Automated Vegetation Monitoring Using Animal-Mounted Sensors

Sensor CDT MRes Cohort 2023/24

August 2024

Team Challenge Final Report

EPSRC Centre for Doctoral Training in Sensor Technologies for a Healthy and Sustainable Future

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Contents

1 Executive Summary

The Sensor CDT Team Challenge 2024 was developed in collaboration with Rothamsted Research with the goal of automatically monitoring vegetation biodiversity in pastures. As shown in Figure 1, the majority of global agricultural land is composed of grassland and pastures where grasses, legumes and forbs are grown and then grazed by livestock [1, 2]. The biodiversity of grasslands plays a critical role in agriculture, ranging from enhancing productivity, improving soil health and affecting climate change [3]. Therefore, sensors that can spatially resolve biodiversity to investigate these factors are of great interest.

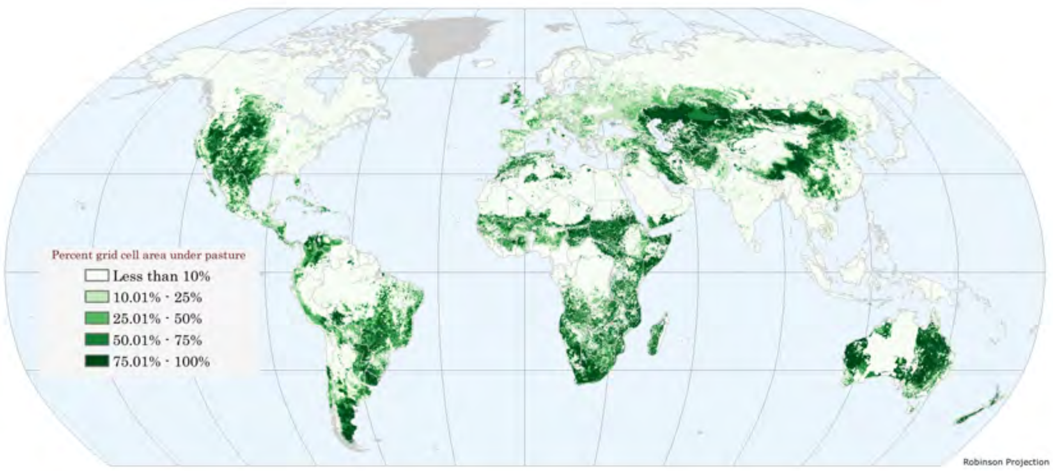

Figure 1: Global distribution of pastures in 2000. Figure from [4].

DAISY is a low-cost sensor system that uses a camera mounted on the collar of cattle to image, classify and monitor vegetation in pastures. This enables the inspection of regions that are difficult to access by humans or vehicles by using non-invasive equipment that does not disturb the land nor the animals. The system is able to autonomously collect data in the field for four weeks and utilizes a Machine Learning (ML) algorithm to classify the images, detecting key vegetative indicators such as clover dominance, frequency of bare soil areas and presence of dung patches. The DAISY sensing system aids end-users in informed decision-making with regards to land and animal management in order to enhance ecosystem health and the quality of agricultural products i.e. animal-derived products. Indeed, a graphical user interface (GUI) integrates the data collected and analysed by DAISY with other existing data such as topography and soil classification. This Team Challenge is an open-source project with the software shared on GitHub in order to allow future researchers to replicate it and promote Responsible Research and Innovation (RRI) principles. Additionally, the project has been shared online via social media and a website with the aim to maximise outreach and engagement.

2 Acknowledgements

We would like to thank the following people for their support and advice:

- Phil Le-Grice, Bruce Griffith, Martin Blackwell, Jane Hawkins, Deborah Beaumont and Paul Harris of Rothamsted Research for guiding our research activities, organising our visits to North Wyke Farm and explaining the Farm Platform.
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3 Project Outline

3.1 Structure and Timeline

The project was completed by 14 MRes students from the 23rd of June 2024 until the 23rd of August 2024. The group structure, depicted in Figure 2, was inspired by the functional model typically found in technology companies, with a product team responsible for understanding customer needs and translating those into system requirements and an engineering team responsible for the detailed design and build of the system. In this project the engineering group was split into two sub teams; one focused on the animal mounted device and one focused on the data processing and visualisation. Each of the three technical workstreams (product, data, device) had a lead to help coordinate and simplify inter-team communication.

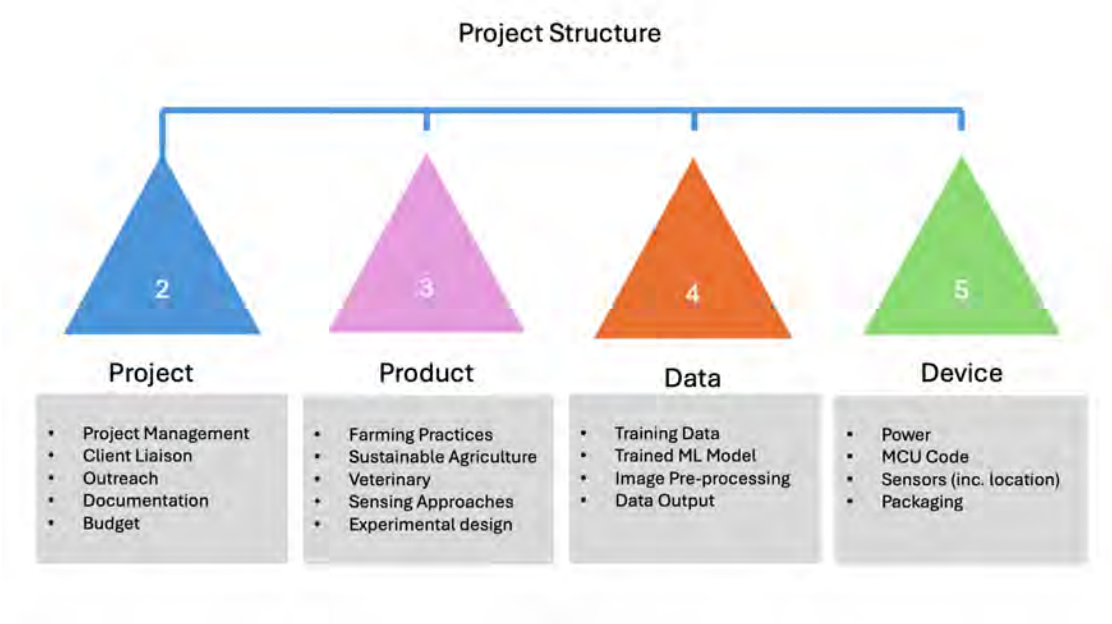


Figure 2: Project workstream organisation, roles and responsibilities.

The roles and responsibilities of each workstream were:

- **Project**: Manage the overall project plan, liaise between workstreams, and develop project-wide deliverables such as documentation and outreach activities.
- **Product**: Define the specification and value of the system, ensuring that the data output meets the project objectives and customer requirements.
- **Data**: Design and develop an image processing and classification system that takes tagged raw images from the device and outputs the aggregated vegetation classifications.
- **Device**: Design and build the physical device attached to the cattle, incorporating all the necessary technology required to autonomously capture high-quality images for several weeks.

3.2 Project Governance

Project tracking and dependencies centered around two key weekly meetings.

- The workstream leads meeting, an in-person meeting every Monday morning, during which team leads presented updates on key tasks completed and key activities planned for the coming week. Project members due to present the weekly update to the CDT management were also invited to attend and contribute.
- The weekly all-hands meeting, a hybrid meeting every Thursday afternoon, during which one or more teams presented detailed explanations of their work. This forum was also used for general updates and discussion across the teams.

3.3 Learning from Previous Sensor CDT Team Challenges

As this is the tenth year of the Sensor CDT team challenge, we wanted to ensure that we were aware of and could take measures to avoid recurring issues encountered in previous years. Former and current students and staff from the CDT were asked to list critical missteps that were made across multiple years. Of these, six were identified as potential risks for the project. Actions were taken to mitigate against these throughout the project.

Scope Creep
Prior team challenges made the mistake of overspecifying their systems and failing to deliver within the time-frame available. To mitigate against this, the detailed planning for the engineering workstreams focused solely on delivering the capabilities necessary to meet the the requirements outlined by the product team. In a commercial context, this is called the minimum viable product (MVP). Additional features which might enhance the user experience, such as transferring images from the device using Wi-Fi, were postponed until the MVP was delivered. For the device team in particular, this focus proved invaluable since integration between different components proved much more challenging than expected.

Late acquisition of training data
Past projects with machine learning components often left the acquisition of training data until the final weeks of the project, limiting time for model optimisation and/or for the acquisition of additional data to fill gaps and improve performance. To avoid this, the priority of the first field trip was the acquisition of over 1000 tagged photographs of vegetation from the Dairy Corner fields of the North Wyke Farm platform. This learning set proved crucial to the fast start made in labelling and in the selection and optimisation of the model.

Communication and Dependencies
Inter-team communication and dependencies were cited as common difficulties in Team Challenge projects. To improve communication and dependency management, we held two key meetings each week and utilized online platforms for team wide and work stream communications.

Underestimating Lead times
Delivery of components from third parties on the critical path had been a common root cause in missed deadlines. With this in mind, components were ordered in well in advance of when they were needed. Despite this, the flexible PCBs due to be delivered one week before final deployment still arrived too late for the final build.

Lack of fallback options
Prior cohorts had run into difficulties when they had a single plan without any fallback options. One of the fallback options of the device team was to construct a device from manually wired components. This fallback plan proved valuable when the flexible PCBs were delayed.

Flagging Morale

Lastly, flagging morale in the final weeks of the project were cited as a common feature in Team Challenges. To mitigate against this, each Friday every team member was asked to score how much they learned, how much fun they had and how satisfied they were with their achievements. These three questions were chosen to cover the emotions often felt by team members on projects. These emotions are typically orthogonal, for example a low score of fun is often balanced by a high score in satisfaction in the final weeks before a deadline. Team members who consistently marked low scores, or any 1s were contacted by the project manager to understand if intervention was required. In week 5, a mid project review was also held in order to expose and deal with any work stream or inter-team problems. More details of this can be found in Appendix A.1.

3.4 Stakeholders

A list of key stakeholders was compiled in the first week of the project to ensure they remained at the forefront of development. The stakeholders were categorised based on their interest in the success of the project and their potential influence of the project (Figure 3).

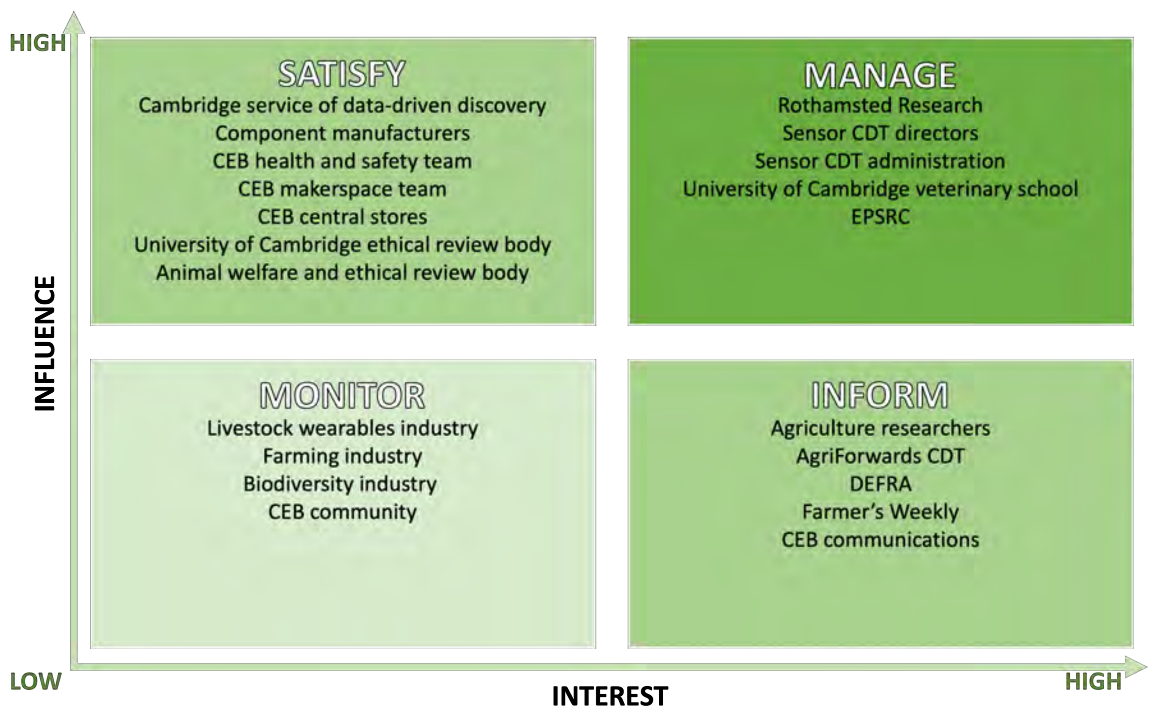


Figure 3: Stakeholder influence matrix of the associated project stakeholders.

We monitored the associated industry sectors throughout to understand and respond to any active changes in the landscape and an outreach programme (see §10) was implemented to ensure that interested parties which were not involved with product development were kept informed on our progress and intentions. Key stakeholders (Figure 3) were engaged on a regular basis and updated on our progress. The engagement strategy for these key stakeholders, as well as for other stakeholders we engaged with directly from other categories, are detailed in Appendix A.2, Table 14.

4 Background

4.1 Motivation and Aims

Ecological sampling has been of academic interest for over 100 years as pasture biodiversity is a good indicator of several variables, including the ecosystem health and agricultural productivity [5, 3]. Indeed, biodiverse pastures provide numerous benefits, including improved soil health and ruminant health and nutrition, in addition to a reduced need for nitrogen fertilisers [6, 7, 8]. However, the current methodologies to assess grassland biodiversity are time-consuming, labour-intensive and in some cases difficult to perform due to field topography. Traditional approaches to ecological sampling involve using a quadrat of fixed size. This quadrat is placed in the test area in a known location, adhering to the chosen sampling methodology. The species within the quadrat are quantified manually, and the process is repeated in a new location. Despite this technique being performed by an expert, there is still some level of subjective bias in assessing the coverage of each species [9]. Therefore, having identified a clear need within the agricultural sector, the 2024 Team Challenge involves designing, constructing and validating a sensor system mounted on grazing livestock that monitors and classifies vegetation biodiversity. This would allow the end-users to sample a larger area in less time and potentially allow for the monitoring of remote areas. DAISY will enable more robust conclusions to be drawn regarding the chemical and physical characteristics of the field due to larger sample sizes over extended periods of time. As fine-scale spatial patterning, systematic and stochastic temporal variables influence interactions between soils, plants and animals, heterogeneity must be considered at correct temporal and spatial scales [10].

The cattle-mounted sensor system proposed addresses these needs by providing a cost-effective, long-lived automated monitoring solution. The DAISY sensor system employs a camera attached to the cattle collar to capture images of the pasture. These images are then processed and analysed using ML models to classify different types of biodiversity indicators, including grass, clover, dung and bare soil patches. This device is designed to operate autonomously for at least four weeks, powered by rechargeable lithium batteries which will be replaced during routine checks such as cattle weighing or deworming. In the first instance, the project aims to provide academic end users, such as Rothamsted Research, with raw data in alignment with the current platform used at the North Wyke Farm. This includes the original image identifier, time, geolocation and detected vegetation coverage type. Rothamsted and other research institutes which decide to take up the technology can use and manipulate the data as they see fit. A graphical user interface (GUI) was developed for end-users interested in improving their farming strategies to extend the value that DAISY can provide beyond the academic community. Moreover, all users are provided with a user manual that includes a description of the principal components of the device, a quick guide to facilitate its use and disposal guidelines which can be found in Appendix B. Overall, this ensures that the collected data are valuable and accessible by all types of end-users.

4.2 Market

The market for this technology is quite large, as the different components of the system were designed to bring value to many stakeholders and groups. As presented above, the human resources and financial costs associated with current sampling approaches are significant. Automated technology could allow larger areas to be sampled more quickly, especially in regions humans find difficult to access. Additionally, mounting the sampling technology on a roaming animal allows continuous sampling over a longer period of time, enabling novel insights into ecological changes on a temporal scale. The implications of this system can thus be valuable to many, ranging from governmental bodies to farmers.

Indeed, the Department for Environment, Food and Rural Affairs (DEFRA), the government ministerial body responsible for regulating agricultural and environmental procedures, has several schemes to incentivise environmentally conscious farming practices. For example, the Sustainable Farming Incentive pilot contains the 'improved grassland standard', which allows farmers to claim subsidies for improving certain aspects of biodiversity [11]. In the first instance, farmers are required to be eligible for applying by proving that the composition of their sward meets two of the three following criteria:

1. Rye-grasses and white clover cover more than 30% of the area
2. Up to 8 species per m^2 (grasses included)
3. Wildflowers and sedges cover less than 10% of the area (white clover, creeping buttercup, docks, thistles and ragwort excluded)

Other schemes, such as the Countryside Stewardship grants GS4 [12] and GS2 [13], also involve assessing factors such as grasses, legumes and bare soil. As DEFRA audits farmers to check their scheme eligibility, a device that is easily deployable to replace the current audits with a data-driven approach would be of interest to streamline and standardise their current process.

Farmers are required to keep accurate records and maintain ongoing communication with DEFRA. This process represents a large human resource, and in some cases, preparing for an audit will discourage farmers from applying for incentive schemes. Providing an easy-to-use tool with integrated data analysis and interpretation will lower the human resources required to obtain biodiversity data and provide data records that can easily be communicated with DEFRA.

Farmers also require quantitative data to guide farming practices. For example, nutritionally dense pasture can reduce farmers' requirements to buy cattle feed, decreasing clover coverage over time can indicate an overgrazed pasture, and certain vegetation composition can indicate that the field requires resowing (see §5.1)[14, 15]. In 2023, 307 hectares of UK land were assessed to be permanent pasture land, which our device could use to monitor and assess to help farmers make sustainable farming choices. [16]

4.3 Market Research and System Benefits

Initial market research into livestock-mounted sensors for biodiversity monitoring found that current approaches to assess grassland biodiversity rely on manual sampling in the region of interest and implementation of standard statistical techniques to assess the spatial data [17]. This includes analysis of the spatial and temporal dependencies of biological and chemical features in the sample space. Notably, manual sampling carries a large time and human resource and requires expertise in species identification. Statistical analysis of geo-spatial data also requires expertise in data science. It is therefore surprising that so few efforts to automate existing sampling approaches have been reported in literature [18]. There is a clear opportunity to develop and implement novel sensor technologies using machine learning approaches to streamline the process of biodiversity monitoring.

Namely, the *Syngenta* biodiversity sensor uses artificial intelligence and machine learning algorithms to quantify bee pollinator species in real time [19]. This is a key example of a novel application of sensor technology and machine learning for assessing animal health and plant productivity in a fixed location. In the context of assessing grassland biodiversity across large sample regions, livestock are now being considered as moving platforms or subjects on which data can be gathered. Current devices include collar-mounted sensors to monitor cattle health and guide 'precision farming'. Agricultural professionals are becoming more interested in data-driven insights to guide their practices [20]. This highlights the opportunity to develop livestock-mounted sensors which can reduce the time and cost burden associated with gathering biodiversity data over large sample regions. It was concluded that a sensor which can classify grass, clover, bare soil and dung would be highly valuable for improving academic understanding of grasslands and displaying quantitative insights for pasture management.

Investigation into Government subsidies suggested that there are many, easily accessible grants to help farmers improve the quality of their pastures. However, a meeting with Tom Turner, an Agricultural Consultant, indicated that intense records keeping and audit requirements deter farmers from applying. As described in §4.2, grant application requires quantitative proof of species coverage (such as 30% rye-grass and clover by area). Any manual sampling approaches for demonstrating that these criteria have been met represents a large human and time resource for farmers. It is therefore clear that a sensor that can quickly gain such data and communicate the results with auditing bodies would be a valuable tool for farmers. This was echoed in a recent Farmer's Weekly Transition Talk (webinar), which focused on the diversification of UK agricultural practices. It was highlighted that to make farms profitable, farmers must explore wider opportunities (such as 'glamping') alongside their existing workload. It was clear that technological developments which ease the process of grant applications, record keeping and pasture monitoring are required. Collaboration with the AgriForwards CDT showed the importance of developing a platform which presents digestible and clear information to aid farmers aiming to use sensor data to guide their practices. While academic end-users would comfortably interpret raw data, farmers would prefer a tool that can visualise the results and output specific action items to guide their practices. This could include information on grazing rotation, fertiliser usage and resewing and encouraged the development of a platform (Graphic User Interface, see §7.3.1) to streamline farming activities through statistical insight.

Discussion with Rothamsted Research outlined the current statistical methods used in biodiversity monitoring and data analysis. These rely on manual sampling approaches to obtain suitable data for geospatial analysis and calculation of global weighted regression. It was therefore identified that a sensor that can obtain suitable data for analysis under standard statistical methods would be valuable to the academic community. This hence guided the sampling approach detailed in 5.3. The Rothamsted Research staff emphasised the importance of sampling the test region sufficiently to gain statistically significant insights, allowing visualisation of the dependencies between present species and explanatory variables (i.e. the chemical and physical characteristics of the field).

A log of the specific insights provided during Market Research are provided in Appendix B.2, Table 15. Having gained this insight, the system benefits were split into six themes:

1. **Image Collection Specifications.** Sufficient camera resolution will allow human and machine classification of the required image features. Estimation of the field of view of the obtained images will allow the extent of the sampled area to be calculated.
2. **Power Management.** An optimised power management strategy will allow sufficient sampling of the region for statistically significant insight into vegetation present in the same region. This will be guided by consideration of the interval at which cattle are typically brought in from their pasture on UK farms.
3. **Data Processing.** Model development to identify the most relevant classes will aid the delivery of an academically and commercially valuable tool for biodiversity monitoring. This includes data transmission and visualisation.
4. **Practical Implementations.** A sensor which is robust to its environment is required. This includes consideration of attachment method to cattle and device protection.
5. **Data output and statistical analysis.** Defining a sampling approach which allows the implementation of standard statistical methods is imperative. The data obtained will hence guide the development of a graphic user interface.
6. **Public outreach.** The work being completed on the project must be actively communicated with the relevant stakeholders. This requires the use of a variety of platforms and media types.

