision are 0.9878 and 0.9813 respectively. The validation F1 score is 0.9845 and the overall validation accuracy of the model is 0.9733, see Figure 4.2. The stage 2 model did not perform as well however, its validation Precision and Recall are 0.9641 and 0.8583 respectively. Its overall validation accuracy is 0.8992, see Figure 4.3. The inference time of both models running on the PC are same at about 25ms or less. Adapting the code and running the models on the Raspberry Pi 4, the inference time is about 120ms, which is still not terrible for real time applications.

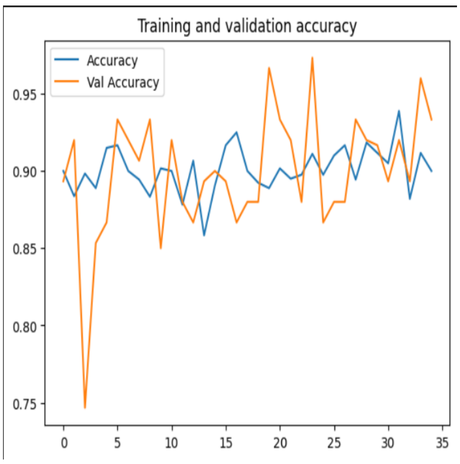


(a) Stage 1 Model Training Progress: Accuracy

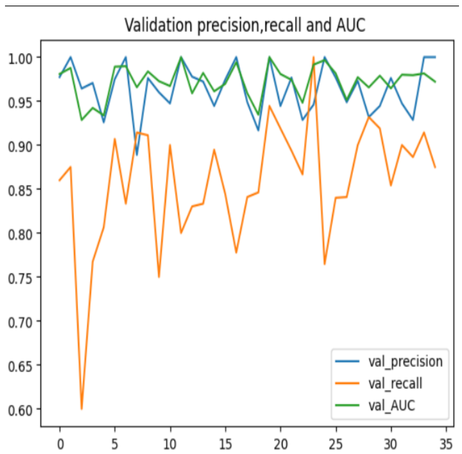


(b) Stage 1 Model Training Progress: Precision, Recall and AUC

Figure 4.2: Stage 1 CNN Model Training/Validation Results



(a) Stage 2 Model Training Progress: Accuracy



(b) Stage 2 Model Training Progress: Precision, Recall and AUC

Figure 4.3: Stage 2 CNN Model Training/Validation Results

5 Discussion

5.1 Hardware

The cost of all sky cameras can be prohibitive to enthusiasts for amateur astronomy (Santos and Ederoclite 2023). One of the aims of this paper is cost reduction, and with this in mind the hardware used represents a lower cost compared to many other all sky cameras solutions. Specifically, this lower cost can be attributed to choices in the design such as using the previous generation Raspberry Pi 4 ($62USD)instead of the current Raspberry pi 5 ($94USD) and even then using the 4Gb RAM version instead of the max spec 8Gb RAM ($79 USD) version. The camera used is one of the cheapest camera meant for planetary astronomy from ZWO called the ASI120MC ($150USD). It is small and compact and a library needed to interface with it in python on the Raspberry pi was free and fairly easy to find and use. Although it is on the cheaper end, this camera allows the user to adjust exposures from the microsecond range up to about 30 minutes and it supports USB 3.0. There are however some drawbacks for its cheaper cost, firstly, the resolution of the camera is not as high at 1.2 Megapixels and the images from the camera can get very noisy when doing the long exposures. These drawbacks however do not prevent one from doing meteor observations as the average length of a meteor's bright flight is 35Km lasting about 0.8s (Colas et al. 2020) which means the meteor streaks are large enough to not require high angular resolutions to observe them. The lens is a 1.8mm focal length giving a 180 degree FOV, the drawback to using a fish-eye lens is the warping and vignetting of the image however there are methods to remap the image such that it removes the warp if required. The camera sensor however truncates part of this view as it is not a square aspect ratio, this limits parts of the sky to the North-East and South-west regions of the image.

Using a generic PoE splitter(about $8USD) would be cheaper than the PoE Hat ($24USD), however the PoE hat was chosen because of space constraints, as it sits directly on the Raspberry Pi, it has a much smaller footprint enabling the entire system to be fit inside the 150x150x70mm project box. The high heat given off by the Waveshare PoE hat however has both advantages and disadvantages to the operation of the all sky camera. The advantage is that higher temperatures help to reduce or prevent condensation during its operating, this is especially important at night when its in operation where the cooler air could cause moisture to build up inside the system. This heat also helps to speed up the evaporation of any water on the camera dome due to rain which lessens the time water droplets obscure images after rainfall. The disadvantage however is that higher temperatures means increased noise in the resulting images, this effect is especially prominent in long exposures such as the 10 second exposures the system uses to collect data. This is however an acceptable trade off, since reduced image quality is much better result than a possibly dead all sky camera system due to moisture build up. The heat is so high that an additional small fan was added to the system that pulls in cooler outside air during operation, there is an inbuilt fan on the Waveshare PoE hat itself that also helps with cooling to prevent any overheating of the camera. The water proof project box used is also fairly low cost ($10 USD) however it has proven to with stand repeated cycles of rain, wind and sun for several months while protecting the delicate electronic components inside. The dimensions are 150mmx150mmx70mm just enough to hold all the components inside, a hole was made in the lid to allow for the 1.8mm fish-eye lens to protrude through. To protect the fish-eye lens and internal components from the elements and allow visibility of the sky, the hole is covered by a 3.1 inch acrylic dome, see **??**. This dome is glued to the project box using pvc cement, hot glue was used as a secondary layer to prevent water entering the system. This method worked well and the systems continue to operate without water damage.

The internal electronics are elevated above the floor of the project box. The idea was that even if a little water entered into the system, it should not affect the normal operation since the electronics are elevated above the floor. No water was however observed at any point in the enclosure even after heavy rain, therefore the first line of defenses were sufficient. Future implementations of the all sky camera may not be so lucky however, making holes on the floor can be considered additionally, this would drain any water that may accumulate inside.

5.2 Pre-processing steps Stages

The parameters used to tune to Hough transform were not set to be restrictive in order to allow for most of the heavy lifting with respect to the detection to be done by the CNN model stage. The minimum line width is one pixel, only 10 points are required to constitute a line with a max line gap of 5 pixels, this configuration detects lines quite loosely. This however results in hundreds if not thousands of possible ROI caused by vaguely line-like structures within a single image. Similar line-like structures can be generated as artifacts from the subtraction process of the motion detection. For e.g. if at time t=0, a cloud is at one location, in the following exposure at time t=1 this cloud may have moved incrementally in a particular direction further eclipsing a clear section of the night sky. Subtracting exposure at t=0 from t=1 one would get what amounts to line like structures that represents the difference in motion of the cloud since the previous exposure at t=0, examples shown in Figure 3.3. Line like structures can also be generated from glares caused by the moon or street lights and the motion of terrestrial objects such as animals and trees swaying due to wind.

5.3 Stage 1 Detection

This model was found to perform really well, the validation AUC of this model is 0.9950, this means this model is very good at accurately classifying objects that are labeled 'interesting' from those that are labeled 'not interesting'. Its overall validation accuracy is 0.9733 which is quite good, but specifically the Recall also known as the true positive rate is 0.9813. This means the model is very good at classifying 'interesting' objects as 'interesting' objects when it observes them. The validation Precision is 0.9812, this means the model has a low rate of detecting objects classified as 'not-interesting' as 'interesting'.

This stage 1 model does the job of cutting out most of the noise in the data coming out of the line detection algorithm. This line detection algorithm is not very strict on what it detects as lines, it will even consider broken lines as lines which means it may output all manner of images as lines. As mentioned previously subtraction artifacts, insects, trees, clouds, light glares etc can under certain instance appear line like to the line-detection algorithm. The validation performance metrics of this stage model suggest it is a very good barrier for all of these false detections. This is likely due to the high similarity among objects considered line-like vs other observed objects/artifacts in the image.