The ways in which these benefits could be optimised to a best case scenario are explored in Appendix B.2.

5 Science and Technology: System Requirements

5.1 Classification Categories

The DAISY model was trained to recognise clover, grass, dung, and bare soil, which indicate field characteristics and can inform farming strategies.

Clover has a high nutritional value and serves as a protein source for livestock, reducing the need for expensive fertilisers and food [14]. Studies have shown that ruminant livestock will consume 70% clover in their diets even when enough grass, which is easier to digest, is available to meet their nutritional needs [10, 21]. Additionally, the critical role of clover in pastures is due to its efficient nitrogen fixation, reducing the need for artificial nitrogen fertilisers required for grass growth, as shown in Figure 4. In a well-balanced and stable sward with approximately 30% clover coverage, there is a supply of N of 180 kg N/ha. Clover is also known to help improve soil structure by affecting soil compaction and enhancing the diffusion of nutrients and water [14].

Figure 4: Nitrogen supply at different proportions of clover coverage. Figure from [14].

Ryegrass efficiently uses the nitrates produced by clover, making it the optimal companion. From a grazing perspective, it has been established that despite ruminant's partial preference for clover, they will still supplement their diet with 30% grass [21]. Evidently, a mixed clover-grass diet is selected for optimal Carbon and Nitrogen intake or to avoid toxicity, which may arise from a single component diet [10]. Ideally, the ratio between grass and clover in a field should be 70:30, however, since this estimation is done by the naked eye, it is important to consider that the clover coverage is usually overestimated because its leaves face up; hence, an apparent 50-60% clover presence would correspond to a true 30% coverage[14].

It is crucial to monitor the levels of clover in a field, as when it is dominant it can highly impact the sward by out competing other crops for light, nutrients and moisture. Several studies have suggested that if the clover content in the field is too large (>>30%), farmers should consider a more intensive grazing approach by moving livestock to clover-rich areas. Other methods to suppress clover dominance include mowing to maintain a height of 3-4 inches or grass growth stimulation via the application of chemicals, e.g. nitrogen [14, 22]. Despite what has been reported in literature, UK farmers seldom struggle with excess clover and are more at risk of low coverage. If the clover content is too low (<<30%), farmers should consider reseeding. This can be done using common drilling or broadcasting seeding methods or via the animals' hooves if 20-40% of bare soil is visible. Notably, clover is reseeded when the soil temperature is warmer, i.e. between April and August and the soil pH is around 6.2-7.0%.[14, 22] This has been reported to have varying success rates and high associated costs for farmers, often deterring them from this approach.

Dung acts as a natural fertiliser, which improves soil health, increases soil nitrogen content, and, after degradation for 112 days, increases the soil pH [23, 24, 25]. This means that these areas will have a larger level of biodiversity; interestingly, clover has been shown to be the first species that regrows in dung patches after decomposition and maintains its dominance for 18 months [26].

Bare soil coverage in a field affects the rate of water evaporation and transpiration [27]. Water evaporation is also influenced by the radiative effects of sunlight on grassland, which reduces the soil surface concentration. Therefore, high coverage of bare soil >>30% affects the radiative sunlight effect, hence impacting the soil properties [28, 29]. Reseeding should be considered if two or more of the following criteria have been met: significantly reduced sward productivity, <60% sown species proportion, high weed levels or evidence of soil compaction[15].

The distribution of dung and bare soil patches is also relevant to analyse the movement of livestock. Indeed, the movement of livestock throughout a field is not random. Dung patches are known to affect livestock behaviour since the animals will stop grazing in those areas, as demonstrated by the 1-2 inches taller sward around it [26]. Despite that cows are shown to cover the entire surface of a field in a few days, they tend to spend more time in locations where distracting elements are present, e.g., water troughs, trees and shading [30]. As the leading cause of soil degradation is grazing behaviour, including grazing exclusion, livestock movement and other explanatory variables such as field topography [31], the proportions of the different classes and their distribution are interesting to consider and analyse.

5.2 Minimum Viable Product

The minimum viable product (MVP) refers to the simplest sensing system that can deliver our brief and represents the technology we intended to deliver in the first instance. The ideation of an MVP as the first collective task allowed for targeted development towards a predefined product for each workstream from the start of the project. Assumed non-negotiable specifications for the MVP were:

1. The system must be able to output academically and/or commercially valuable data.
2. Location must be determined in real-time sufficient to understand the photographed areas.
3. Images must be tagged with time and location.
4. Device must be able to work autonomously for four weeks.

In order to achieve the four specifications, the following key working assumptions (KWAs) were agreed upon:

- There will be one device per field.
- The device will be attached to a standard commercial cattle collar.
- The product team will devise a sampling strategy in conjunction with the device team for taking photographs.
- The device intelligence will be limited to the following: power management, location awareness, logic for the decision to take a photograph and image storage.
- Removable, rechargeable lithium batteries will power the device.
- Images are stored and collected in an SD card.
- Data output will be in the form of a delimited text file with time, location coordinates and basic structured data.
- Image preprocessing, classification and feature extraction will be done on a different device, such as a laptop or in the cloud.
- The model will classify images containing grass, clover, dung and bare soil.

5.3 Sampling Approach

5.3.1 Background

A thorough sampling strategy is required to capture statistical patterns within ecological datasets. Often data is collected using metal frame quadrats and quantifying the coverage of each species with roots growing within the frame. Although quadrat sampling techniques require data collection in deliberate and pre-established locations to obtain data suited to statistical analysis, a limited number of samples can be taken due to time and resource constraints. The DAISY cow-mounted system has the opposite restraints wherein a large area can be sampled passively, but the sampling locations cannot be controlled. Sampling each region at a higher density will allow more robust inferences to be made regarding the distribution of vegetation, cow behaviour and the chemical and physical attributes of the field.

Collecting data with a 'random' methodology allows the application of statistical techniques that can identify aspects of non-randomness and dependencies between classes within the dataset. Clustering of clover is an example of self-dependence, or a positive association between the individual plants. Non-homogeneous distributions of classes highlight negative associations [17]. Ecologists can interpret non-random characteristics to attribute patterns between vegetation and other ecological factors and explanatory variables. One such method is geographically weighted regression (GWR), which investigates the non-stationary relationship between two variables, e.g. clover presence and soil class, in order to spatially analyse the data considering their geographical location in the sampled area and to predict distributions in unsampled regions[32].

Random sampling is characterised by the control of the following three variables:

1. **Extent:** The study area (i.e. the field being grazed) must be fixed
2. **Lag:** The distance between samples
   The sampled locations must not overlap; thus, the lag must be a positive value. As the DAISY's GPS has a horizontal accuracy of 1.5m, ideally the lag could be controlled by taking additional pictures only after the cow has moved out of the GPS error range of the previous image, or by filtering out the extra images taken within this range. (Figure 5).

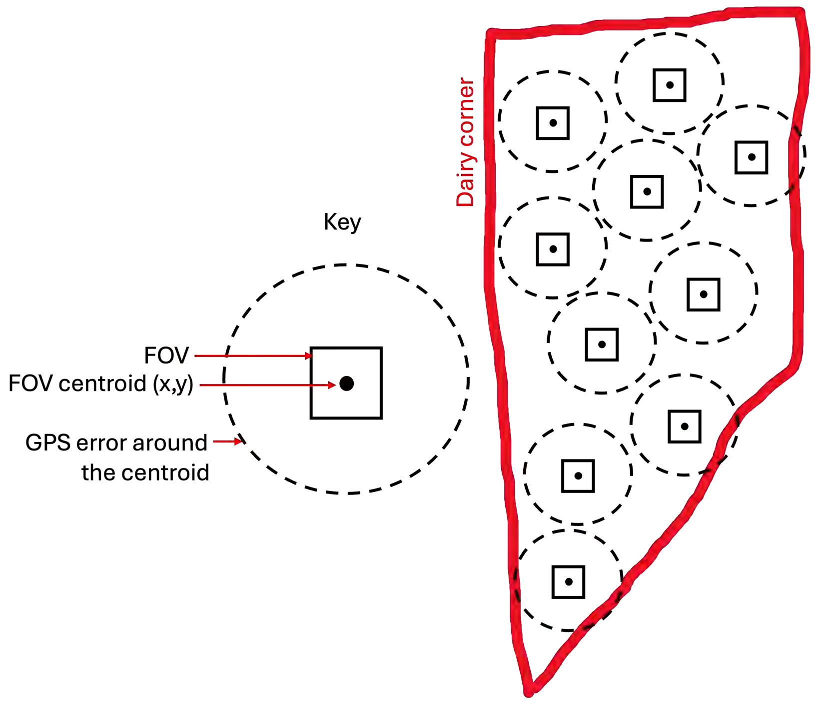


Figure 5: Illustration of an approach for controlling the lag. Each image is tagged with a set of coordinates (x,y), which are attributed to the FOV centroid. The GPS errors of adjacent images must not overlap.

3. **Support:** The size of each sample unit
   In quadrat sampling, this is fixed by using the same-sized quadrat throughout a study. For the DAISY sensor, the sample unit refers to the camera's field of view (FOV). To fix the FOV, the distance of the camera to the ground also needs to be fixed.

5.3.2 Inherent Limitations of Cow-Mounted Sampling

The concept of animal-mounted sensing is exciting due to the prospect of hands-off continuous monitoring. However, this sensing modality carries limitations inherent to the uncontrollable behaviour of livestock and the prolonged periods of time that the technology will be deployed without human intervention. In developing this project, it was important to consider these gaps and mitigate them where possible.

The first clear limitation is the non-random movement of cows and the perceived limited ability of a mounted sensor to sample a whole field when cows have preferred grazing and resting areas. In 2023, Romero-Ruiz *et al.* investigated the movement of cows throughout the entire grazing season. This study first demonstrated that their movement can be described using the Levy parameters of rotation angle (θ) and travelling distance (r). Therefore, they were able to replicate the animal movement pattern using the Levy walks model. Interestingly, the results show that the cows move in groups over a large portion of the grazing area during most days, hence covering the entire surface in a few days. Indeed just two steers were able to cover a large proportion of the field in one day (Figure 6)[30]. Whole field coverage is also implied as the authors describe that soil compaction due to grazing is even across the field at the end of the season. Although over- and under- sampling is unavoidable, the ability of cows to cover large proportions of the field in short periods of time demonstrates their credibility to be good vehicles for DAISY. Additionally, by attaching DAISY to multiple cows per pasture we will be able to maximise the sampled area (see §5.3.3).

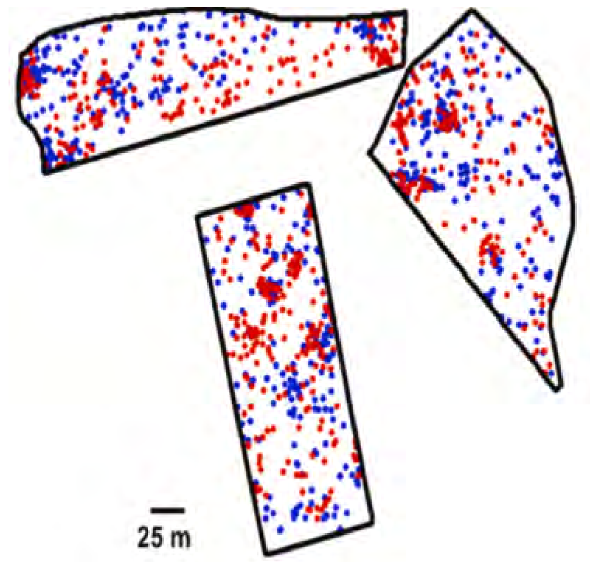


Figure 6: GPS locations of two steers (red, blue) after one day of grazing. Figure from [30]

Along similar lines, as the MVP specifies attachment to a standard cow collar, random movement of the device as the cow lifts and lowers its head must also be considered as it is inevitable. In our system, the extent is naturally fixed, and a strategy for controlling lag was devised. Altering the MVP specification to include a clause on fixing the device height was discussed extensively, with Data-based solutions also being explored. However, due to the nature of mounting DAISY on livestock, fixing device height and, therefore, FOV was deemed unrealistic. As this means the size of each sample unit cannot be fixed, a random sampling strategy cannot be used.

During quadrat sampling, the metal frame is placed on the ground and the grass is parted around the edges to clearly outline which roots are within the sampling area. When assessing the presence of species the individual will manually part the vegetation to ensure that all herbage that is hidden below longer grasses are assessed. DAISY is positioned on the underside of the cow's neck and captures images from above the vegetation meaning that some herbage will be hidden. For example, grasses are likely to obscure clover in the image due to their height. In the instance of a low clover:grass ratio, the picture may not capture a true representation of clover coverage, leading to incorrect classification. This cannot be avoided with the cattle-mounted ML system described.

By attaching technology to a grazing animal, human interference with the device is limited. As cattle will spend prolonged periods of time in pasture and specialist equipment such as cattle crushes will be required to mount the sensor in many instances, removal of the device for charging batteries will only be possible on an approximately monthly basis. This creates a key device bottleneck related to the longevity of the battery. Figure 7 shows how battery life directly limits how often we are able to transmit the collected images (i.e. daily via Wi-Fi or monthly via SD card) as well as the total area we are able to sample (dependent on the interval between images). Appendix B.2 describes some of the best-case scenarios that could be delivered by the DAISY sensing system. In many cases, the best-case scenario cannot be achieved due to battery life constraints. In the device design, the requirement of the battery to last 4 weeks was considered as a system boundary and other decisions about the functionality were made to fit within the battery limitation.

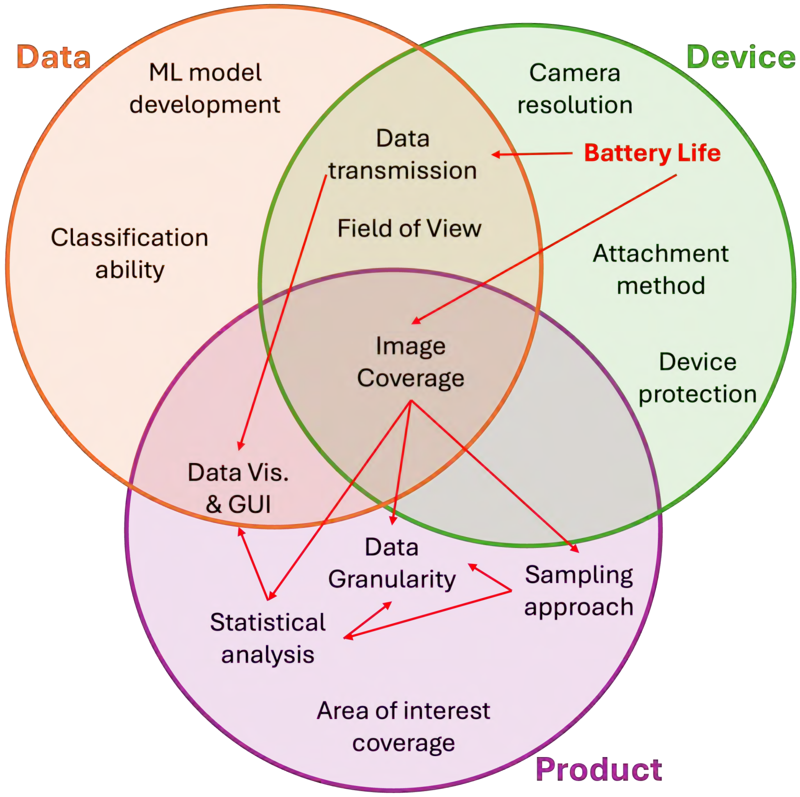


Figure 7: Influence diagram highlighting the impact of battery life on other components of the DAISY system. Venn diagram boundaries represent the remits of different workstreams.

Considering the inherent limitations of livestock-mounted sensors, from sampling to hardware and their implications on the overall system, random sampling was deemed an inappropriate method for this purpose. A sampling approach through which appropriate insights can be gained by using the DAISY device in pasture land is outlined in §5.3.3.

5.3.3 Final Approach

A suitable sampling approach robust to the inherent limitations of cattle-mounted sensors is required. This includes deploying the optimal number of sensors per herd for a sufficient sampling period. Similarly, device hardware limitations must be considered to determine the optimal rate at which the camera should capture images and how this data should be stored and transferred. This is in order to sample the chosen region with a sufficient number of data points to draw statistically significant insights from each test. Lastly, software considerations are essential in determining which of the obtained images are of sufficient quality to be used for analysis of spatial patterns. This deviates from manual, random sampling because a strict sample scheme is pre-determined with a known number of usable data points. To ensure a sufficient number of high quality data samples are obtained, the following factors were agreed.

Field coverage: 3-5 DAISY units will be deployed per herd. The cows will be chosen with the help of the Rothamsted Research experts to cover as much of the field as possible i.e., to select the dominant and most active cows. This will ensure sufficient field coverage for appropriate sample density, as per Romero-Ruiz *et al.* (2023)[30].

Sampling with camera sensor: The camera sensor will take 5 pictures per hour. The current estimation suggests that at this rate, the battery will last up to 1 month. This will be sufficient to achieve the required sample coverage and will be confirmed during testing.

Image storage: Images obtained during the sample period will be stored on an SD card, and collected when the device is retrieved after 4 weeks. Cows in Rothamsted are brought in for weighing at 4-week intervals, therefore the data retrieval will not disturb cow behaviour and impact sampling.

Image preprocessing: Images are segmented into smaller 244x244 pixel images.

Image processing: the ML algorithm will classify the images based on the presence, or absence of grass, clover, dung and bare soil in each picture.

Model Validation and Testing: this will carried out using a hand-held device utilising the same ML algorithm as the cow-mounted sensor. This is further described §8.

5.3.4 Data Insights and Output

Data granularity is an important consideration in providing maximum value for the end-users. Providing raw data for academics will be straightforward and will allow them to make their own inferences or perform their own analyses. However, for non-academic and commercial users (such as farmers, or DEFRA auditors), the data output must go beyond raw data and simple visualisation. Statistical and spatial inferences must be presented in an accessible and user-friendly way. This includes the integration of the sensor data with datasets describing the chemical and physical nature of the field and will allow the relationship between the classes i.e., grass, clover, dung and bare soil and explanatory variables to be presented. For example, data describing the topography of the field, such as the elevation, slope and aspect data presented in digital elevation models with 1m resolution, the width of the field borders and soil class must be integrated with the samples obtained using the sensor. The sample distribution i.e. where the images are taken can also be used to infer patterns in cow movement and behaviour, such as rejected regions of the field. This is fully explored in Appendix C.

The data obtained by the cow-mounted sensor will consist of images taken with time and GPS location data attached. The data output will therefore consist of an array of images with binary presence/absence data at each location. This will be displayed using a GUI, as described in §7.3.1

6 Science and Technology: Device

6.1 Design Concept

The system requirements outlined in §5.2 were considered to design a sensor that operates to the level needed and is of value to the stakeholders and end-users. A list of priorities was established for the hardware, and all design decisions throughout the development of the sensor were based on the following:

1. **Protect the system from environmental hazards.** All components must resist elements such as moisture, dust, high temperatures and mechanical impact to maintain functionality and ensure longevity.

2. **Minimise energy usage.** All components and actions must be selected and optimised, respectively, to ensure they can be powered during the entire planned use, incorporating efficient power management strategies and energy-saving modes.

3. **Maximise image quality.** The images must have a high resolution and clarity, with minimal blurring due to camera stabilisation during recording. The camera lens should be recessed into the casing to prevent the cattle from smudging or damaging it.

4. **Minimise impact of the sensor on cattle wellbeing.** When mounted on the cattle, the sensor must not cause any discomfort to the animal or alter their behaviour. Therefore, the size and smoothness of the casing, as well as the attachment location and mechanism must be carefully planned.

As such, we first determined the types of raw data required and the components that can produce this. Images of the grazing pasture will be captured in addition to the current time and location. To this end, a camera, real-time clock (RTC) and global positioning system (GPS) module must be incorporated into the device. A microcontroller unit (MCU) will interface with each of these components, execute the embedded code required to control them and dynamically manage the device's power consumption. A power source with the appropriate battery life and an SD card are required to sustain the electronics and data storage, respectively. Finally, these components will be packaged in a case that can be mounted onto commercially available cattle collars and will protect the sensor from the environmental conditions encountered on farms. The resulting design concept and ideation process is depicted in Figure 8. Alterations to the initial MVP, which arose during the development of the sensor, are detailed in Appendix D.1.

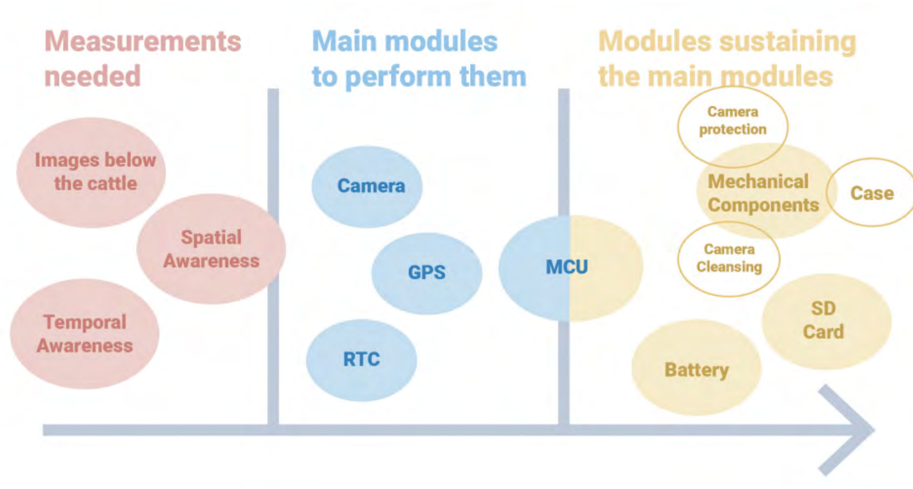


Figure 8: Device requirements, modules and related considerations.