5.4 Stage 2 Detection

Meteors are what we want to detect, they are the result of pieces of space rock from comets or asteroids colliding with the atmosphere and are usually characterized by straight lines that fades in and out as the meteor brightens during ablation, also known as bright flight, and then dims after disintegration (Colas et al. 2020). There can be chunks left over after this bright flight period that collide with the ground, and are called meteorites. The lines any particular meteor creates in the resulting images from the all sky camera during its bright flight can be very thin to several pixels thick, with variable colors and lengths. The color variation is dependent on the chemical make up of the meteor but the line lengths in the exposures of the all sky camera depends on many factors such as the meteor's velocity, composition and incident angle with Earth on entry all of which affects how far it can travel before disintegration.

The second class, aircraft can be very easy to distinguish visually, they are characterized by intermittent bright points along its path. Fainter signatures of aircraft can look very much like a meteor in a still frame, however there is a way to distinguish them. The aircraft will usually have an alternating color pattern, e.g. red-blue-red-blue etc. Information of previous frames can be used to distinguish aircraft from meteors, however this paper only looks at the object within a frame without context from previous frames.

After the first stage model removes the unwanted images, there are four remaining classes of images left. Based on the data collected, although meteors are the desired class they are also the the rarest to be observed. Airplanes, cosmic rays and even the whatever 'not interesting' image that manages to slip through tend to be much more common. It it understandable why aircraft would be much more common as there are flights everyday and night.

There is a type of line that was observed and initially confused for being meteors, however observation of this type of line behind other objects and their sometimes curved nature suggested these were not objects in the sky. To observe aircraft, meteors, satellites or other objects, straight line of sight is required. However with cosmic rays, since they can pass through other objects, they can be observed behind rocks or trees in the field of vision of the camera. The curvature observed in many of these 'cosmic ray' lines also rules them out as an object. Meteors and satellites would always appear to travel in straight lines, aircraft lines may be curved but the degree of curvature observed is too much for it to be an aircraft. Drones are another possibility but at the brightness these cosmic ray lines are observed, the intermittent or colored lights on a drone would also show up in the image. There is also the fact they occur randomly and not in a continuous sequence of lines between consecutive frames. Cosmic rays are observed to be far more common than meteors and even aircraft based on the data collected over five months, this is because they are caused by the bombardment of earth by high energy particles(cosmic rays) in the upper atmosphere (Niedzwiecki et al. 2019). These collisions create secondary particles, mostly Muons that rain down on earth. Muons can be thought of as a heavier electron. Because of their greater mass, they have more penetrating power. Muons appear as bright but thin lines or dots depending on the angle they interact with the camera sensor. The lines can be straight, curved, occur in pairs etc., see Figure 5.1.

The validation AUC of the stage 2 model is about 0.97, which is quite good, the means it will distinguish between the classes of meteors and not meteors quite well, the validation precision is 0.9641 which means the model has a low rate of false positives. This translates to it being less likely to identify non-meteors as meteors. However the Recall is not as good at 0.8583, meaning the model misses more positive instances, in other words it is more likely to miss detecting meteors.

5.5 System as a whole

One way to deploy the system as network of cameras would be to use the capable processing power on the Raspberry Pi 4 to do the detection. This would mean doing the inference on the camera system itself. Each camera would detect if it has observed a meteor and only send data when it has observed one. In a case where there are a lot of ASCs, this would be advantageous since it would reduce the amount of storage and processing power required from the central server. The drawback would be that if any meteor was technically observed but not identified by the

Figure 5.1: Image showing the variation of cosmic ray artifacts

detection software om the camera there would be no way to revisit the data, since it would not be sent to the central server. On the flip side, one could deploy in a manner where all cameras send all their data to the central server. This would be more reliable but also more expensive, since the server would have to be very capable in terms of storage capabilities and processing power. All the data would be stored and can be reanalyzed if necessary.

A full deployment with multiple cameras over a large geographical area would however have a different hardware topology to the one used in this paper. Each camera would need its own internet connection which would likely take the form of piggybacking off an existing WiFi network, using mobile data modems or satellite internet for the most remote locations. This would necessitate VPNs for secure delivery of data back to the central server regardless of the specific configuration as discussed previously in this section. There would also need to be some form of synchronization system in place to ensure multi camera detections can be correlated.

Creating a network

6 Conclusion

The capability to capture the entire sky in a single exposure is a useful measurement for scientific and amateur applications. It enables one to observe meteors, capture cloud data, study light pollution etc. The All Sky Camera which is used for this application has undergone several evolutions to improve its capabilities from using film and rotating mechanisms to now using digital sensors and specialized software. The use of CNN's is another stage of improvement. Specifically for meteor research/observation, CNN's are now being used for detection. The issue with previous software implementations was that they relied on static parameters that were pre-defined. CNN's have the ability to learn the general range/idea of what would constitute an image of a meteor, given enough data, this is difficult to encode as a set of parameters.

From this paper it is apparent ASCs can be built to detect meteors without needing to overcome a high cost barrier, this would make it a more feasible task to deploy networks in Jamaica and the wider Caribbean. More work is needed to fine-tune the accuracy from a single station deployment stand point however with more data and multi-station detection, it is very evident the accuracy can be improved considerably. Based on the results, the camera may miss some instances of meteors but when they are detected, it does so with high confidence.

Using Low cost materials/parts, ASCs can be built that can reliably withstand varying weather conditions without exposing internal components for at least several months continuously. This lowers the barrier needed to implement a network of these cameras since consumer grade equipment can suffice. One just has to be careful that the enclosure used has a seal, and the mount for the system is solid to prevent wind damage. Elevation of the internal electronics above the floor of the enclosure is also a plus in case the worst happens.

For future work, having several devices working in tandem in network can improve detection/classification accuracy. This would be because meteor are often observed high in the atmosphere, therefore ASCs can be placed about 80KM apart to observe them, by synchronizing the ASC this would filter out false detections from a single station and improve the overall accuracy. The use of CNNs can potentially solve the challenges with implementations of meteor networks. For one they tend to employ legacy methods for meteor detection that uses static parameters. These can result in a lot of false positives being generated which necessitates manual oversight of the detection. This paper has shown that CNN models are a valid alternative, where they can be trained to detect meteors automatically at high accuracy and recall. It was also demonstrated that these CNN models can work locally on the camera system itself reducing the load on a central server for a network implementation. By using Low cost parts and creating a hardware solution that works it shows that an all sky camera system can be created relatively inexpensively which means it can reduce the barrier of deployment in third wold regions like the Caribbean and also for amateur astronomers.

REFERENCES

https://allskeye.com/.

"AllSkEye." AllSkEye. Accessed November 14, 2023. https://allskeye.com/.

Anghel, Simon, Dan A Nedelcu, Mirel Birlan, and Ioana Boaca. "Single-station meteor detection filtering using machine learning on MOROI data." *Monthly Notices of the Royal Astronomical Society* 518, no. 2 (November 29, 2022): 2810–2824. ISSN: 0035-8711, 1365-2966. https://doi.org/10.1093/mnras/stac3229.

Audureau, Yoan, Chiara Marmo, Sylvain Bouley, Min-Kyung Kwon, François Colas, Jérémie Vaubaillon, Mirel Birlan, et al. "FreeTure A Free software to capTure meteors for FRIPON," 2014.

Blaauw, R., and K. S. Cruse. *Comparison of ASGARD and UFOCapture.* Conference Name: Proceedings of the International Meteor Conference, 30th IMC, Sibiu, Romania, 2011 Pages: 44-46 ADS Bibcode: 2012pimo.conf...44B. January 1, 2012.

Boaca, Ioana, Maria Gritsevich, Mirel Birlan, Alin Nedelcu, Tudor Boaca, François Colas, Adrien Malgoyre, Brigitte Zanda, and Pierre Vernazza. "Characterization of the Fireballs Detected by All-sky Cameras in Romania." *The Astrophysical Journal* 936, no. 2 (September 1, 2022): 150. ISSN: 0004-637X, 1538-4357. https://doi.org/10.3847/1538-4357/ac8542.