The development of the sensor was thus considered in three parts: (i) casing, (ii) electronics, and (iii) embedded software, worked on concurrently and in an iterative fashion.

6.2 Casing

6.2.1 Background and Idea

As a prequel to designing the casing for the electrical components on the cow, the type of attachment to the cow was considered. The three positional attachment locations considered are shown in Figure 9 based on current methods of attachment for bovine monitoring. The attachment mechanisms, their previous uses and their advantages and disadvantages for the purposes of this project are shown in Table 1.

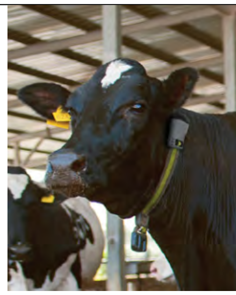
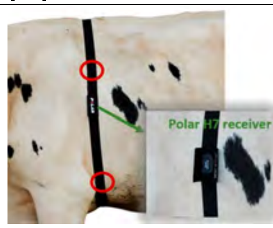
Attachment Mechanism	Example Use	Advantages	Disadvantages
Collar	 Dairy cow wearing SCR Heatime Pro System, which helps monitor herd health.	Easy to access and attach. Commonly used for cattle monitoring, so commercially available.	Increased likelihood of motion artefacts due to movement of cow's neck
Ankle Strap	 Cow wearing an ankle motion energy harvesting device from ref. [33].	Close proximity to the ground minimizing obstacles in FOV.	Increased likelihood of camera lens becoming obstructed i.e. by dirt and consequent decreased image.
Waist strap	 Cow wearing a Polar equestrian chest strap and Polar H7 receiver for heart rate monitoring from ref. [34]. Red circles indicate the placement of electrodes.	Lack of variation of FOV, preferable for random sampling method	High likelihood of damage to the device when the cows lie down.

Table 1: Comparison of attachment mechanisms considered for the device.

The collar was ultimately the preferred attachment mechanism primarily due to the prevalence of collars in agricultural monitoring contexts. Accessing standard collars for testing and prototyping was therefore relatively easy. Any potential improvements in image quality from an ankle or waist strap were deemed insufficient to justify the additional difficulties in practically developing a prototype.

Most commercially available cow collars with integrated sensors are composed of a lightweight device on the side of the cow's neck (side-of-the-neck sensor) with a corresponding weight to compensate and keep the sensor in place. A consideration for sensor positioning on the collar is the specific application that that sensor needs to perform and its impact on the cow's wellbeing. For example, the SCR sensor (seen in Figure 10) lies flat on the neck to allow the sensor's heart rate tracking application.

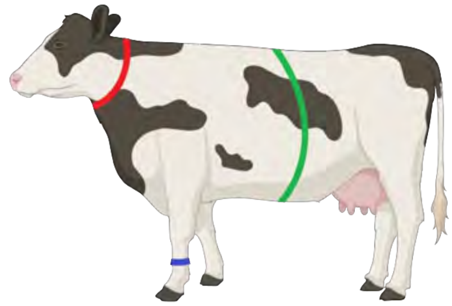


Figure 9: Different potential positions for a mounted biodiversity sensor on a cow. Red indicates a collar, blue indicates an ankle strap and green indicates a waist strap.

The balancing weight and the buckle attachment are designed to maintain the correct placement and prevent the sensor from slipping along the length of the collar. The placement provides minimal irritation to the cow, with the sensor out of its peripheral vision.

Another historically notable component seen on cattle collars are bells. Hung at the bottom of collars with the natural swing and subsequent ringing of the bell due to gravity and the movement of the cow, they allowed farmers to keep track of the cow's location in a field. A camera sensor located underneath the cow's neck, held there by gravity, was therefore considered as an alternate collar attachment location to the side-of-the-neck sensor. The primary concern with this attachment mechanism was the inevitable movement of the camera, which would likely result in motion artefacts in the images taken.

There were ultimately two possibilities for collar attachment:

- **Side-of-the-neck attachment** in a similar fashion to existing sensors with a balancing weight or a
- **Hanging bell attachment** which would sit at the bottom of the collar and be held there by gravity.

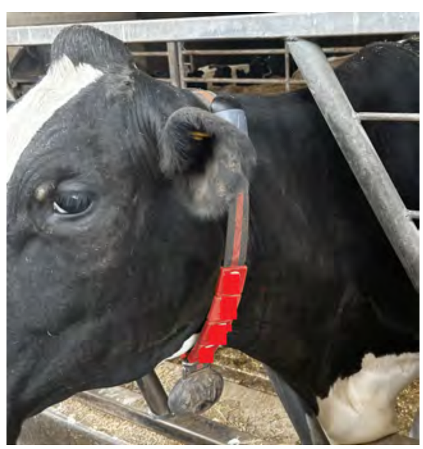


Figure 10: Dairy cow from the University of Cambridge Vet School wearing a Lely cow collar with an SCR Herd Monitoring sensor device.

Figure 11: Left: Side-of-the-neck attachment being tested on a cow. Right: Hanging bell design being tested on a cow. Both tests were carried out at North Wyke Farm, a facility part of the Rothamsted Research Institute. The collars used in testing are Kvikk Durable collars for cattle from Shearwell Data.

6.2.2 Case Technical Requirements and Considerations

For any design that would be selected, as the aesthetic design would be secondary to the functionality, technical requirements for the case were compiled as follows:

- **Camera protection**: To ensure images are taken with sufficient detail of the ground vegetation, the camera must be unobstructed from both the cow and the lens kept clean from mud and dirt which are abundant for cows roaming in fields. By insetting the camera inside the device, an effective funnel would prevent mud from splashing onto the lens and a laser cut acrylic lens cap can enable easier cleaning of the device if splashed by mud.
- **Image stabilisation:** Proposed methods of image stabilisation could be achieved implementing a spring/ball bearing mechanism on the camera module to reduce the vibration for cow movements. Image stabilisation could also be implemented through the camera firmware and attachment to the collar.
- **Durability:** As the device was to be 3D printed, the type of material used was important due to the wear and tear that the device will be subjected to when mounted on the cow. Materials like thermoplastic polyurethane (TPU), polylactic acid (PLA) and nylon were considered with Fused Deposition Modeling (FDM) or Selective Laser Sintering (SLS) printing to yield a strong, durable, impact and water resistant print.
- **Waterproofability and dust resistance:** The device must be at least splashproof to withstand the potential environmental conditions during use. To achieve this, pressure-formed plastic around a PLA 3D printed device and gaskets between joints were trialled and resin glue was used to seal ingress points around permanent pieces.

6.2.3 Final Design Selection

The first prototype testing was in the style of the side-of-the-neck attachment and can be seen in Figure 11. This design was initially pursued as it was thought that the flat attachment on the side of the cow's neck would have fewer motion artefacts as the device would be fixed rather than freely swinging. Following the examples of current sensors, a buckle attachment was 3D printed in TPU, due to the flexible nature of it as this was deemed most comfortable for the cows, and screwed into a PLA-printed housing, as its tougher nature could offer better protection for the components. The housing was comprised of an upper piece and a lower piece which held the electronic components. Both parts were assembled together with M4 screws and inserts housed in the printed pieces. A detailed diagram of this prototype can be seen in Figure 12. A weight was used at the bottom of the collar to counteract the weight of the device to keep it in place on the neck of the cow.

When this device was mounted onto the cow for testing, the cow was notably agitated. It was hypothesised this was due to the white colour of the device being visible in the cow's peripheral vision thus causing distress. The weight of the collar and the feeling of having an object around the neck may have also been factors in causing the cow's distress. The weight hanging at the bottom of the collar was also insufficient to counteract the weight of the sensor, so it slipped on the cow's neck rather than being fixed.

To overcome the issues highlighted in the first device testing, it was decided that a hanging bell design would be the better collar attachment mechanism. The bell being largely out of sight from the cows peripheral vision meant the cow would be less disturbed by the device's presence and gravity would stabilise the device rather than moving it from its intended fixed position. It was also thought that the angle of the camera to the ground would be reduced by the hanging bell as the lens should be directly above the ground. The final hanging bell prototype used on the cows can be seen in Figure 11.

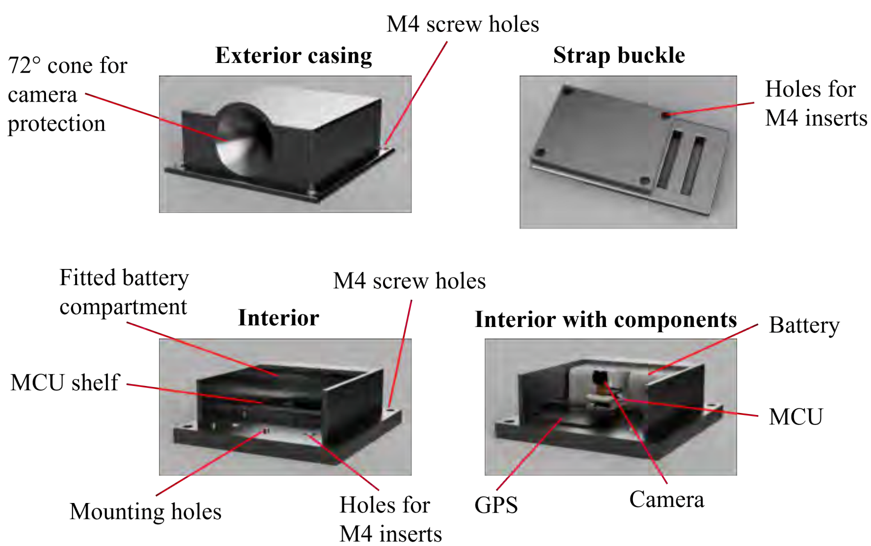


Figure 12: Labelled CAD design of side-of-the-neck prototype. The device was printed in PLA with 1mm acrylic pressure formed over the exterior casing.

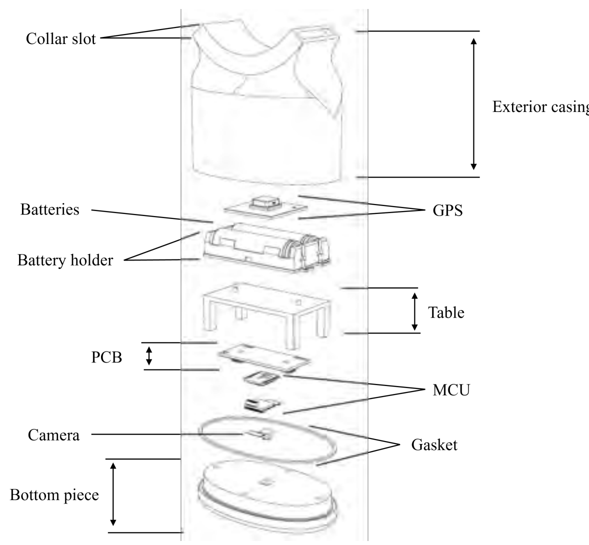
6.2.4 Final Design Specifications

The specifications of the final device design were as follows:

- SLS-printed nylon exterior casing with integrated attachment onto the collar by a custom-sized slotted opening at the top of the device. The slotted opening is curved to conform to the shape of the cow's neck and is isolated from the electronic components by nylon, a more durable material, so the electronics are not susceptible to water damage from this opening. The slotted opening was made to be wider than the exterior casing itself to reduce how much the device could swing on the collar by increasing the contact area of slot with the collar.

- FDM-printed PLA bottom piece with a protective 72° funnel around the hole extruded for the camera to sit in. 72° was chosen to allow the full range of the camera lens whilst offer the maximum possible protection from splashes of mud or dirt. A piece of 1.5 mm laser-cut acrylic was placed at the apex of the funnel as a lens cap and was glued into place using resin.
- M4 inserts and M4 screws were used to join both parts of the exterior casing together. A laser-cut rubber gasket was placed between the exterior and bottom pieces when screwed together to increase water resistance. The main exterior casing also houses a table to stow the PCB and other components easily inside whilst allowing full access to all of them during the process of device assembly.

(a) Photograph.



(b) Exploded schematic.

Figure 13: Images of device used in last Devon field test.

6.3 Electronics

6.3.1 High-Level Overview

We designed a standalone device that captures images every 5 minutes, saves them to a microSD card and records the current location and time in an accompanying comma-separated values (CSV) file. Component selection, outlined below, was driven by the need to balance performance and power efficiency.

Microcontroller (MCU) and SD Card Module

We first selected the microcontroller board, as its characteristics, including its performance, memory capacity and number of general-purpose input/output (GPIO) pins, heavily influence our other component selections. The Seeed Studio XIAO ESP32S3 Sense development board was selected as the basis of the device. It has a small form factor, a wide array of software libraries, low current consumption of 14 μA during its deep-sleep power mode [35] and an expansion board that provides an SD card reader and a flexible printed circuit (FPC) connector for a camera. Each component was connected to the ESP32 using I^2C protocol.

Camera

The OmniVision OV5640 camera has sufficient resolution (5MP), built-in image signal processor (ISP), excellent dynamic range (68dB) and internal autofocus engine (which mitigates focusing errors from cattle movement) [36]. This camera is available with a range of focal lengths, each offering a different field of view (FOV), including 72°, 120° and 160 °. The 72° lens provides a balance between area photographed and number of pixels per feature. The OV5640 is highly compatible with the ESP32S3 architecture and affordable enough for mass production.

GPS Module

Several GPS chips, including the Quectel L80, Zhongke AT6558 and u-blox SAM-M8Q, were compared. The u-blox SAM-M10Q was selected for its accuracy (1.5 metres), short acquisition time (1 second from a 'hot start') and low standby current consumption (32μA in hardware backup mode) [37].

The GPS module can capture longitude, latitude and altitude (above mean sea level) to accurately geolocate DAISY using the widespread NMEA-GGA message specification. The SAM-M10Q also acquires the current time and date, which is used to drive any time of day logic and is recorded along with position data. Finally, the position dilution of precision (PDOP) is used to determine when the GPS has acquired sufficient number of satellites for an accurate location.

The GPS module's acquisition time increases to 23 seconds when locating satellites from a 'cold start' (when the device's last known position and almanac/ephemeris readings are unknown) [37]. Therefore, the SAM-M10Q's V_BCKP pin was pulled high at all times to avoid an excessive time to first fix (TTFF) between samples.

Power Switch

A tilt sensor was incorporated to ensure the device is only powered on when it is in its normal orientation, hanging vertically downwards from a cow's neck. When not mounted, the device can be kept powered off by keeping it inverted. This avoids the need for an external power switch and maintains the integrity of the case against the ingress of water and dust.

Batteries

The device is powered by two 18650 Li-Ion cells. These cells were chosen rather than powering the device via the USB interface. Powering via USB is less efficient due to the requirement to boost the battery voltage to the USB standard of 5V and then drop it again in the voltage regulator of the development board. 18650 cells are easy to remove and charge, and are safer and more robust than the alternative Li-Poly batteries.

6.3.2 Initial Power Consumption Tests

The XIAO development board with the SD Module and camera was connected to a SAM-M10Q development board and power consumption was monitored using various sketches to activate the core functions, including GPS location, taking and storing a photo and deep sleep shown in Fig. 14.

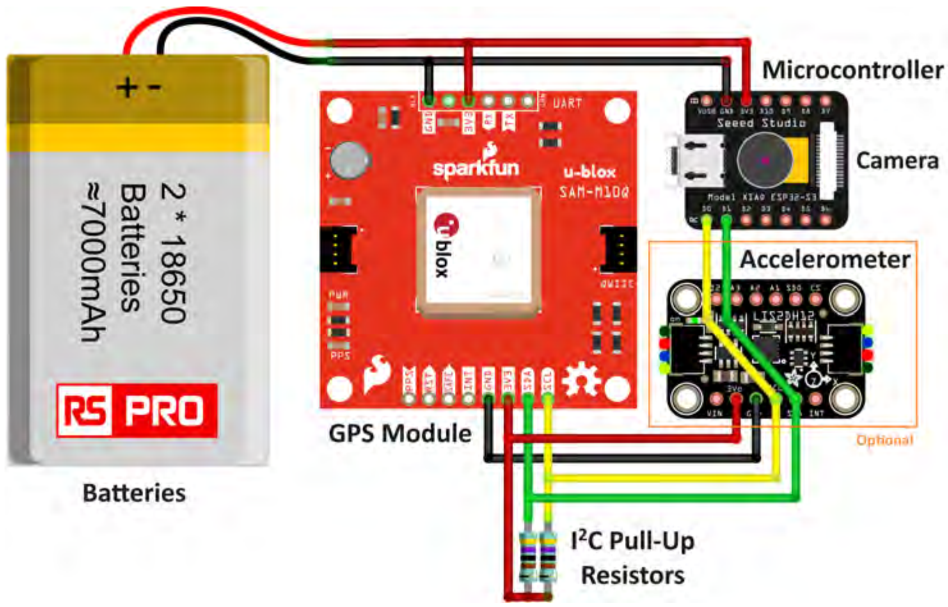


Figure 14: Fritzing diagram of the initial prototype.

These early tests revealed several challenges to battery life. The XIAO expansion board does not provide access to the power down (PWDN) pin nor the autofocus power pin on the OV5640 camera. The PWDN pin is shorted to ground, as shown in Figure 15, and the autofocus pin is permanently connected to the supply voltage. Therefore, the camera could not be turned off and constantly drew as much as 100mA, drastically reducing our device's battery life.

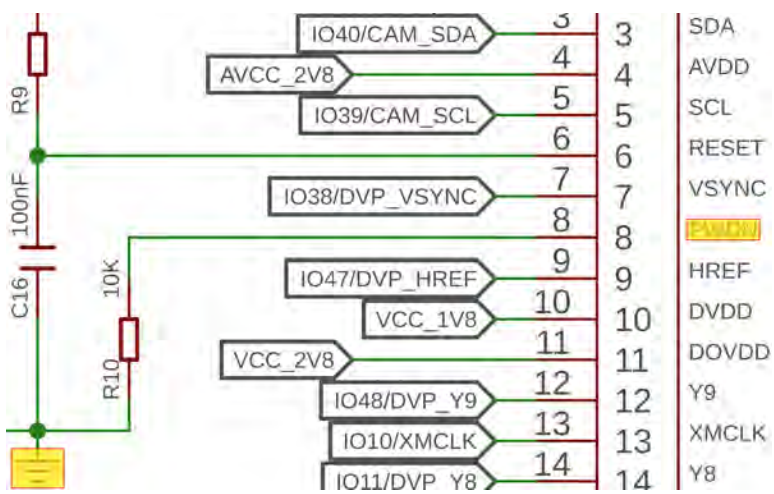


Figure 15: Partial schematic of the XIAO ESP32S3 Sense's expansion board, showing how the OV5640's PWDN pin is shorted to ground (from [38]).

Secondly, the GPS consumes a total of 9mA in power save mode, necessitating a need to be able to remove power from this board during deep sleep, by switching this through a transistor controlled with logic from the MCU.

To resolve these two issues, we designed a custom printed circuit board (PCB) that connected the core components, provided access to the OV5640 PWDN pin and added power gating to the GPS module.

6.3.3 Custom PCBs

The PCBs are fabricated from flexible polyimide, allowing them to be wrapped around the battery and reduce space. Some sections of the PCBs are stiffened with a glass-reinforced epoxy substrate. To reducing the risk of solder joints breaking surface-mount devices (including capacitors, resistors and the GPS module) are mounted over these stiffened sections. To design these boards, we implemented the following three-step process in EasyEDA Pro.

Pseudo-Circuit Diagram

A pseudo-circuit diagram was created containing high-level representations of each board, as shown in Figure 56. This helped us brainstorm new ideas without having to source exact components or worry about electrical rule checking (ERC) errors. We set out the purpose of each board (including the extension cables for the camera and accelerometer) and any key connections between them (such as the OV5640's power down and autofocus pins).

Final Schematic

Secondly, we translated this into an actual schematic, as shown in Figure 57. Where possible, standard SMD parts were chosen for speed and cost of manufacture. We divided the schematic into functional blocks, such as 'pull-ups and connectors', 'battery circuit' and 'expansion boards & camera', so other team members could easily review and verify our design.

Final Layout

Before determining the final layout we physically prototyped the outline in flexible card and experimented with various orientations and shapes to optimise the placement. A key consideration in the final layout is the requirement to separate the GPS antenna from potential sources of interference and incorporating a $5cm^2$ ground plain between the antenna and the other components.

The final layout is shown in Figure 58. The flexible joints between the main board and the camera, accelerometer and power switch sections were cut after receiving the final design to leave four different parts. Figure 16 showcases the ground and power planes (in red and blue, respectively) positioned on either side of the microcontroller section, as well as two large mounting holes (in yellow).

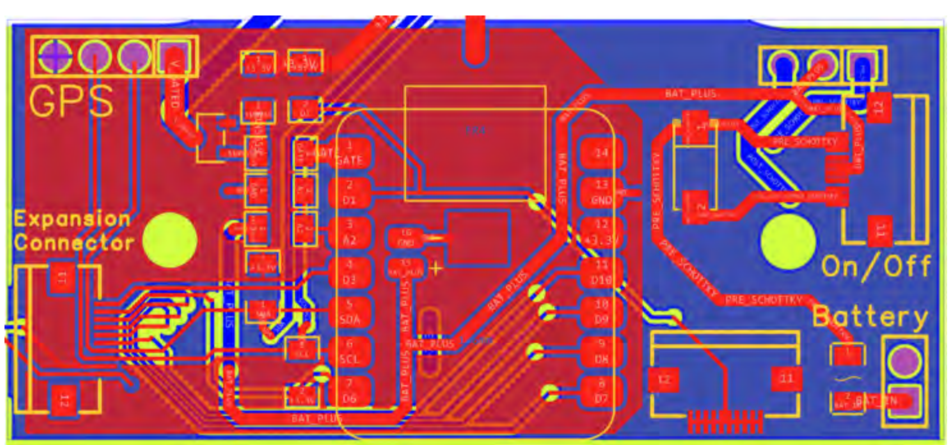


Figure 16: Partial layout of the microcontroller's accompanying PCB containing a ground plane (in red), a power plane (in blue) and two mounting holes.

6.3.4 Flexible PCBs - Notable Features

Bespoke OV5640 Connector An FPC was designed for the OV5640 camera to expose the camera power pins, allowing us to turn off the OV5640 between samples. We routed this pin to the D1 net of the microcontroller, allowing us to turn off the OV5640 between samples using a 100kΩ pull-up resistor and turn it on again by setting D1 low through our embedded code.

GPS Power Gating A p-channel MOSFET was inserted between the 3.3V net and the VCC/VCC_IO pins of the GPS module, as shown in Figure 17. The V_BCKP pin is always connected to the 3.3V net, ensuring that the GPS module can quickly connect to any satellites from a 'hot start' after the microcontroller wakes up.

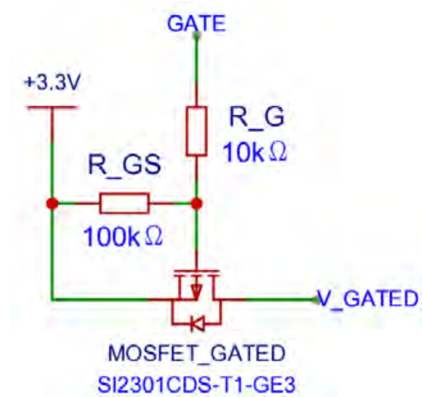


Figure 17: GPS power gating circuitry with one MOSFET and two resistors.

Protection Circuitry

We installed a 500mA fuse for over current protection (Figure 18). Decoupling capacitors were added throughout, filtering out high-frequency noise and smoothing any transient power supply variations. A larger electrolytic capacitor was added with the tilt switch to de-bounce vibration noise.

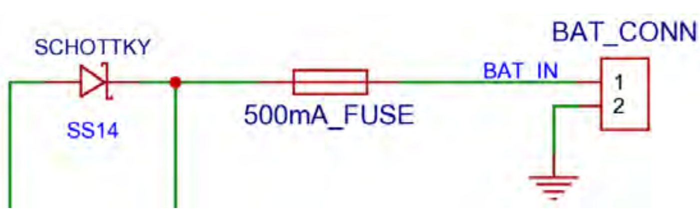


Figure 18: Schematic containing fuse for overcurrent protection.

Battery Voltage Sensing

A simple voltage divider was used to monitor the voltage across the battery. This value was recorded in the CSV file together with the date-time stamp and this provides useful insight into power consumption and battery life.

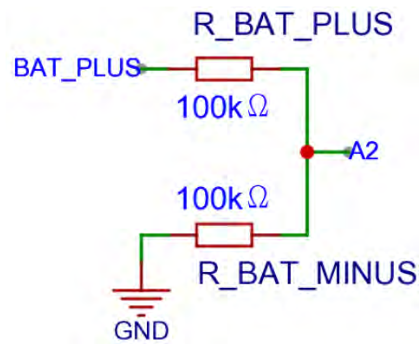


Figure 19: Battery meter circuitry with two resistors connected between pin A2 and the two battery terminals.

Figure 20 shows our complete flexible PCB.

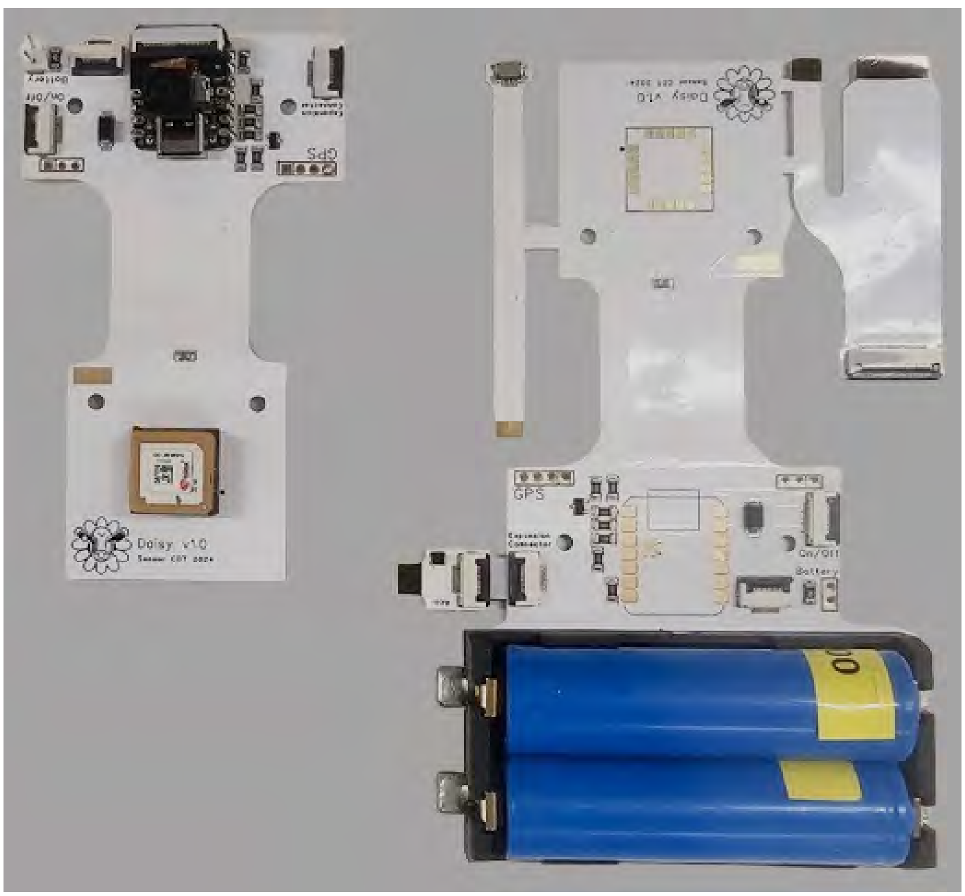


Figure 20: Flexible board and FPCs (right). Board with components (left).

Bespoke Expansion Connector

Additional boards (including the LIS2DH12 accelerometer) can be added using a 10-pin connector.

This connector provides access to all non-used GPIO pins, the I^2C pins (SDA and SCL), power and ground.

6.4 Embedded Software

An embedded software, also known as firmware, was developed to control the device. The code was generated collaboratively, using our repository on the University of Cambridge's GitLab [39]. Different iterations and versions of the code were developed, enabling hardware and image quality testing, as well as firmware logic optimisation. The final version that was uploaded to the sensors has been made public, allowing potential users to easily implement a functional code on the device, and also enabling further modifications or additions for specific user needs or future project-related work.

6.4.1 Firmware Structure

The software was developed for the micro-controller to co-ordinate the activity of the various components. An object oriented [40] approach was employed throughout the firmware. This abstraction of code into object classes offers many advantages such as: (1) simplifying complex systems into manageable modules that closely represent their real-world counterparts, (2) making data more secure through private encapsulation of variables and functions, and through controlled access to object states, (3) enhancing code maintainability by modifying an object without affecting other parts of the system, and (4) increasing the code flexibility to be adapted onto other systems by either adding, modifying or removing certain classes, easing the incorporation of other device components with minimal software modification [41].

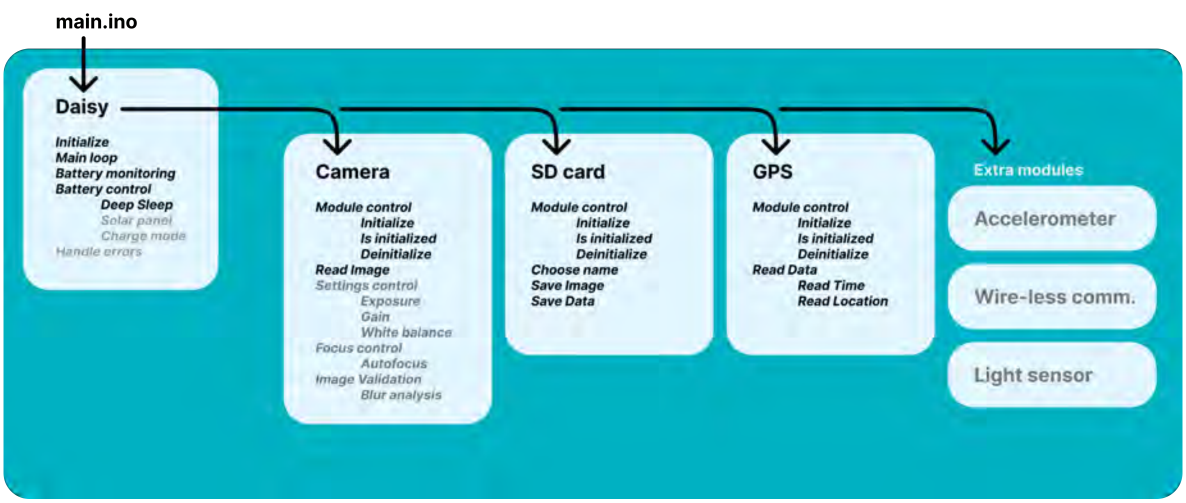


Figure 21: Schematic depicting the object-oriented structure of the developed firmware. Each encapsulated module represents a class, with the different tasks defined within, and the arrows exposing dependencies. The tasks/ modules in grey colour represent further actions/ components that could be easily integrated into the firmware of the device but were not pursued in its completion because of time limitations.

The final firmware structure is shown in Figure 21. As seen in the schematic, the developed library files are organised into classes that represent the physical components of our device, facilitating the independent management and development of each module. Each module can be programmed concurrently without inadvertently causing merge conflicts. The uploaded main.ino file only contains functions of the Daisy class, which, in turn, incorporates all other classes defined in the libraries. Since each object is an instance of its class, and there is only one instance per custom class in the firmware, Figure 21 represents both the object and class structure used. The different tasks within each object represent actions the code executes, typically by a single custom function, and are conceptually and technically linked to each corresponding component. To translate these executable tasks to real electronic commands, pre-developed libraries for each electronic component were utilized, requiring proper definition of pins and buses to ensure MCU-to-component communication.

6.4.2 Developed Functions and Firmware Logic

The developed functions, related to the tasks of Figure 21, are briefly explained below.

Working functions:

- Daisy – MonitorBattery: Obtain an ADC corrected value of the battery pin's voltage.
- Daisy – DeepSleep: The esp_deep_sleep() function of the MCU board is already embedded in the system. The function commands a change in the internal MCU energy management to a lower consumption mode. In theory, the only modules remaining active should be the ULP Coprocessor and the internal RTC. Through testing, it was discovered that the Camera and the GPS modules would remain active if not forced to do so.
- Module – ModuleControl: All three active modules (Camera, SDCard, and GPS) have module control functions that allow initialisation (setting up the pin connectivity, their configuration, the communication route such as I^2C, and the possible mode of action), deinitialisation (forcing the inactivity of the modules through pin connectivity), and assessing the state of the module (by returning Boolean outcome that represents it being active or not).
- Camera – ReadImage: The image is captured onto the camera's frame buffer, then the information is copied to a memory allocation in the MCU, and the frame buffer cleared and returned for further acquisitions.
- SDCard – ChooseName: The /images folder is created and a name for a new image is properly attributed to it. To do so, the file names of each image were decided to always be the number corresponding to the sequence of acquisition done, fore example the third picture taken is named "3". Therefore, the function reads all the files in the directory to determine the highest number and returns the following number.
- SDCard – SaveImage: The image information given by ReadImage is written in a .jpg file, with the name attributed by ChooseName, and saved within the microSD memory Card.
- SDCard – SaveData: This function contains SaveImage, and therefore, the image information is saved as explained above. Moreover, all data given from ReadBattery and ReadData, as well as the name of the image given by ChooseName are written in a .txt file (in a comma-separated value (CSV) format), and saved within the microSD memory Card.
- GPS – ReadData: The GPS information is prompted by the GPS module and saved in an internal allocation. The GPS asks for the time in ISO standards, the location (latitude, longitude and altitude above mean sea level) by trilateration, and the position dilution of precision (PDOP), which quantifies the location accuracy. As the GPS module returns an altitude of -17000 before achieving a fix, an if statement checks that none of the constituent parts of the location string matches this value (using C's strstr() function). If a fix is not achieved within 60 seconds, as determined from C's millis() function, the GPS reading is aborted.

Embedded functions:

- Daisy – Initialise: Start serial communication (if possible) and initialize MCU pins and buses.
- Daisy – MainLoop: Execute the main firmware logic. Figure 22 depicts the sequence of the tasks carried out during a cycle of data acquisition of the device, organised into the different component modules. As shown in the flowchart, the device first wakes up from the deep sleep mode and initialises all modules. Camera and SDCard initialisation present a check for an achieved initialisation build within. The Camera and GPS modules acquire the data, and the information is saved in the SDCard. In parallel, the time obtained through the GPS module is read and saved. Then deinitialisation of all modules is triggered. Finally, the device is programmed to enter deep sleep for varying durations depending on the time extracted from the GPS. During daylight hours (assumed 8 am to 8 pm), the device goes into deep sleep for 5 minutes. However, during night-time, the sleep duration increases to 30 minutes. This 30-minute interval was chosen as a safeguard against potential resets at the night. If the device were to be reset and the sleep interval was much longer, such as 12 hours, there would be a significant risk of failing to capture images during the next daylight cycle. By keeping the interval at 30 minutes, the device can periodically wake up to check the time and ensure that no crucial images are missed, even if a reset occurs overnight.

6.4.3 Firmware Iterations and Challenges

As mentioned above, many iterations and versions of the code were generated until the presented functional firmware was achieved. During this development phase, many major and minor practical aspects of coding with our system were realised, allowing us to overcome challenges and move forward with the project. Some of the more notable learning outcomes are commented on below:

- Arduino IDE settings: The ESP32-board package was to be installed and PSRAM activated for the MCU and Camera modules to work.
- GitHub repository management: Despite now being evident, the need to only upload a compiling alteration of the code, resolving conflicts, or respecting other modules was a major learning point.
- Standard coding nomenclature: The naming of functions and variables following a pre-established nomenclature was key to maintaining coherence between custom libraries. For instance, all functions and variables were decided to start in capital letters, similar functions of different modules were named the same, objects were defined as Class_, etc.
- Working mode: The execution of the deep sleep function would disconnect the board from its serial communication, and therefore, uploading of the code would not happen. The first approach to solve this consisted of rebooting the board before uploading the new version, through the manual trigger of a button on the MCU. Afterwards, a "working mode" function was generated to avoid going into deep sleep when a serial connection was active.
- Hardware connectivity: To ensure that hardware components were behaving as expected without the use of a digital multimeter, the activation or deactivation of embedded LEDs was implemented as a visual output.
- Camera PWDN pin control: One of the most important observations during the firmware development was the detection of a lack of power consumption reduction when deinitialising the camera module. This led to the understanding that the XIAO board did not have control over the power down (PWDN) pin of the camera, which had major implications for the PCB final design.

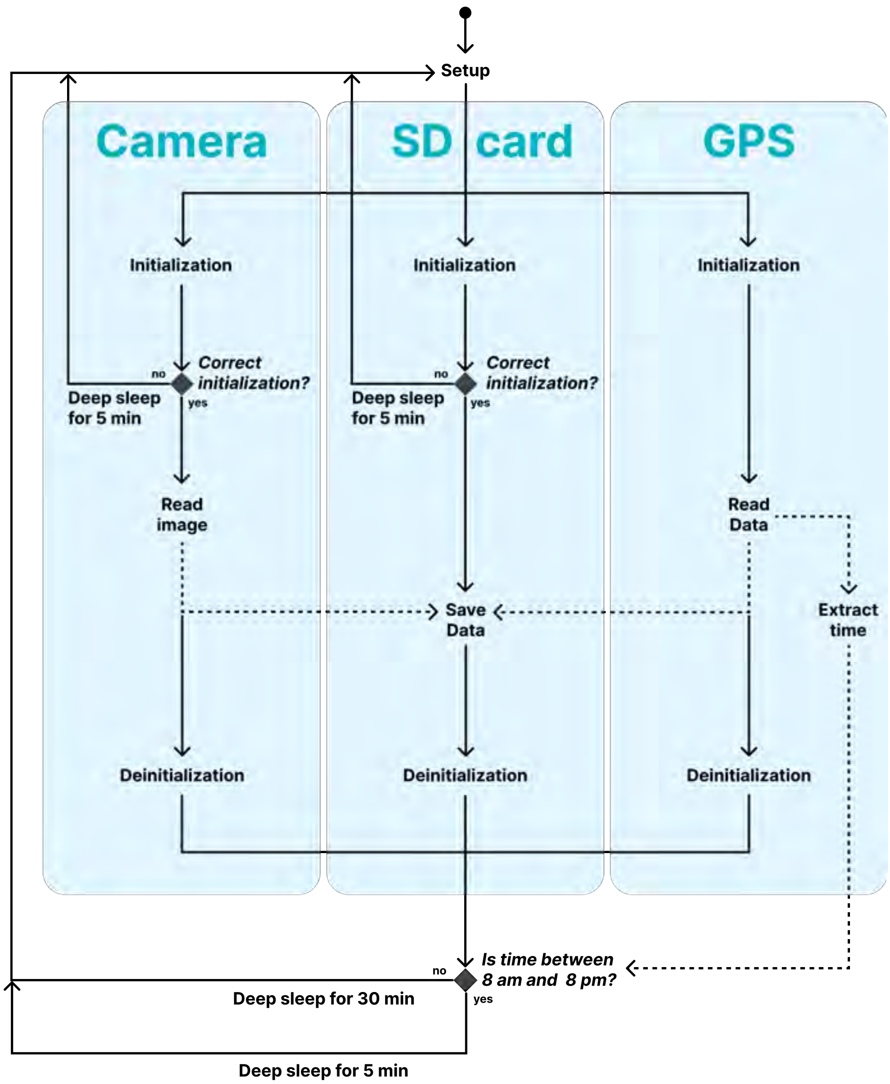


Figure 22: Schematic depicting the logic flowchart for a cycle of data acquisition. The different functions and checkpoints are distributed among the three main modules. Solid arrows represent the sequence of tasks executed, while the dashed arrows represent the flow of information required to execute a function.

6.5 Assembly and Testing

After designing the casing, electronics and uploading the embedded software, the device was assembled as seen in Figure 13. Details of the assembly can also be found in the User Manual (see Appendix B). The device was attached to the device collar through the slotted opening. The device collar had a quick-release mechanism which made it easy to then be clipped around the cow's neck. This was done when cows were in a crush to minimize their movements during attachment in case the cows reacted badly to the mounting of the collar. An example of this can be seen in Figure 23.

Testing of the device was done on- and off-cow. On-cow tests aimed to assess function of the hardware and durability of the casing in the field, whereas off-cow tests were useful to assess progress of the different components towards the MVP and inform critical decisions. The primary mode of device

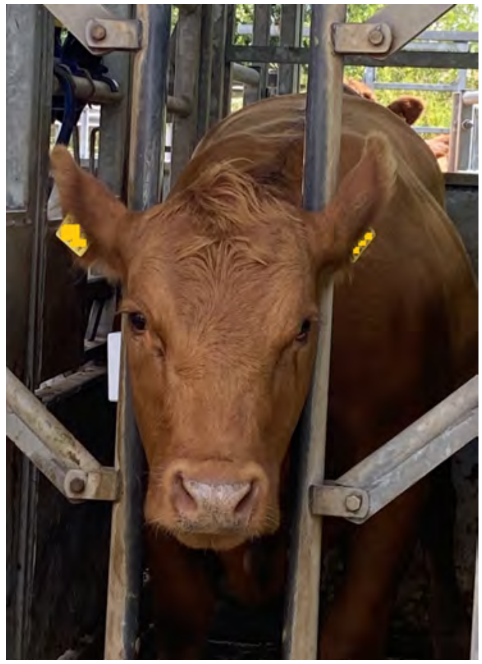


Figure 23: Cow in metal crush to hold its neck in place. Image taken at Rothamsted Research, North Wyke site during side-of-the-neck prototype testing.

testing was by mounting devices onto cows themselves. Initial testing of the PLA-printed hanging bell case robustness was done at the University Vet School. The sensor was mounted onto the cow for 24 hours and did not remain attached to the collar during this timeframe, as the casing broke at the collar slot (seen in Figure 24), prompting the selection of a more robust material like nylon for this part.

Figure 24: Result of on-cow PLA casing durability test.

As for off-cow testing, these included iterative testing of the hardware and firmware during development and water resistance testing. Indeed, the former were done consistently throughout the project to validate changes to hardware and firmware and track the output of these changes. The latter was done on the final prototype mimicking Ingress Protection (IP) rating tests, a standardized system to determine an enclosure's resistance to dust and liquids. Aiming to assess the sensor for an IP rating of 42 (IP42), the device was placed under a water spray less than 15 degrees from vertical for one hour. There was slight dampness around the gasket when opening the casing, however the electronics inside the sensor were dry after this test. An image of the case during testing is shown in Figure 25.

Figure 25: Testing environment and sensor for IP rating before (left) and after (right) one hour of water spray.

7 Science and Technology: Data

With the device providing a means of capturing images, a system for estimating the biodiversity within them and presenting the results to the user was required. The system is data-driven, thus this section includes a description of the dataset used to train and validate the models, followed by the models tested, and finally the presentation of the model predictions to the end-user.

7.1 Dataset

7.1.1 Existing Datasets

Large datasets, comprising thousands of labelled images, are essential for building accurate deep learning models for machine vision and image classification applications. This has been successfully achieved using established datasets such as ImageNet, MS COCO, and Flickr30k. However, many image classification problems cannot be effectively addressed with these general-purpose datasets. For specialised applications, datasets need to be relevant to the specific task.

In the case of classifying grassland biodiversity, such a model would need to be trained on a dataset that is representative of the real-world samples it will be used on (i.e. images of plant species found in grassland). When researching existing datasets that could be leveraged for this task, some promising publicly-available options were found (see Table 2):

Although the GrassClover dataset seemed to be the obvious starting point for the task at hand, the lack of image labels precluded efforts to train an image classifier. The PlantNet and iNaturalist datasets, on the other hand, contain thousands of labelled images of a wide range of plant species. Crucially, both contained Clover (genus *Trifolium*), which meant that existing models trained on these datasets could already distinguish the presence of this important species of grassland plant.