"Cameras – ZWO ASI." Accessed November 14, 2023. https://astronomy-imaging-camera.com/product-category/cameras/.

Castro-Tirado, Alberto J., Martin Jelínek, Stanislav Vítek, Petr Kubánek, Josep M. Trigo-Rodríguez, Antonio De Ugarte Postigo, Tomas J. Mateo Sanguino, and Igor Gomboš. "A very sensitive all-sky CCD camera for continuous recording of the night sky," 70191V. SPIE Astronomical Telescopes + Instrumentation. Marseille, France, July 12, 2008. https://doi.org/10.1117/12.789361.

Ceballos-Izquierdo, Yasmani, Dwayne Free, Ashley Hughes, Frankie Lucena, Eddie Irizarry, and Manuel E Grullón. "Meteors and bolides across the Caribbean," 2022.

Cecil, D., and M. Campbell-Brown. "The application of convolutional neural networks to the automation of a meteor detection pipeline." *Planetary and Space Science* 186 (July 2020): 104920. issn: 00320633. https://doi.org/10.1016/j.pss.2020.104920.

Colas, F., B. Zanda, S. Bouley, S. Jeanne, A. Malgoyre, M. Birlan, C. Blanpain, et al. "FRIPON: a worldwide network to track incoming meteoroids." *Astronomy & Astrophysics* 644 (December 2020): A53. issn: 0004-6361, 1432-0746. https://doi.org/10.1051/0004-6361/202038649.

Deppermann, Charles E. "An Improved Mirror for Photography of the Whole Sky." *Bulletin of the American Meteorological Society* 30, no. 8 (October 1, 1949): 282–285. issn: 0003-0007, 1520-0477. https://doi.org/10.1175/1520-0477-30.8.282.

Dev, Soumyabrata, Florian M. Savoy, Yee Hui Lee, and Stefan Winkler. "Nighttime sky/cloud image segmentation." In *2017 IEEE International Conference on Image Processing (ICIP)*, 345–349. 2017 IEEE International Conference on Image Processing (ICIP). Beijing: IEEE, September 2017. isbn: 978-1-5090-2175-8. https://doi.org/10.1109/ICIP.2017.8296300.

Doug Welch, Anthony Tekatch. "Sky Quality Meter." http://unihedron.com/projects/darksky/.

Fassig, Oliver L. "A REVOLVING CLOUD CAMERA." *Monthly Weather Review* 43, no. 6 (June 1915): 274–275. issn: 0027-0644, 1520-0493. https://doi.org/10.1175/1520-0493(1915)43<274:ARCC>2.0.CO;2.

Fernández, Carlos Hernández, José Carlos Rodríguez, and Yebes Observatory. "Detection of aircraft traces in nighttime all-sky camera images using deep learning," 2023.

Hänel, Andreas, Thomas Posch, Salvador J. Ribas, Martin Aubé, Dan Duriscoe, Andreas Jechow, Zoltán Kollath, et al. "Measuring night sky brightness: methods and challenges." *Journal of Quantitative Spectroscopy and Radiative Transfer* 205 (January 2018): 278–290. issn: 00224073. https://doi.org/10.1016/j.jqsrt.2017.09.008.

Haputhanthri, Dilantha, Daswin De Silva, Seppo Sierla, Damminda Alahakoon, Rashmika Nawaratne, Andrew Jennings, and Valeriy Vyatkin. "Solar Irradiance Nowcasting for Virtual Power Plants Using Multimodal Long Short-Term Memory Networks." *Frontiers in Energy Research* 9 (August 16, 2021): 722212. ISSN: 2296-598X. https://doi.org/10.3389/fenrg.2021.722212.

Hill, Robin. "A lens for whole sky photographs." *Quarterly Journal of the Royal Meteorological Society* 50, no. 211 (July 1924): 227–235. ISSN: 0035-9009, 1477-870X. https://doi.org/10.1002/qj.49705021110.