Dataset	Size	Description	Reference
iNaturalist 2021	2.7M (training)	Large-scale dataset of 10,000 plant and animal species	[42]
PlantNet300K	306,000	Image dataset containing 1,081 plant species	[43]
GrassClover	31,600 (unlabelled)	Dataset of high-resolution images of dense grass/clover mixtures	[44]
VegAnn	3,775	Diverse dataset of multi-crop images for segmentation tasks	[45]

Table 2: Example datasets with size, description, and references.

However, the images in PlantNet300K and iNaturalist are of a higher magnification and were taken by humans with plants or animals being the main objects that nearly fill the entire image. In contrast, the images taken by the animal-mounted sensor will be at a distance with no attention to positioning the main objects in the centre. In addition, as illustrated in §5.1, identifying dung and bare soil patches is also valuable for pasture management. Thus, we chose to collect and create a custom dataset.

7.1.2 Data Gathering

The image collection was conducted in Dairy Corner at the North Wyke Farm. The objective was to manually collect images that closely resemble the images that will be collected by the device when mounted on cattle. Thus, images were all taken at a 90-degree angle from the ground with a camera-to-ground distance approximately waist high. This distance is similar to the height of the device when mounted on cattle. No strict height was given during the image collection so that the ML model trained could adapt to different heights of cattle. Images were acquired using phones, cameras of various makes, and a prototype device with a specific camera model that was used in the final device. Grass is the dominant object in the Dairy Corner. Thus, to prevent grass from being over-represented in the dataset, the images were acquired with the intention to include clover, dung, or bare soil patches (i.e. not randomly sampled). In the end, 1048 images were collected.

7.1.3 Initial Image Preprocessing

Modern image processing models, such as Convolutional Neural Networks (CNNs), process input images with sizes of at least 224x224 pixels. Therefore, to ensure our dataset is compatible with all these models, we split each image into a smaller grid of 224x224 pixel fragments, as shown in Figure 26. These fragments overlap by 60 pixels to ensure features such as clovers do not potentially get cut off at image boundaries, since the nearest neighbouring fragment will contain the whole feature in its overlapping region. This method ensures minimal feature loss from the fragmentation approach.

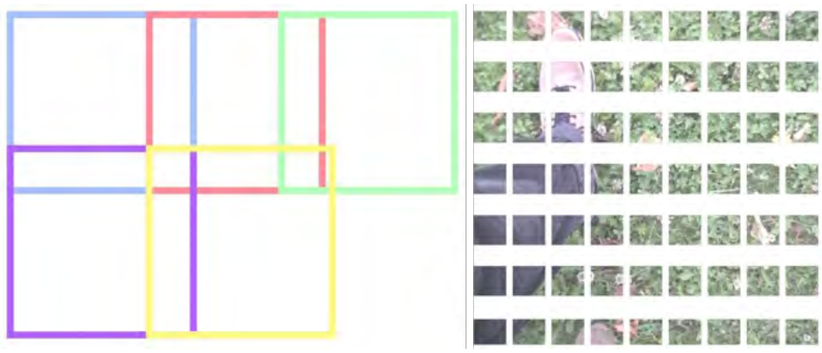


Figure 26: Right: a fragmented image[1]. Left: an illustration of overlapping fragments.

To ensure the fragments cover reasonable portions of the images (224x224 pixels in a 4k image is a much smaller portion than in a 1080p image), we downsample the images to a consistent pixel density before fragmenting them. This ensures that we generate a similar number of fragments per image. As the device camera has a resolution of 2048x1536 pixels, we select this as our target down-sampling resolution. Thus, for an input image with size WxH pixels, we calculate the scale factor $S = \sqrt{(W * H)/(2048 * 1536)}$ and downsample the image to a new resolution of WSxHS pixels using the `Image.resize` function in the Python Imaging Library.

After the initial image processing on our dataset, it consisted of 36,738 fragments.

7.1.4 Labelling

To train our model and validate it, we require a labelled dataset specifying the expected prediction for each fragment. As determined in §5.1, the most crucial metrics for biodiversity are the presence or absence of grass, clover, bare soil or dung. Thus, we labelled our fragments with a binary yes/no result for these elements. Since the dataset contained fragments with noise from the data collection procedure (such as the data gatherers' shoes, trousers or hands), the 'artefact' label was reserved for such noisy fragments so they could later be discarded.

To label the images, we initially considered using the popular web-based tool Roboflow[2]. However, since a large number of fragments was to be labelled and their pricing scales with the number of images labelled, it was too expensive. Thus, we used Label Studio[3]: a popular affordable, open-source data labelling platform.

While Label Studio suited our needs, it is only available as a web server for local deployment. Since we intended to crowd-source labelling by splitting tasks across all members in the project, we required a shared instance. To achieve this, we hosted a Label Studio instance on the cloud in an Amazon Web Services (AWS) Elastic Compute Cloud (EC2) virtual machine, with the fragments loaded directly onto the machine. Furthermore, since Label Studio by default uses an on-disk SQLite database which crashes with multiple users or complex queries, we hosted a robust PostgreSQL database on an AWS Relational Database Service (RDS) instance. This configuration enabled members of the project to visit a web link (`https://tinyurl.com/sensor-cdt-labelling` at the time) and collaboratively use Label Studio conveniently within their web browser.

[1] `https://stackoverflow.com/questions/59350701/splitting-very-large-images-into-overlapping-boxes-blocks-tiles-sections-python`

[2] `https://roboflow.com`

[3] `https://labelstud.io`

Group members labelled fragments via the interface shown in Figure 27. After training an initial model on a subset of the labelled fragments, we integrated this model into the labelling procedure to provide predicted labels and confidences (a.k.a. 'prediction scores') for the fragments, as shown in Figure 27. Then, we sorted the images by their confidence to prioritise low confidence images, focusing our labelling efforts on the most insightful fragments. Furthermore, since most of the fragments contained grass (since the original images were mostly grass with clover, dung and soil sparsely scattered inside), the predicted labels were used to focus on fragments containing under-labelled species, improving the balance of our dataset. This was achieved by creating separate tabs for each predicted label, as shown in Figure 27.

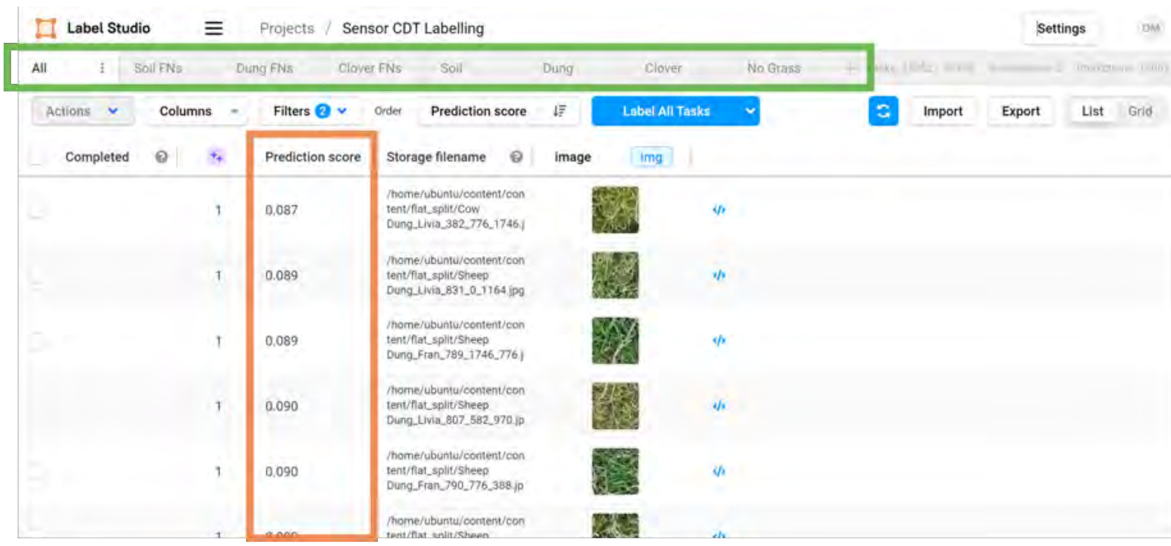


Figure 27: Label Studio web interface. Orange box: predicted confidences. Green box: per-class tabs.

With our labelling workflow in-place, we periodically exported the labels from Label Studio as a CSV, forming the uncleaned versions of our datasets. To clean them, we subsequently removed duplicates, discarded artefact fragments, and balanced them, as detailed in §7.1.5. Ultimately, the group labelled 21,676 out of 36,738 fragments in total. Table 3 shows a final ranking of the number of fragments labelled per person in the project.

Rank	First Name	# Fragments Labelled	Data Team? (Y/N)
1	Jiayi (Maxwell)	7137	Y
1	Raluca	3060	N
2	Gratsiela	2757	N
3	Stephen	2314	N
4	Leon	1976	N
5	Oriol	1124	N
6	Francisco	1056	N
7	Omar	1043	Y
8	Livia	1010	N
9	Abbie	689	N
10	Francesco	415	Y

Table 3: Number of fragments labelled per person in the group project. We rank Jiayi and Raluca both first as non data-team labelling efforts were voluntary.

7.1.5 Balancing

A balanced dataset, which includes a comparable amount of data associated with each class, is critical for ML model performance. Over-represented classes in the training dataset can lead to models becoming biased toward those classes. Over-represented classes in the validation dataset can lead to over-estimation of model accuracy. In single-label classification, without collecting more data, this can be solved by upsampling (through image cloning or augmentation) or downsampling (through removing images) appropriate classes to achieve an even distribution. However, multi-label classification (MLC) was used in this project. In comparison to single-label classification, images in MLC can be associated with over- and under-represented classes simultaneously. Thus, it is challenging to decide which images need to be upsampled or downsampled in an MLC dataset [46].

As shown in Table 4, the dataset is imbalanced with grass being the most over-represented class. Thus, the label combinations were split into minority, clover majority, soil majority, dung majority, and grass majority, as indicated. Balancing by downsampling would result in significant data loss for the majority groups, therefore upsampling was employed as the minority groups had a small count. To generate images for up-scaling, the image augmentation methods of applying rotation, mirror, brightness changes, motion blur, and Gaussian noise were used. The parameters of each augmentation were randomly selected, without replacement, from a discrete list that had been qualitatively determined. The criterion for these parameters was that the resulting image should, at the same time, look significantly different from the original image and from images that had applied the same augmentation method but with different parameters (Appendix E.1). The parameter list for all augmentation methods allowed 17 different augmented images to be generated from the same original image.

To generate a more balanced dataset, different amounts of augmentation were applied based on their label frequency. The balancing approach was to up-scale the components equally in the minority group first, then up-scale the components in the majority group to an appropriate amount to achieve an even distribution of each label in total. In the end, the grass majority would be down-scaled. Different up-scaling factors for the minority and majority groups were experimented with. SCUMBLE (Score of ConcUrrence among iMBalanced LabEls) and MeanIR were used to assess the improvement in the balance of the dataset [47].

As shown in Table 5, the balance method 1 shows the largest reduction in SCUMBLE and MeanIR, indicating that this method generated the most balanced dataset. This is confirmed by manual inspection of the label distribution (Figure 28). Then, augmented image fragments were generated based

Label Combinations	**Count**	**Scaling Group**
Clover, Grass, Dung, Soil	4	Minority
Clover, Soil	4	Minority
Dung, Soil	25	Minority
Clover, Grass, Dung	64	Minority
Dung	64	Minority
Clover, Grass, Soil	80	Minority
Grass, Dung, Soil	100	Minority
Clover	253	Clover Majority
Soil	883	Soil Majority
Grass, Soil	1767	Soil Majority
Grass, Dung	1936	Dung Majority
Clover, Grass	3354	Clover Majority
Grass	11596	Grass Majority
Dung (Total)	2193	NA
Soil (Total)	2863	NA
Clover (Total)	3759	NA
Grass (Total)	18901	NA

Table 4: Label distribution before balancing. The total count is the sum of all fragments containing the label, irrespective of whether another label is also presented.

	Balance Method 1	**Balance Method 2**	**Balance Method 3**
Minority SF	17.000	17.000	10.000
Clover Majority SF	0.000	1.061	0.000
Soil Majority SF	0.000	1.029	1.108
Dung Majority SF	0.000	0.000	1.267
Grass Majority SF	0.011	0.011	0.011
MeanIR	1.617	1.627	1.777
MeanIR Diff.	-3.696	-3.686	-3.536
SCRUMBLE	0.032	0.033	0.046
SCRUMBLE Diff.	-0.080	-0.079	-0.066

Table 5: Different balancing methods and their impact on MeanIR and SCRUMBLE score. The grouping is as indicated in Table 4. SF: scaling factor. Original Count $\times$ SF = After Balancing Count. A non-integer scaling factor means that a randomly selected subset of fragments was augmented one time more than the others. MeanIR Diff and SCRUMBLE Diff are the differences between the dataset after balancing and before balancing.

on the scale factors of balance method 1 (Table 5) and merged with the original dataset. This final balanced dataset, referred to as the *large dataset*, was then used for ML model training and validation.

In addition to the large dataset, we compiled a smaller dataset containing 2891 fragments for early experimentation. Table 6 lists the per-class counts for the fragments in the dataset, referred to as the *small dataset*.

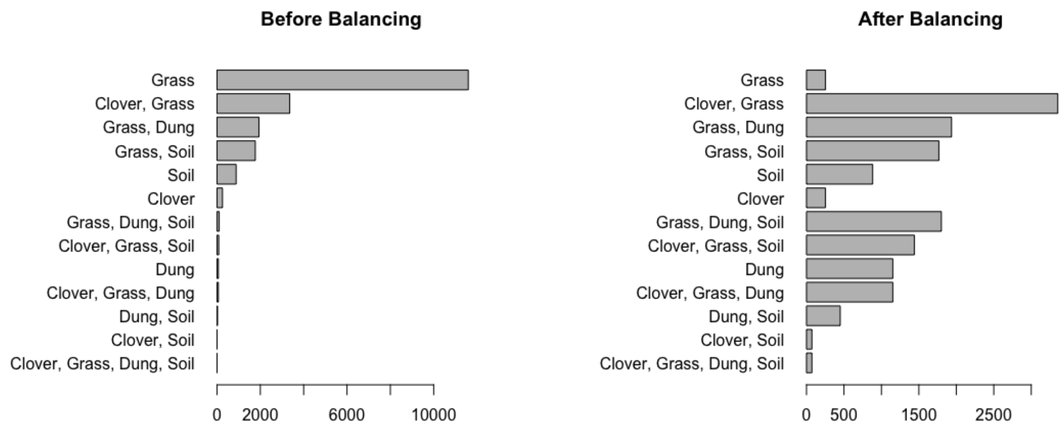


Figure 28: The distribution of label combination before and after balancing using balancing method 1. The x-axis is the number of fragments of each label combination.

Class	**# Fragments**
Grass	2122
Clover	1004
Soil	1007
Dung	1004

Table 6: Number of fragments per class in the small dataset.

The small and large dataset were split into a training and validation subset, with an 80% of the data for training and the remaining 20% for validation. This allowed us to validate our models on datasets separate from the ones they were trained on, preventing 'data leakage' whereby the model achieves unrealistically high accuracy by testing it on the data it was trained on. For the small dataset, this was achieved by sampling an 80/20 split for each individual class after balancing. For the large dataset we split the fragments in each 80/20 split before balancing, and then balanced the training and validation subsets separately, with the same upsampling factors to preserve the split ratio.

7.2 Machine Learning Model

7.2.1 Literature Review

Deep learning, a subset of ML, involves the use of multi-layer neural networks, inspired by biological neural networks in the brain, to automatically learn complex patterns from raw data. CNNs are a type of deep learning architecture particularly effective at analysing images. They are composed of layers of convolutions (see Figure 29), where the network applies small filters (kernels) across the image to detect patterns such as shapes and edges. In agriculture, CNNs have been used to automate a wide range of tasks by processing and analysing various types of images derived from ground-based or aerial sensors [48]. These networks automatically learn to identify and distinguish features relevant to agricultural applications, such as crop health monitoring, pest detection, and yield prediction from raw image data. Thus, CNNs can assist in decision-making processes, enabling more efficient and precise management of agricultural resources.

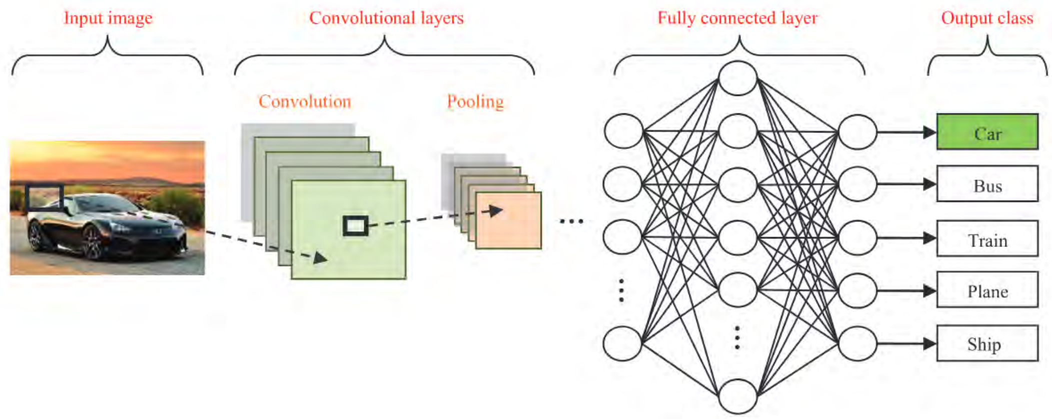


Figure 29: Image classification using CNNs. From [49].

Given that CNNs are a well-established deep learning framework for image classification, a variety of different CNN approaches and architectures were explored to investigate whether they could be adapted to the task of classifying grassland biodiversity.

As outlined in [50], CNNs can be leveraged for three broad types of image analysis:

1. Image classification: Assigns the entire image to a predefined class based on its content.
2. Object detection: Identifies and localises specific objects within an image, usually by drawing bounding boxes around them.
3. Image segmentation: Divides an image into regions (segments), labelling each pixel according to the class it belongs to.

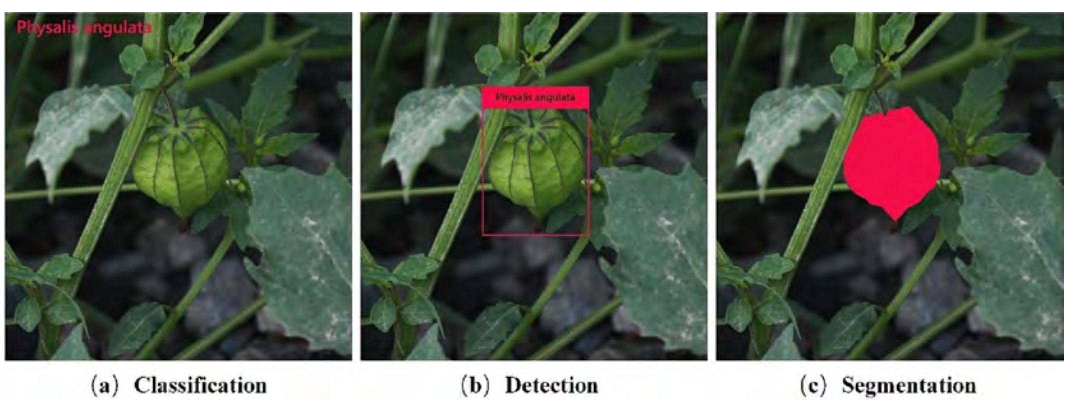


Figure 30: Visualisation of different types of image analysis. Taken from [50].

Due to difficulty gathering training data for detection and segmentation, focus was placed on image classification for this project. A CNN can be employed for classification tasks by using the network to learn increasingly abstract features as visual data passes through successive layers, allowing it to differentiate between different types of image. This typically involves the use of a fully connected layer at the end of the network to combine features and output a probability distribution over a set of predefined classes (see Figure 29); the image is assigned to the class with the highest probability via a Softmax function. Alternatively, a Sigmoid activation function can be used in the final layer to output independent probabilities between 0 and 1 for each class, facilitating multi-label classification.

Simple CNN architectures have been successfully applied for tasks such as classifying images of hand-written digits, as presented in a review by O'Shea and Nash [51] in 2015 and shown in Figure 31. Later, larger CNNs were developed by the computer vision community and trained on the ImageNet database: a diverse collection of random images from the internet. Many of these CNNs have successfully been applied for agricultural tasks [52], with the state-of-the-art (SOTA) listed in Figure 32. Now, specialised CNNs such as DeepVerge [53] are being developed to count road-side biodiversity, as shown in Figure 33.

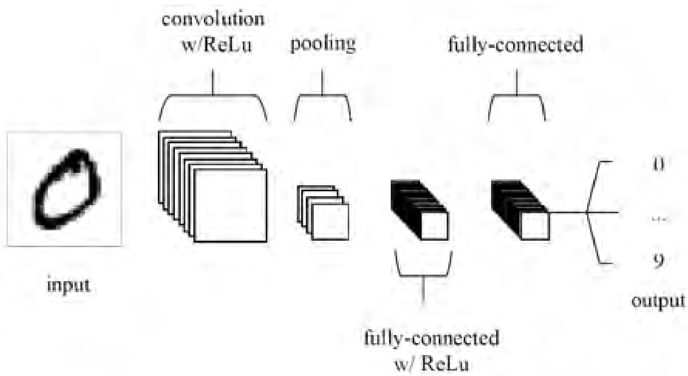


Figure 31: Simple CNN by O'Shea and Nash [51].

Architecture	# parameters	Description	Example
InceptionV3 (Szegedy et al., 2016)	24 million	42 layers that are built on the inception module	• https://github.com/josemenber/image-based-crop-anomaly-detection • https://github.com/angshumanroy77/cropdiseaseclassification
AlexNet (Krizhevsky et al., 2017)	62.3 million	5 convoluional and 3 pooling layers with ReLU activation followed by fully connected layers	• https://github.com/Dharmendra444/Crop-Desease-Classification-Using-Alexnet • https://github.com/Prajwal10031999/Plant-Diseases-Classification-using-AlexNet
VGG16 (Simonyan & Zisserman, 2014)	138 million	A deep 16-layer model with stacked convolutional layers and pooling layers that feed 3 dense layers	• https://github.com/anirudhjak06/Crop-Disease-Detection • https://github.com/LeadingIndiaAI/Weed-Detection-in-Dense-Culture-using-Deep-Learning-
ResNet50 (He et al., 2016)	25 million	Uses residual blocks to solve the vanishing gradient problem	• https://github.com/josemenber/image-based-crop-anomaly-detection • https://github.com/shreyas-muralidhara/Leaf-Wilting-Classification-Transfer-Learning
DenseNet121 (G. Huang et al., 2017)	7.6 million	121 layers where all layers are connected to each other	• https://www.kaggle.com/code/marquis03/densenet-121-plants-classification
Unet (Ronneberger et al., 2015)	30.1 million	Encoder-decoder model that use skip connection to prevent resolution loss	• https://www.kaggle.com/code/atharvakadeth/farm-plot-detection-unet

Figure 32: SOTA CNNs for agriculture by El Sakka et al. [52].

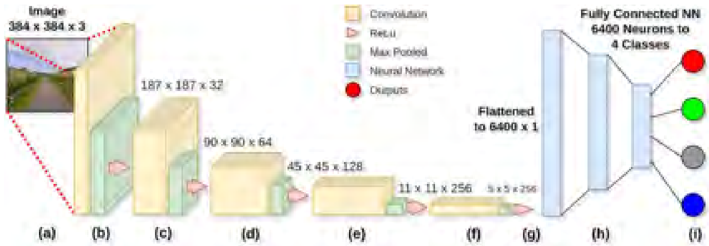


Figure 33: DeepVerge CNN by Perrett et al. [53].

In this project, simple models were trained from scratch, and pre-trained SOTA models were fine-tuned using transfer learning. This technique enables the use of a network that has already been trained on a large dataset, which can then be fine-tuned for a specific classification task. This approach is especially beneficial when training data is limited, as it considerably reduces the time and computational resources needed to train a CNN from scratch. By modifying the output layer to match the number of classes in the dataset, the network can be retrained to effectively classify images within the smaller dataset. When training or fine-tuning the neural networks, numerical optimisers such as Adam aim to minimise the loss function by approximating its derivative. The loss function is an aggregation of the residual errors between the expected and actual predictions; Binary Cross Entropy is commonly used for multi-label classification, as shown in Equation 1.

$$\mathcal{L} = -\frac{1}{N} \sum_{i=1}^{N} \sum_{c=1}^{C} y_{ic} \log(\hat{y}_{ic}) + (1 - y_{ic}) \log(1 - \hat{y}_{ic}) \tag{1}$$

Equation 1: The binary cross-entropy loss for multi-class classification, where N is the number of samples, C is the number of classes, y_{ic} is the true label for class c in sample i, and $\hat{y}_{ic}$ is the predicted probability for class c in sample i.

When training ML models, especially on large datasets, overfitting can cause the model to not generalise to unseen data. The model will perform well on already seen data, but poorly on unseen data. Two popular techniques to prevent this include regularisation and dropout. Regularisation adds a penalty proportional to the size of the weights into the loss function, commonly scaled by an L2 norm, as shown in Equation 2. This prevents the learned weights from being too large, ensuring they are more uniform. Dropout reduces overfitting by randomly deactivating a portion of neurons during each training iteration. This forces the network to learn more robust features, improving generalisation.

$$\mathcal{L}_{\text{total}} = \mathcal{L} + \frac{\lambda}{2} \sum_{j=1}^{M} w_j^2 \tag{2}$$

Equation 2: The total loss $\mathcal{L}_{\text{total}}$ with L2 regularisation, where $\mathcal{L}$ is the original loss (e.g., binary cross-entropy), λ is the regularisation parameter, M is the number of weights, and w_j represents the weight parameters. λ penalises large weights to prevent overfitting.

Ensembles further improve model performance by combining multiple models and 'voting' on their outputs. As shown in Figure 34, an ensemble comprises several base models followed by a voting or weighting mechanism – often another neural network – that aggregates their outputs for a final prediction. This approach leverages the strengths of each model, often leading to higher accuracy than any single model alone.

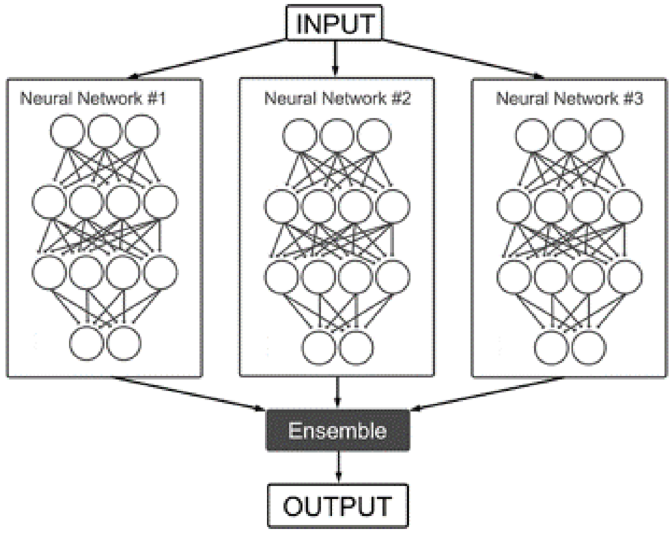


Figure 34: Ensemble model[4].

7.2.2 Implementation

After identifying the relevant model architectures and training methods, we implemented a collection of models in Python using the popular PyTorch library. The mature models and experimental pipelines were ultimately implemented in separate Python modules confirming to a common interface, improving the organisation and re-usability of our implementation.

Our implementation comprised 9 core models:

1. For each SOTA model listed in Figure 32, except UNet as it is a segmentation model, we used the existing implementations in PyTorch with weights pre-trained on the ImageNet.
2. We harnessed an open-source ResNet50 model pre-trained on the iNaturalist dataset by Horn et al. [42], using the weights from their GitHub repository[5].
3. We harnessed an open-source ResNet50 model pre-trained on the PlantNet dataset by Garcin et al. [43], using the weights from their public repository[6].
4. As baselines, we implemented from scratch in PyTorch the simplest CNN shown in Figure 31 by O'Shea and Nash [51] and the DeepVerge CNN shown in Figure 33 by Perrett et al. [53], since the simple CNN was easy to implement ourselves and DeepVerge had no public implementation.

In addition, we implemented three ensemble models with different sizes, which can be found in our open-source implementation. These ensembles take a variable number of input models, perform inference on them, and then weight their outputs with a small, medium or large fully-connected networks (perceptron). We freeze the weights of the base models to ensure only the voting perceptron is trained.

In the implementation of each model, we adjust the fully-connected output layer to have four outputs with a Sigmoid activation function, corresponding to our four outputs (P(Grass), P(Clover), P(Dung)

[4] `https://medium.com/@alexppppp/how-to-train-an-ensemble-of-convolutional-neural-networks-for-image-classification-8fc69b087d3`

[5] `https://github.com/visipedia/newt/tree/main/benchmark`

[6] `https://lab.plantnet.org/seafile/d/01ab6658dad6447c95ae`

and $P(\text{Soil})$). For each SOTA CNN, we also experimented with adding an additional small perceptron to the end of the model. This contained two hidden layers with 512 and 256 neurons respectively, followed by the output layer with 4 neurons, with ReLU activations between the hidden layers and Sigmoid in the output layer. When fine-tuning these SOTA CNNs, we froze the early layers' weights and unfroze the later layers' weights since we wanted to fine-tune the decision-making layers while keeping the feature-extraction intact.

To evaluate the performance of our models, we measured their overall Keras Binary Accuracy[7] and TorchMetrics Multi-Label F1 Score[8] on the validation dataset, as well as their per-species accuracies and confusion matrices.

To train and validate our models, we initially utilised Google Colab's GPUs, however this was not scalable as only one model could be trained at once. Since the models had a variety of hyperparameters to vary (the learning rate, regularisation amount (λ) and dropout probability), as well as different architectures (different combinations of layers to fine-tune, whether the model has an extra perceptron, and the size and number of base models for ensembles), we required a means of training models more efficiently.

To expedite training, we used Cambridge's High Performance Computer (HPC)[9] since it is free for moderate usage for researchers at the University of Cambridge and enables parallel model training. To do so, we implemented SLURM batch scripts for our training and validation jobs, and submitted different array jobs for different models via the `sbatch` command. SLURM, the HPC workload manager [54], then distributed the execution of the jobs across multiple machines in parallel, enabling us to train up to 64 models simultaneously. Our models were trained and validated on the Intel Xeon processors within the Cascade Lake partition of the CDS3 cluster, and the NVIDIA A100-SXM-80GB GPUs within the Wikes3 partition of CDS3.

Finally, to prevent overfitting, we implemented L2 regularisation via the `weight_decay` parameter of the Adam optimiser[10] and dropout by adding PyTorch dropout layers[11]. We chose to only apply dropout to only the later fully-connected layers of our CNNs since this is the common practice introduced by Srivastava *et al.* [55]. We also stopped training early if enough epochs/iterations passed without an improvement in the validation F1 score ('patience'), and output only the weights from the iteration with the highest validation F1 score. Figure 35 shows an example training curve from one of our experiments.

[7] `https://www.tensorflow.org/api_docs/python/tf/keras/metrics/BinaryAccuracy`
[8] `torchmetrics.classification import MultilabelF1Score`
[9] `https://www.hpc.cam.ac.uk/high-performance-computing`
[10] `https://pytorch.org/docs/stable/generated/torch.optim.Adam.html`
[11] `https://pytorch.org/docs/stable/generated/torch.nn.Dropout.html`

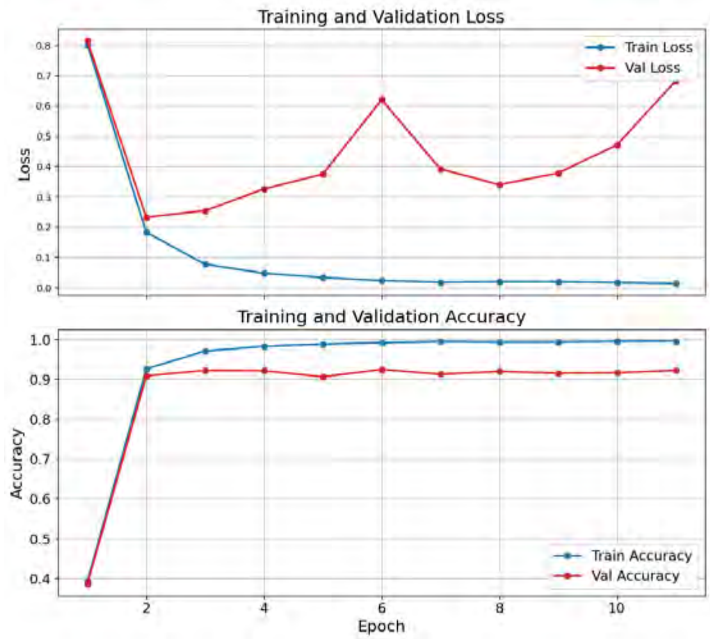


Figure 35: Example training curve, showing the loss and accuracy over epochs.

7.2.3 Results

To obtain the best model, we trained 916 models, split into three main experiments. In what follows, we refer to the ResNet50 pre-trained on the iNaturalist dataset as the 'iNaturalist' model. Similarly, the 'PlantNet' is the ResNet50 pre-trained on the Pl@ntNet-300K dataset. 'SimpleCNN' and 'DeepVerge' are the baseline CNNs described in §7.2.2.

We trained our individual models on the HPC CPUs, but required its GPUs for the ensembles. When interpreting our results, we refer to the 'best' models as those with the highest F1 score.

Experiment 1: Small Dataset Fine-Tuning

The purpose of this experiment was to narrow the set of parameters for our SOTA models for future experiments. We fine-tuned the following model architectures: DenseNet121, iNaturalist, PlantNet, ResNet50, InceptionV3, VGG16, AlexNet.

For each model architecture, we varied the learning rate, whether the model has an additional perceptron, and the number of outer layers fine-tuned. Appendix E.2.1 provides the full parameter listing. In total, we trained 520 models.

Appendix E.2.1 also lists the performance of each model, and Table 7 shows the performance and parameters of the best model for each architecture. We use the model parameters in Table 7 in our subsequent experiments.

Model Name	Accuracy	F1 Score	Learning Rate	Perceptron? (Y/N)	# Layers Fine-Tune
iNaturalist	95.0%	94.6%	0.0001	N	5
DenseNet121	95.1%	94.5%	0.0001	Y	7
PlantNet	94.2%	93.3%	0.0001	N	3
InceptionV3	94.1%	93.1%	0.0001	Y	10
VGG16	93.8%	93.1%	0.0001	Y	6
ResNet50	94.0%	93.1%	0.0001	Y	3
AlexNet	92.9%	91.7%	0.0001	Y	7

Table 7: Best individual model for each architecture on the small dataset.

Experiment 2: Large Dataset Individual Models

The purpose of this experiment was to identify the best performing individual models on our final large dataset. We fine-tuned the same models as in Experiment 1, however using the best parameters found for each model in Experiment 1. Furthermore, we trained the SimpleCNN and DeepVerge models from scratch.

For each model, we varied the parameters related to overfitting: the dropout probability and the regularisation weight decay. We also varied the learning rate within a good range identified from Experiment 1. Appendix E.2.2 provides the full parameter listing. In total we trained 296 models.

Appendix E.2.2 also lists the performance of each model, and Table 8 shows the performance and parameters of the best model for each architecture. From these results, we conclude that iNaturalist and DenseNet121 are our highest performing models, with overall accuracies of $\sim 92\%$. While iNaturalist's F1 score is marginally larger than DenseNet121's, DenseNet121's overall accuracy is marginally larger than iNaturalist, so they are both the highest performing depending on the metric used. This is surprising, because DenseNet121 was only pre-trained on ImageNet, as compared to iNaturalist which was pre-trained on a comprehensive dataset of plants. This leads us to hypothesise that further training DenseNet121 on the iNaturalist dataset is a promising direction for further improvements. Note that the accuracy goes down on the large from the small dataset as it is $\sim$ 6x larger and contains more diverse and harder-to-label images, facilitated by targeting low confidence images in labelling.

Model Name	Accuracy	F1 Score	Learning Rate	Dropout Probability	Regularisation Weight Decay
iNaturalist	92.2%	92.2%	0.0001	0.1	1e-05
DenseNet121	92.3%	92.1%	0.0001	0.3	1e-05
ResNet50	91.8%	91.5%	0.0001	0.3	
PlantNet	91.8%	91.3%	0.0001	0.3	
InceptionV3	91.2%	91.2%	0.0001	0.3	0.01
AlexNet	91.2%	91.0%	0.0001		0.0015
VGG16	90.6%	90.4%	1e-05	0.3	
DeepVerge	89.7%	89.0%	0.0001	0.5	
SimpleCNN	80.1%	79.6%	0.0001	0.1	0.01

Table 8: Best individual model for each architecture on the large dataset.

As expected, our baseline models perform the worst, with our simplest model (SimpleCNN) performing the worst with $\sim 80\%$ accuracy. We observe a significant increase in accuracy with DeepVerge ($\sim 90\%$) compared to SimpleCNN, demonstrating the need for a more complex model, however our baseline models still perform worse than our pre-trained SOTA CNNs, as expected.

In addition to the overall accuracy of the models, we analysed their per-class accuracies and confusion matrices to understand their strengths and weaknesses. Figures 36 and 37 show the overall accuracy and confusion matrix for each class for our top two models (iNaturalist and DenseNet121) respectively. We observe a high false-positive rate for grass predictions, lowering the grass accuracy to the worst out of the classes (92.8%). Despite the poor performance for grass, the other classes have much higher accuracies, with the most important class (clover) achieving up to 96.9% accuracy. Note that the overall accuracy of the models are lower than the per-class accuracies because multiple classes can be incorrectly predicted for the same fragment.

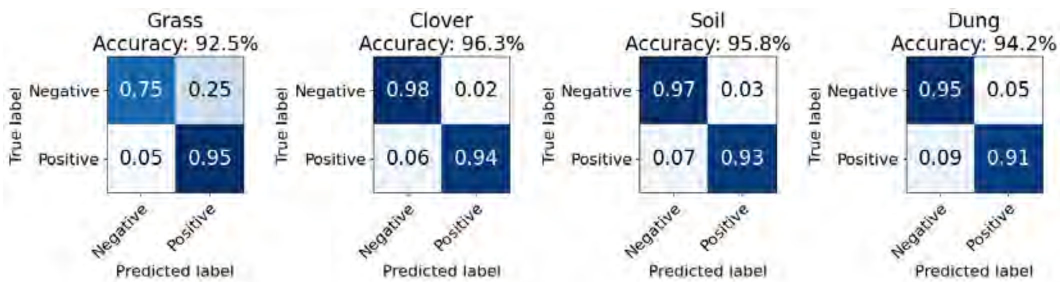


Figure 36: Per-class confusion matrices and accuracies for our best iNaturalist model.

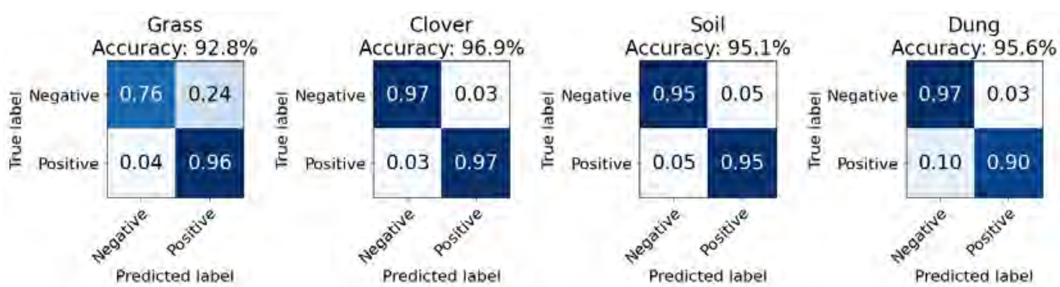


Figure 37: Per-class confusion matrices and accuracies for our best DenseNet121 model.

Experiment 3: Large Dataset Ensembles

The purpose of this experiment was to identify the best performing ensemble model on our final large dataset. Our ensembles contained the best version of each individual model identified from Experiment 2.

We varied parameters relating to the ensemble architecture: the number of best-performing models it contained and its size (number of layers and neurons). We also varied parameters related to overfitting: the dropout probability and the regularisation weight decay. Finally, we varied the learning rate. Appendix E.2.3 provides the full parameter listing. In total we trained 100 ensembles.

Appendix E.2.3 lists the performance of each model, and Table 9 shows the performance and parameters of the best ensemble. This ensemble comprised 5 base models with a large voting perceptron, as shown in Figure 38. The results indicated that our top-performing ensemble achieved an overall accuracy of 93.0%, outperforming any individual model.

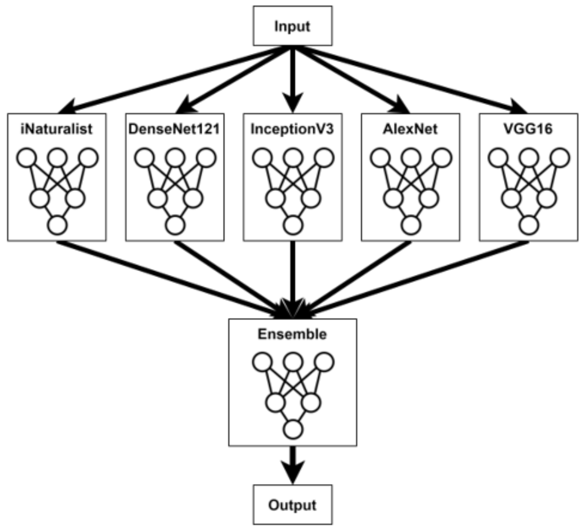


Figure 38: Best ensemble model architecture.

Accuracy	F1 Score	Learning Rate	Dropout Probability	Weight Decay	Size	# Base Models
93.0%	93.0%	0.001	0.3	0.01	3	5

Table 9: Best ensemble on the large dataset, using the top 5 models in Table 8 (excluding PlantNet and ResNet50 as they are both variants of ResNets and iNaturalist is the best-performing ResNet).

The per-class accuracies and confusion matrices shown in Figure 39 revealed improved accuracy for soil and dung classifications, though there was a slight decrease in accuracy for grass and soil compared to our best DenseNet121 model. Notably, the ensemble exhibited an increase in false positives for grass (from 25% to 34%), suggesting potential overfitting. Addressing this overfitting remains a subject for future research; we hypothesise that the issue may stem from the larger neural network's susceptibility to overfitting and possible labelling inconsistencies (e.g. images with small patches of grass). Despite this, the ensemble improved clover accuracy from 96.9% to 97.4% and achieved the best accuracy on the data team's large dataset.

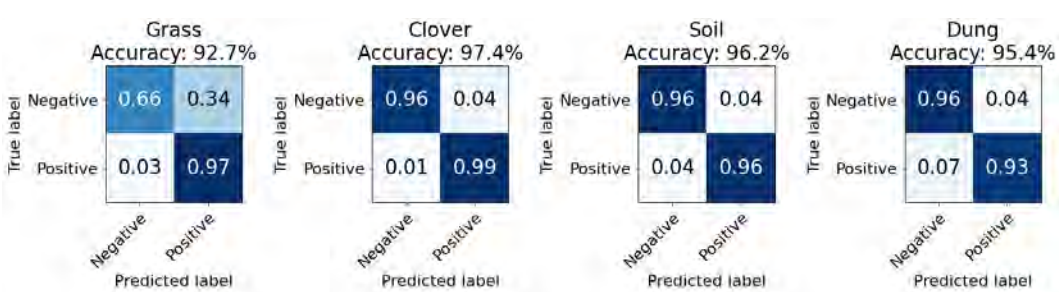


Figure 39: Per-class confusion matrices and accuracies for our best ensemble.