Lothon, Marie, Paul Barnéoud, Omar Gabella, Fabienne Lohou, Solène Derrien, Sylvain Rondi, Marjolaine Chiriaco, et al. "ELIFAN, an algorithm for the estimation of cloud cover from sky imagers." *Atmospheric Measurement Techniques* 12, no. 10 (October 21, 2019): 5519–5534. ISSN: 1867-8548. https://doi.org/10.5194/amt-12-5519-2019.

Mandát, Dušan, Miroslav Pech, Jan Ebr, Miroslav Hrabovský, Michael Prouza, Tomasz Bulik, and Ingomar Allekotte. *All Sky Cameras for the characterization of the Cherenkov Telescope Array candidate sites*, arXiv:1307.3880, July 15, 2013. arXiv: 1307.3880[astro-ph].

Niedzwiecki, Michal, Krzysztof Rzecki, Marta Marek, Piotr Homola, Katarzyna Smelcerz, David Alvarez Castillo, Karel Smolek, et al. *Recognition and classification of the cosmic-ray events in images captured by CMOS/CCD cameras*, arXiv:1909.01929, October 7, 2019. arXiv: 1909.01929[astro-ph].

Santos, G, and A Ederoclite. "Development of an allsky camera based on commercially available hardware and open-source software," 2023.

Sennlaub, Rabea, Martin Hofmann, Mike Hankey, Mario Ennes, Thomas Müller, Peter Kroll, and Patrick Mäder. "Object classification on video data of meteors and meteor-like phenomena: algorithm and data." *Monthly Notices of the Royal Astronomical Society* 516, no. 1 (August 31, 2022): 811–823. ISSN: 0035-8711, 1365-2966. https://doi.org/10.1093/mnras/stac1948. arXiv: 2208.14914[astro-ph].

Shields, Janet E., Monette E. Karr, Richard W. Johnson, and Art R. Burden. "Day/night whole sky imagers for 24-h cloud and sky assessment: history and overview." *Applied Optics* 52, no. 8 (March 10, 2013): 1605. ISSN: 1559-128X, 2155-3165. https://doi.org/10.1364/AO.52.001605.

Shirasuna, Victor Yukio, and Andre Leon Sampaio Gradvohl. *Image dataset for the creation of an automatic system for meteor fall detection.* V. 0.1, April 14, 2023. https://doi.org/10.5281/ZENODO.7830131.

Silva, Renato Moraes, Ana Carolina Lorena, and Tiago A. Almeida. "Detecting the presence of meteors in images: new collection and results." In *Anais do XV Encontro Nacional de Inteligência Artificial e Computacional (ENIAC 2018)*, 128–139. XV Encontro Nacional de Inteligência Artificial e Computacional. São Paulo: Sociedade Brasileira de Computação - SBC, October 22, 2018. https://doi.org/10.5753/eniac.2018.4410.

Suk, Tomáš, and Stanislava Šimberová. "Automated Meteor Detection by All-Sky Digital Camera Systems." *Earth, Moon, and Planets* 120, no. 3 (December 2017): 189–215. ISSN: 0167-9295, 1573-0794. https://doi.org/10.1007/s11038-017-9511-z.

Tóth, Juraj, Leonard Kornoš, Pavol Zigo, Štefan Gajdoš, Dušan Kalmančok, Jozef Világi, Jaroslav Šimon, et al. "All-sky Meteor Orbit System AMOS and preliminary analysis of three unusual meteor showers." *Planetary and Space Science* 118 (December 2015): 102–106. ISSN: 00320633. https://doi.org/10.1016/j.pss.2015.07.007.

Voronych, Oleksandra, Robert Höller, Germanno Longhi Beck, and Wolfgang Traunmüller. "Solar PV nowcasting based on skycamera observations." *Advances in Science and Research* 16 (February 28, 2019): 7–10. ISSN: 1992-0636. https://doi.org/10.5194/asr-16-7-2019.

Walker, David E., Hugo E. Schwarz, and Edison Bustos. "Monitoring the night sky with the Cerro Tololo All-Sky camera for the TMT and LSST projects," edited by Larry M. Stepp, 62672O. SPIE Astronomical Telescopes + Instrumentation. Orlando, Florida , USA, June 14, 2006. https://doi.org/10.1117/12.671567.