7.3 Presentation

After developing the machine learning model, we designed an image processing pipeline and a graphical user interface (GUI) to allow users to upload images, make predictions on the four classes, and analyse the results. This enables even non-expert users to apply the models to their own datasets.

7.3.1 Graphical User Interface Requirements

As described in §5.3.4, a critical aspect of this project is managing data at the right level of granularity to create a valuable product. We developed an interactive GUI that integrates the data collected by the device and combines it with other relevant datasets, such as field topography and soil class. This user-friendly platform enables the end-users to visualise the distribution of different species and assess how this is affected by other variables in the field. The DAISY GUI represents a valuable tool designed to support the end-users with actionable insights, ensuring that they can make informed decisions and implement an effective action plan for their practices.

The primary requirements of the GUI were motivated by the need to create a seamless, user-centric experience, allowing users to leverage advanced machine learning models without having the technical background. These requirements include:

- **Image Management**: Upload images with metadata including coordinates, timestamp, and field details.
- **Model Management**: Upload custom machine learning models for inference on the datasets.
- **Inference Execution**: Perform inference on uploaded images using pre-trained machine learning models, enabling real-time rapid analysis.
- **Result Storage**: Securely store both raw images and inference results for retrieval and further analysis.
- **Visualisation**: Generate interactive maps of the field to visualise species distribution, incorporating both spatial and temporal dimensions.
- **Segment Identification**: Implement an algorithm to allow for detection of specific segments of the images corresponding to the model's prediction.
- **Statistical Analysis**: Calculate field-level statistics from the result stored and provide the user with a comprehensive list of insights.

7.3.2 Graphical User Interface Implementation

A user interface design tool (Figma) was used for wireframing and prototyping, enabling continuous collaboration between designers and developers, to ensure the final product met the functional and aesthetic requirements. The technology stack was selected to provide a balance between performance, simplicity, and ease of use. The following technologies were used to implement the DAISY GUI:

- **Backend**: The backend was built using the **FastAPI** for its ease of integration with Python-based machine learning workflows, performance, and ability to manage RESTful API calls. The backend was divided two service to allow for more precise debugging and error handling:
  - **App Service**: Managed the coordination of image and model creation, retrieval, updating, and deletion (CRUD operations).
  - **Inference Service**: Handled the deployment of machine learning models and performed image analysis and results handling operations.

- **Frontend**: The frontend was developed using **React** and **TypeScript**, offering a industry-standard and responsive user interface. Additionally the following libraries were used to develop a smooth user experience:
  - Axios: Allowed to manage HTTP requests to the FastAPI backend.
  - Recoil: Allowed to handle the state management of the complex application states with simplicity.
  - ArcGIS: Allowed to integrate web maps in the GeoJSON format for encoding a variety of geographic data structure.
- **Database**: **DynamoDB**, a key-value NoSQL database, was selected as our primary storage of information due to its flexibility of schema, ideal for handling image data and results from model outputs.
- **File Storage**: **Amazon S3** was used as our file storage system as it provides both a secure and scalable storage for images, models and inference results.

7.3.3 Graphical User Interface Deployment

After in-depth testing of the platform in a local environment, the DAISY GUI was deployed to a production environment, making it accessible to users globally. The deployment was implemented using Amazon Web Services (AWS) and the following architecture:

- EC2 instances: We used two EC2 instances to host the two FastAPI backend services. Each of the two services was running as Docker containers.
- S3 and DynamoDB: The backend was integrated with the Amazon S3 file storage system and Dynamo DB for data management.
- NGrok: In order to expose the FastAPI services securely over the internet with SSL certificates, we utilized NGrok as an API Gateway, simplify the tunneling of requests from external clients to our local services
- Firebase: The React frontend was deployed on Firebase, chosen for its ease of deployment with a simple `firebase deploy` command and built-in security features for hosting.

Through this deployment strategy, the DAISY GUI was made accessible to external users, delivering a powerful field-analysis tool accessible through the following link: `https://sensor-c.web.app`.

7.3.4 Graphical User Interface Functionalities

The GUI was built to accomplish three primary functions: data management, machine learning prediction, and image visualisation.

The first function, **data management**, comprehends the uploading, storing, and retrieval of images within both the S3 file storage system and the DynamoDB tables. Similar sets of functions were implemented for uploading and retrieving new machine learning models, as well as fetching classification results. Specifically, the following functions were developed:

- `post_image()`, `get_image()`, `delete_image()`: Functions to manage image storage.
- `post_model()`, `get_model()`, `delete_model()`: Functions to handle machine learning model management.
- `get_prediction_results()`: A function to retrieve inference results.

The second function, **machine learning prediction**, includes the set of tasks required to analyse uploaded images using our machine learning models. The central function, `predict_all_images()`, was created to handle the inference process asynchronously. To perform predictions, the function downloads from S3 specific model weights and images, loads the weights into the appropriate model architecture, and then divides the image into 80 fragments. Inference is performed on each of the fragments, resulting in an 80x4 matrix, where 4 represents the number of classes. For each class, the highest prediction score among the 80 fragments is selected as the probability of that class being present.

Finally, **image visualization** is implemented through the creation of a map using the ArcGIS library. Images and their related data are visualized by storing map elements as GEOJSON files, which are loaded into the platform. This allows users to visualize the distribution of predictions across their field. The final output is illustrated in Figure 40.

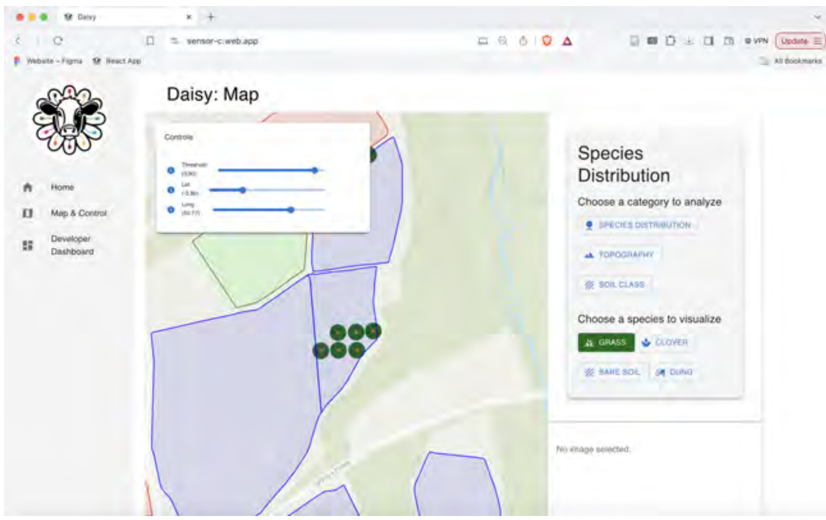


Figure 40: DAISY GUI Platform Map and functionalities.

8 Testing and Validation

During manual quadrat sampling, the surveyor will estimate the coverage of a species of interest and then assign the species an associated 'Domin score' (Table 11). We hypothesized that the ML model would have a limit of detection, perhaps around score 3, where the clover is mostly present as individuals rather than in patches and hence produce false negatives. To test the frequency of false negatives, we produced a moderate library of clover images for each Domin score wherein all these images should be labeled as positive for clover. When passed through the iNaturalist, Densenet and Ensemble models, at a probability threshold of 0.7, all 3 models were able to detect clover in 100% of images and correctly assign all the clover label to images even in the Domin score 1 category. In addition, the Ensemble and Densenet models maintained 100% correct clover classification up to a probability threshold of 0.99, showing that our models were not subject to false negatives for the clover category.

Table 10: The Domin scale and the species coverage ranges which relate to each score. The number of images in our library to represent each score is also shown.

Species Coverage (%)	**Domin Score**	**Number Of Images Collected**
91 – 100	10	6
76 – 90	9	5
51 – 75	8	6
34 – 50	7	9
26 – 33	6	6
11 – 25	5	13
4 – 10	4	21
< 4 (many individuals)	3	13
< 4 (several individuals)	2	14
< 4 (few individuals)	1	18

Table 11: The Domin Scale

To assess the model's ability to successfully classify clover, grass, bare soil and dung across the full Domin score range, testing and model validation was carried out at North Wyke Farm. This allowed the model's predicted results to be compared to ground truth data obtained using standard manual sampling methods (as described in §5.3.1). The first manual dataset was obtained in Dairy Corner using a 25m sample grid. A 50cm (x) by 50cm (y) quadrat was used at each of the 24 sample points to specify the regions over which species presence would be recorded. The Domin scale was then used to quantify the presence and coverage of grass, clover, soil and dung with a discrete score (from 1 - 10) as described in Table 11

Having manually recorded the approximate coverage, images were taken at the same points and input in the model. This was carried out during week 4 of the project, when the device camera was not yet ready to be used in the field, therefore these images were captured using mobile phones.

Upon visual inspection of the results, Dairy Corner had little clover coverage and that a field with greater clover coverage would allow for more meaningful data for testing. The second round of manual sampling was hence carried out in Dairy East. 32 sample locations were selected in a grid formation with 25m increments between each point. At this time, a hand-held device inspired by a trundle-wheel, with the same camera as the cow-mounted device, was used. Images were captured at the investigator's command using a button, detailed in Appendix F.1 and shown in Figure 41. This device allowed for efficient gathering of images representing the same vegetation patches for which ground truth data had been collected.

Figure 41: Hand-held device in use at Rothamsted North Wyke Farm.

Images collected during manual sampling of Dairy Corner (Figure 42A) and Dairy East (Figure 42B) were pooled into a dataset representing the ground truth of vegetation distribution at the North Wyke Farm. This dataset was analysed using the Ensemble model and the classifications assigned by the model for each image were compared to the manual ground truth classifications. The proportion of correct predictions made by the model for each category is shown in Table 12.

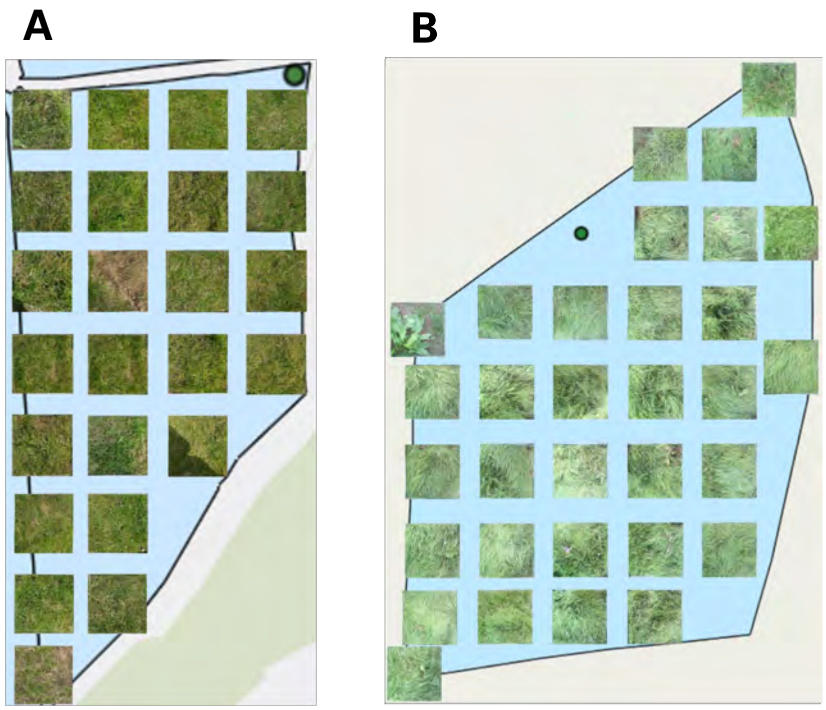


Figure 42: Visual representations of the fields at the North Wyke farm which were samples for ground truth data with the images captures at each GPS location overlayed. Dairy corner (A) images were captured with a mobile phone camera whereas images for dairy east (B) were captured using the hand-held device.

Table 12: Proportion of correct predictions made by the Ensemble method for each category at confidence thresholds of 0.5, 0.7 and 0.9

	Correct predictions on full image (%)			
Threshold	**Grass**	**Clover**	**Bare soil**	**Dung**
0.5	100	31	75	23
0.7	100	31	81	23
0.9	57	31	81	23

Table 12 demonstrates a lower accuracy than expected considering the 97.4% clover accuracy cited in §7.2.3. This low accuracy is thought to be caused inadvertently by image fragmentation. When quadrats are considered during manual sampling, they are treated as one entity and classified as such. However, during the preprocessing of images by the DAISY workflow, these same images are split into smaller fragments, which have an accuracy of 97.4%. The error on each fragment (2.6%) this propagates to the greater image and only one fragment with a false positive classification can cause the entire imaged to be falsely classified. Therefore, our results show a high number of false positive results due to a mismatch between the scale at which the model processes information and the impact that this fragment has on the classification of the full image.

Another reason for the inaccuracies observed is due to oversights in collating representative training data. The majority of training data is similar to the image shown in Figure 43A: short grass due to grazing activity, with dry soil due to hot weather. However, the majority of the validation dataset is composed of images similar to Figure 43B: long grass that is wet due to rainfall. This length of grass and weather condition is not comprehensively represented in the training data and we believe this has led to model to falsely classify such images as 'dung' resulting in dung false positives.

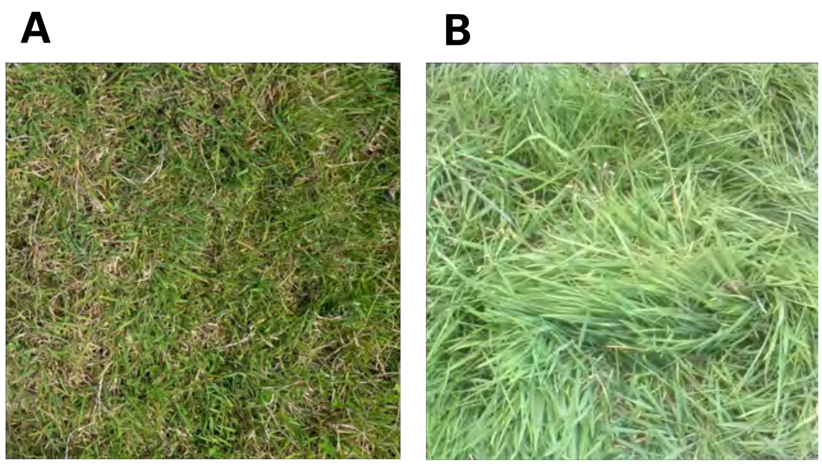


Figure 43: Sample images collected during manual sampling. (A) Image collected in Dairy Corner which resembles grass and weather characteristics of the training set. (B) Image collected in Dairy East.

A potential approach to data analysis to solve the mismatch described above is with the use of the mean coverage metric. Herein, all fragments are analysed and the proportion of the image that has been positively classified with the category of interest is quantified. To explore this further, the library of clover images corresponding to Domin scores was used. These images were processed by the iNaturalist, Densenet and Ensemble models. Based on the number of fragments within each image that were positively tagged for clover, the clover coverage was calculated. The mean clover coverage of images was calculated and correlated with a corresponding Domin score. Figure 44 shows the predicted cover from the model compared to the true cover from manual sampling. All models consistently overpredict the coverage, therefore the false positives still impact the model output and deviate from the ideal correlation (dashed line), with iNaturalist predicting in a similar range. However, a correlation exists between the true and predicted coverage. Particularly Densenet and iNaturalist showed strong correlations between true and predicted coverage (with Pearson's coefficients of 0.97 and 0.98 respectively), however surprisingly the ensemble shows the lowest correlation (with a Pearson coefficient of 0.88). As discussed in §7.2.3, this may be due to the ensemble overfitting on the data team's large dataset. Upon further development, this mean confidence approach may be viable for interpreting the percentage presence of vegetation within images.

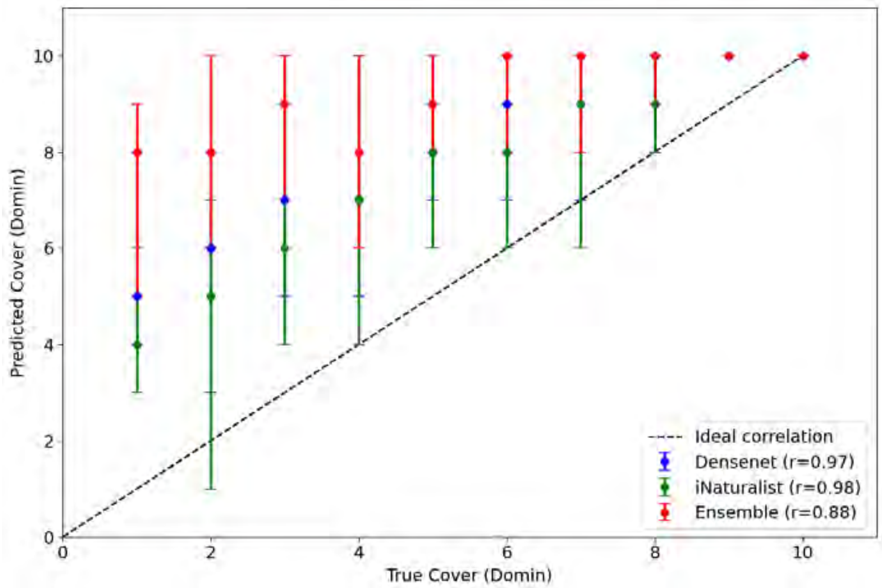


Figure 44: True clover coverage versus predicted clover coverage using the Domin scale.

In conclusion, our validation investigation brought to light 3 main findings:

1. There are inherent difficulties with error propagation in a methodology using image fragmentation due to the impact of false positives, making binary yes/no classification challenging.
2. A dataset that is not fully representative of all conditions (e.g. sward height, wet or dirty grass) will cause classification issues and will struggle to correctly predict the classes.
3. A mean coverage approach rather than binary can be more valuable to obtain insights similar to those from manual sampling.

Since our model can accurately predict percentage coverage (and consequently the Domin score), achieving up to a 0.98 Pearson's correlation coefficient, we propose using the model exclusively for percent coverage analysis at its current stage.

9 Responsible Research and Innovation (RRI)

9.1 Ethical Considerations

Research involving the testing of novel technology on animals is now a closely regulated field in research. It is important to consider the ethical, legal and scientific reasons for optimising the quality of the research.

9.1.1 Ethical and Legal Optimisation

To carry out this optimisation, the guidelines set out by Norecopa, Norway's National Consensus Platform for the advancement of "the 3 Rs"(Replacement, Reduction, Refinement) were applied [56]. A fifteen-point checklist allows scientists to prepare for animal experiment planning. During this project, the applications of the principles were prepared into a research protocol for review by members of the Rothamsted Research team and external bodies such as UK AWERB (Animal Welfare and Ethical Review Body). The principles were also applied when obtaining permissions from the University of

Cambridge Veterinary School animal welfare board to execute experimental research on large farm animals.

The level of risk associated with the intervention was deemed low as cattle collars are commonly used as part of normal husbandry and farm management. The risks were further minimised by the team by carrying out water ingress tests, utilising as many off-the shelf hardware components as possible and maintaining extremely high standards for hardware assembly. The casing was printed in shatterproof materials such as sintered nylon, to reduce the possibility of fracture.

Following the "3 Rs" of Russell & Burch [56], the protocols aimed to Replace, Reduce and Refine the experiments described as per Table 13.

Name	**Simple Definition**	**Research protocol considerations**
Replacement	Replace the use of animals in areas in which they would have been used.	This project builds on the common agricultural practice of mounting devices on collars, straps, bridles worn by farm animals. The objective of the work was to identify if new technology can be incorporated into these systems to better enable pasture biodiversity and quality monitoring. It was essential that animals are used. The sensor device was mounted on cattle to collect the minimum amount of data required to prove the sensor's usefulness. Furthermore, the model validation and preliminary data collection was carried out via handheld device, maximizing work off- animal.
Reduction	Minimise the number of animals used in experiment.	The proposal was a pilot study, therefore more than one cow was suggested to be used to obtain viable results, in the event of a device breaking and/or coming offline during the period of data collection. The number of deployed sensors could be reduced although this would increase the risk of reduced data due to device failure.
Refinement	Minimise the pain, suffering, distress or lasting harm that research animals might experience.	It is accepted in literature that a cow will cover a field of the size selected for the experiment in a few days [57]. The length of time for collar wearing was set to 4 weeks in this study. This was done to synchronise the application and removal with the cattle weighing schedule. The animal was not removed from the field and placed in a crush more frequently because of this intervention. The time the animal spent inside the crush was also minimised by applying the collar as quickly as possible, with the components prepared ahead of time. If the device negatively impacts the animal's health further adjustments to the device such as change of shape and weight, and location of attachment can be carried out.

Table 13: Analysis of the 3 R framework and how it was applied to our Team Challenge.

9.1.2 Scientific Optimisation

When optimising the quality of the research, scientific integrity must be maintained. The data obtained in the project was stored securely on Microsoft hosted cloud storage, only accessible to name individuals within the University of Cambridge IT network. The team produced conclusions and claims only when supported by results of high quality. These conclusions and interpretations were also recorded at short intervals and stored safely, including backing up on One Drive. All results and conclusions were recorded and communicated, even when negative in nature. The data was kept available for re-interpretation, in the event the need arises. Finally, each step of the process was optimised using the input of our collaborators at Rothamsted Research, this was emphasised to achieve maximum value from the animal trials.

Additional considerations for the project also include the ethics of beginning and end of life handling of the products. As a project funded by the Engineering and Physical Sciences Research Council, public finances were used to carry out this research. The team chose to make all aspects of the project publicly available (open source), enabling other researchers to build on the work carried out. There is a particular lack of open-source code available online in the ML aspect of this Team Challenge. By releasing our resources, we would fill some of the gaps in the literature. The end of life of the product was also particularly considered. As mixed materials are contained, it is important to follow manufacturer's instruction of disposal of the commercially available hardware parts. In particular, improper battery disposal can lead to creating harmful waste and the potential of creating flammable material. To ensure that these instructions are followed, the User Manual included disposal instructions in detail (Appendix B).

10 Outreach

To share our work, four key groups that would benefit from having more information about this project were identified: the agricultural community, the academic community, future scientists, and the general public. Despite the limited communication channels available, it was crucial to reach each of these audiences effectively.

10.1 The Agricultural Community

The UK Agricultural Community is composed of 216,000 holdings, many hiring one or more employees [58]. To reach this audience, the most prominent media outlets focused on the agricultural audience were identified and approached. This included Farmers Guardian, Farmer's Weekly and Farmers Guide.

An article about the DAISY sensor was featured in Farmer's Weekly, a United Kingdom-based magazine and website, on 26th of July 2024 (see Figure 45) [59]. Its target audience includes the agricultural and farming sector with a long history in relaying information of current news and affairs, business advice, technology and machinery, livestock farming, and environmental issues. The Audit Bureau of Circulation confirmed that Farmer's Weekly had 664,689 unique monthly users monthly of their Website/ App in 2023 [60].

The article was authored by the machinery editor Oliver Mark, who interviewed eight members of the DAISY team. The focus of the interview was directed towards the hardware availability and low cost, as well as the novel data analysis approaches. The piece also highlights impacts of the sensor development for farmers such as additional grant funding possibilities and reduced costs due to reduction in fertilising. The team emphasised the collaborative nature of the work with Rothamsted Research, ensuring the engagement of one of the primary stakeholders.

Figure 45: Snapshot of the DAISY article in Farmer's weekly [59].

10.2 The Academic Community

The project aimed to keep the Cambridge academic community involved in the project as closely as possible. We collaborated with the CEB communications team to produce and share content to reach a wider audience of academics and future STEM students. This included a Facebook post sharing the article written about DAISY in Farmer's Weekly generating 3 likes (Figure 46). Members of the DAISY team also participated in the filming of video content for the CEB website/ YouTube channel. This longer form content focused on the field work and mounting of the sensor, as well as our collaborators at Rothamsted Research.

Three students of Gonville and Caius College were interviewed by the College Communications Officer. The information in the college newsletter is often conveyed at a level of complexity appropriate for prospective students to engage with. This fits particularly well with the aims of the project to reach as many future STEM students as possible as well as fulfil the stakeholder needs for student recruitment.

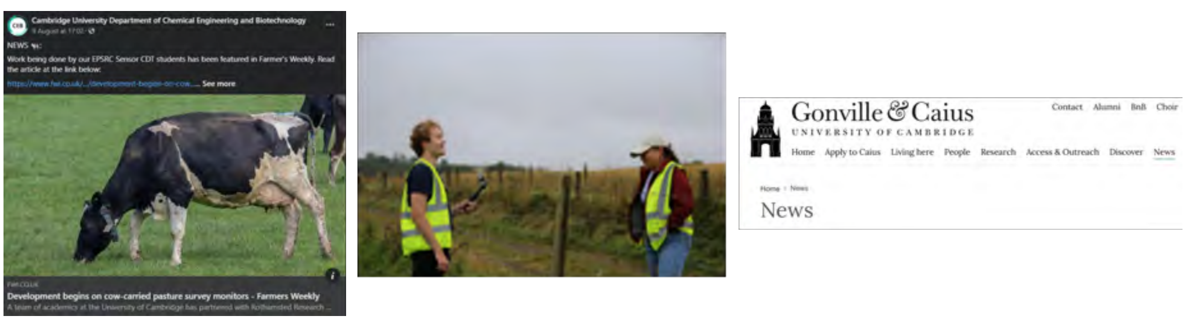


Figure 46: Snapshot of Facebook post made by the Department of Chemical Engineering and Biotechnology (CEB) about the success of DAISY (left), interview with CEB Social Media & Communications Coordinator (middle) and the Gonville and Caius College News page (right)

10.3 Future STEM Students

Engaging students in outreach activities at the age of 16-18 can result in more students from underrepresented backgrounds pursuing STEM degrees at university [61]. The project explored ways to engage this specific age-group to introduce them to the collaborative, interdisciplinary nature of the project.

Figure 47: DAISY team members presenting the DAISY poster at the CEB open day.

The DAISY team presented a poster during the University of Cambridge Department of Chemical Engineering and Biotechnology (CEB) Open day on the 4-5th of July 2024. Two team members can be seen with the poster in Figure 47.

This presentation was directed at future scientists and engineers aged 16-18 who are focused on identifying a department and field of study of interest. The team engaged the students via a visually appealing poster, which included images of the target species the sensor will identify, a schematic of the hardware and a visual step by step guide of the data analysis system. There was a particularly heavy emphasis on infographics which has been shown to increase engagement with a non-technical audience [62].

10.4 The Public

10.4.1 Branding

For wider public outreach, a name and logo were first developed. The name D**AI**SY was chosen and displayed with the letters AI shown in an alternative colour or in bold to highlight the use of machine learning. The name DAISY was chosen since it is the name of a common flower and also an archetypal name for cows in Western English speaking countries such as the United Kingdom and the United States.

The logo (Shown in Figure 48) combines various aspects of the project in a modern aesthetic way. The electronic tracks that line the daisy shape and are designed and coloured to show the association to the Sensor CDT and the UN Sustainable Development Goals. The colours selected and the connotation is particularly important as this project is focused towards creating technology to reach the goals on: zero hunger (2), clean water and sanitation (6),and sustainable cities and communities (11). This project specifically addresses sustainable consumption and production (12), climate action (13) and improved life on land (14) [63].

Figure 48: An image of the DAISY logo.

10.4.2 Social Media

Social media activity was focused primarily through Instagram (see Figure 49). The content was curated to show insights into the hardware, ML predictions but mostly into the sensor mounting and collaborative work with Rothamsted. Creating posts about the farm animals, which the device is applied on, creates a pleasing aesthetic and engages audiences of different ages and backgrounds. It specifically engages a non-technical audience. To create an attachment to the page, the cows were often introduced by name (for example Princess, a cow at University of Cambridge Vet School).

Engagement with the Instagram profile was very high, with the page reaching 873 accounts, the majority of which were non-followers, since the creation of the account in July 2024. There were 237 visits to the profile and 14 accounts engaged with the external links associated with the profile, such as the website. The Instagram profile collected 67 followers in 30 days. The post with the widest reach was recorded to be the post announcing the article published about DAISY is Farmer's Weekly posted on the 8th of August. A particularly high surge of following was recorded on that day with followers growing by 37 accounts on the day of the post.

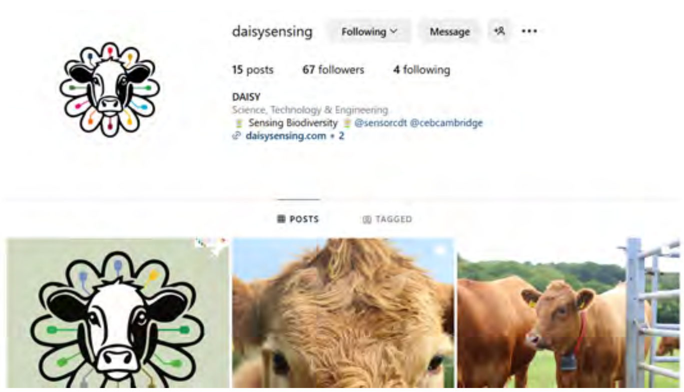


Figure 49: Snapshot of the Daisy Instagram page.

10.4.3 Website

A website to provide project background, context and highlight our collaborations was created using WordPress. The domain 'daisysensing.com' was selected due to the simplicity of the domain name as

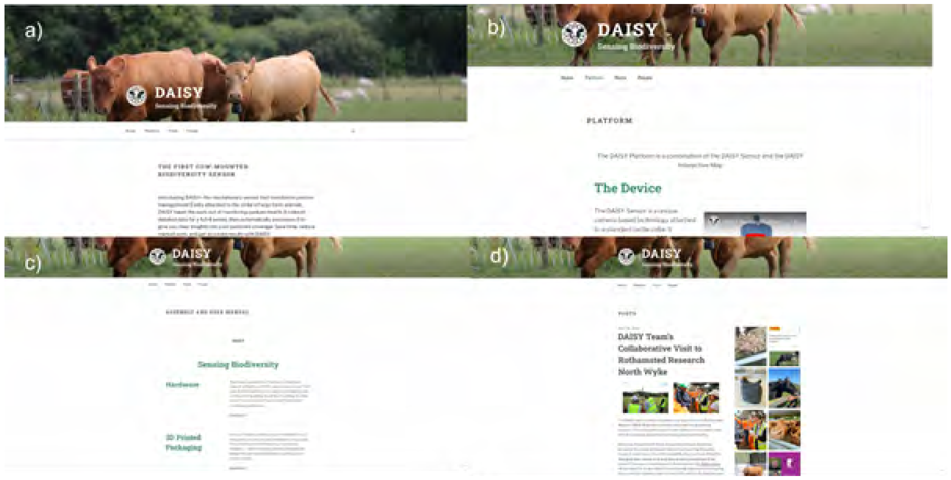


Figure 50: A snapshot of the DAISY website, including the a) Home page, b) Platform page, c)the Assembly and User Guide page and c) the Posts page.

well as the identical Instagram handle used. The site was designed to be visually appealing to the general public and the complexity of the ideas and writing when conveying information were pitched for the same audience. The pages are tuned to convey the product's market value or purpose (Figure 50) or dedicated to house the open-source device assembly and user manuals. The website also provides a direct link to the GUI built to analyse and display the data from the DAISY sensor.

Figure 51: Additional insights into the content of the DAISY website.

From the 25th of July to 12th of August, the website recorded 91 visitors. Of these, there were two peaks in visitors recorded, as can be seen in Figure 52 - on the launch of the website and again on the 8th-9th of August. These peaks can be associated with the surge in subscribers on Instagram on the same date and the Instagram post announcing the Farmer's Weekly article release on Instagram.

When reviewing the reach of the website geographically it was found that although 91% of the views were located in the United Kingdom, the website also reached Israel, United States and mainland Europe (see Figure 51). The popularity of each page was also compared, with the Platform page receiving the most visits.

In conclusion, our outreach efforts have successfully expanded our project's impact, engaging diverse audiences and creating new streams to interact with hard to reach stakeholders. Through clear communication and active engagement, we've made our project a valuable resource for different communities, helping to keep it relevant and attractive.

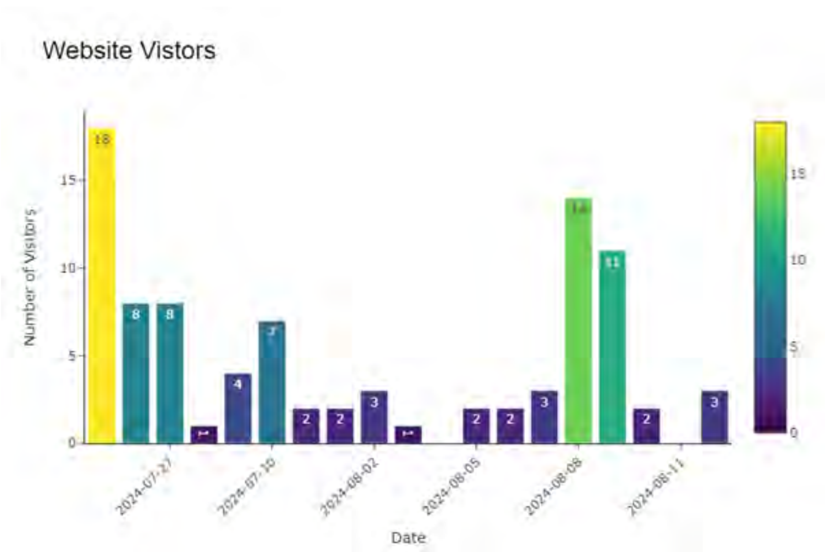


Figure 52: Website statistics showing the visitors reached by our websites during the project span (launch 25-Jul to 12-Aug).

11 Future Plans

11.1 Device Optimisation

11.1.1 Hardware

A photodiode could be connected to the microcontroller to automatically prevent it from taking images at night allowing for seasonal or local variations in lighting conditions, unlike the fixed sleep schedule our device currently follows. A significantly more compact casing can be designed around the PCB that replaces the XIAO ESP32S3 Sense. GSM functionality can be added to the cattle-mounted device, foregoing the need for manual data transfer from a microSD card. However, this will significantly increase the system's overall power consumption, so this transmission must be heavily duty-cycled, and the total battery capacity should be increased to account for the additional energy required.

11.1.2 Embedded Software

The auto-exposure (AE) functionality of our camera module can be optimised to avoid blown-out images. Furthermore, embedded code can be added for any new components (such as the photodiode mentioned above) and on-device image compression can be performed to allow for image transfer over wireless links. Finally, a dedicated debugging mode can be integrated.

11.2 Short-Term Model Development and Statistical Analysis

As detailed in §5.3, statistical methods can be used to interpolate the distributions of grass, clover, bare soil and dung in unsampled regions of the field. These methods include geospatial statistics and Global-Weighted Regression (GWR) and require high sample coverage to make statistically significant predictions. The required advance of the sensor would be to optimise the hardware and data sampling approach to allow such methods to be implemented with a reasonable degree of statistical significance. As the group have already collected manual quadrat samples of the field and are now proficient in the technique, the improved machine learning and offline statistical models can be validated by ground-truth data acquired at the time of product testing.

Each statistical method can be applied to specific use cases and are as follows.

Geo-statistical Methods.

1. **Analysing Spatial Dependence**

   Geostatistical methods can describe the relationship between space and the variable being investigated by quantifying spatial dependence and auto-correlation of the data of interest.

2. **Spatial Prediction and Interpolation**

   Distributions are predicted in unsampled regions using methods such as Kriging. This requires analysis of spatial dependence, as above.

3. **Spatial Variability and Uncertainty**

   Geostatistical tools can quantify and visualise the uncertainty in interpolated data.

Geographically Weighted Regression

1. **Local Relationships**

   GWR allows the investigation of spatially varying relationships between variables, such as the change in clover distribution with changes in elevation.

2. **Heterogeneous Spatial Data**

   Identification and modelling of non-stationary distributions of vegetation, such as clover.

3. **Exploring Local Spatial Patterns**

   Identification and visualisation of local spatial patterns and variations in anisotropy.

4. **Regression Analysis with Spatial Context**

   Spatial variability is accounted for in regression modelling.

11.3 Future Use-Cases

1. **Large-scale farming and sampling inaccessible regions.** Large-scale cattle farms and ranches can be up to 800,000 acres in area. The cattle are therefore taken in from their pastures much less frequently than in typical UK farms. To sample such large regions, more images are required to create a statistically relevant vegetation map. An optimised sampling strategy and improved (longer) battery life would be required in this context. Further, the investigator would have very little control over the movement of the animal and thus the region being sampled. Device development to include wireless data transfer would be useful to allow real-time updates to the GUI from remote locations, rather than having to manually retrieve an SD card.

2. **Improved accuracy of grass, clover, dung and bare soil classification and mapping.**

   While the sensor can be developed beyond the scope of this project to classify more species, classifying grass, clover, bare soil, and dung has been identified as the most academically and commercially relevant use case. Therefore, there is value in continuing to optimise the model so that it can more accurately differentiate between these classes. Reduced machine error will improve the confidence with which predictions can be made in both sampled and unsampled regions, improving the accuracy of the results obtained.

3. **Red clover identification.**

   Red clover is of agricultural and academic interest because it contains oestrogen. This impacts the fertility of livestock grazing in areas with abundant red clover. A sensor which can detect red clover would be useful in guiding grazing activities and avoiding infertility in livestock [64]. This will include training the machine learning model on a dataset which contains red clover.

4. **Invasive species identification.**

   Invasive species, such as nettles, thistles, bracken and hogweed, are often unpalatable to grazing livestock. For productivity and animal welfare, farmers would find use in a sensor that can notify them of invasive and unpalatable species in their sward [65]. This will include training the machine learning model on a dataset that contains nettles, thistles, bracken, and hogweed.

5. **Fox detection.**

   Foxes are known to prey upon farm animals and transmit diseases, such as Weil's disease and roundworm [66]. Training the model to detect fox dung would allow farmers to be notified if the livestock were at risk.

6. **Badger detection.**

   Badgers are known to carry diseases harmful to livestock and humans, including tuberculosis (TB). Being an endangered species, farmers cannot easily remove badger sets from their land. Adapting the model to allow identification of badger dung would allow livestock to be moved away from potentially harmful badgers sooner, reducing TB transmission [67].

7. **Anomaly detection.**

   Field anomalies can result from natural and induced processes. For example, a sudden decrease in clover cover in an unfertilized field could suggest that nitrogen-containing compounds have leached off a neighbouring field and made their way into the sample area. The GUI can be programmed to flag significant temporal changes in the characteristics of a field sampled multiple times.

8. **Plants of scientific or medical interest**

   While this project has mainly focused on determining distributions of species and field characteristics, identifying single individuals is also useful. Training the Machine Learning model to identify indicator species would give insight into numerous chemical and physical characteristics of the area, including changes in climate, local food chains and soil quality. This would improve understanding of the natural and induced systems operating in the region without requiring manual sampling. Locating sought-after plant species used in producing high-value items or pharmaceutical products could be a key use of the future device.

12 Conclusion

The Sensor CDT Team Challenge 2024 was developed in collaboration with Rothamsted Research with the goal of automatically monitoring vegetation biodiversity in pastures. With various potential approaches for this project, we chose to consider our strengths, weaknesses and interests, as well as feasibility in 10 weeks. Ultimately, the brief selected was to monitor pasture using cameras mounted onto grazing livestock. The group was divided into four workstreams, specifically tasked with (1) **Project** management and outreach, (2) understanding the current technological landscape and defining **Product** specifications, (3) designing and fabricating the **Device** including hardware and embedded software, and (4) developing a Machine Learning model trained on a large quantity of appropriate **Data** and deploying a user-friendly platform to display the results. Two weekly meetings and various communication platforms were used to ensure easy and constant collaboration between the workstreams.

The Product Team conducted initial market research to guide the development of the device and its software. Considering related technologies that exist - whether cattle-mounted or biodiversity sensors - and the limitations of the current manual sampling techniques, informed decisions were made regarding how our device can fill these gaps in the market and create value for academics, farmers, governmental bodies and more. A novel sampling and validation approach was also devised to support the Data Team's ML model efforts.

Informed by the requirements for the Product, the Device Team explored various designs for a durable casing, ultimately opting for an iconic bell shape hanging from the cattle collar and ruggedised to survive in the field. The use of SLS and FDM 3D printing to respectively create a nylon exterior and PLA bottom piece, assembled with a rubber gasket and screws, allowing the resulting case to be sufficiently robust and water resistant for the application. Aiming to minimise the size and burden of the sensor on the cattle, the electronics were selected considering their power consumption and miniaturised with the design of custom PCBs. The embedded software was developed to control the device using an object-oriented approach with the camera, SD card and GPS modules having respective functions that operate harmoniously to capture an image, tag the time and location and save this to an SD card - an output format compatible with the pipeline developed by the Data Team.

Building on this foundation, the Data Team developed a machine learning system to analyse the images and visualise the results. A dataset of 36,738 fragmented images was gathered and labelled, followed by quantitative balancing of the multi-label dataset, resulting in a final dataset with approximately 6,000 fragments per class. State-of-the-art CNNs for species classification were trained and fine-tuned, applying techniques to reduce overfitting, and combining them into a large ensemble, resulting in 916 trained models. The best model achieved 93.0% overall accuracy, including 97.4% accuracy for clover classification. Finally, a user-friendly GUI for machine learning inference and visualisation was developed, with our model notably achieving a 0.98 Pearson correlation coefficient in predicting clover coverage compared to ground-truth validation data.Though it was found that the model tends to overpredict the binary presence of some classes (dung and clover), statistically significant correlations were found between true clover coverage and that predicted by the models.

Responsible Research and Innovation (RRI) principles were rigorously considered throughout the project, as the impact of the technology extended to many stakeholders, as well as the cattle it was mounted on. The software for this project is shared on GitHub and the device specifications on our website, as this Team Challenge is an open-source project in order to allow future researchers to replicate it. The project has also been shared via social media and a website to maximise outreach and engagement with a wide audience.

The technology developed over the short course of 10 weeks has shown promise for agricultural monitoring and can be improved further to create more value for the end-users. Device optimisation is suggested to focus on increasing the sophistication of the device without compromising simplicity - incorporating a photodiode to assess lighting conditions and creating accessible ways to add modules in the firmware or debug. As for the model, increased statistical analysis such as GWR and optimisation of the current ensemble to mitigate the effect of false positives is suggested. Finally, while monitoring vegetation biodiversity is of interest to some, the technology can be applied to other use cases like identifying different species or detecting animals in pastures, as well as plants of scientific or medical interest.

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A Appendix - Project Outline

A.1 Weekly Temperature Checks

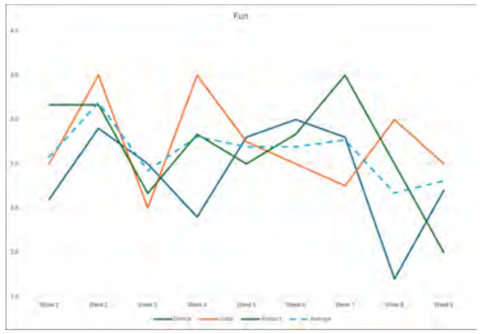


Figure 53: Fun score average by work stream (whole team average also shown).

Figure 54: Satisfaction score average by work stream (whole team average also shown).

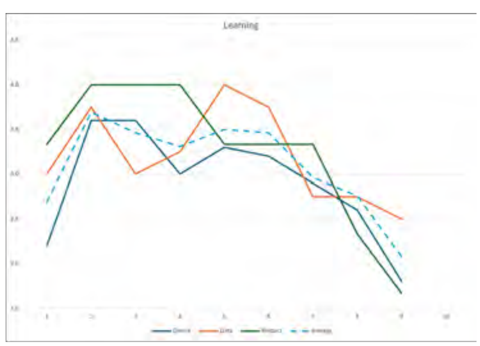


Figure 55: Learning score average by work stream (whole team average also shown).

A.2 Stakeholders

Table 14: Analysis of stakeholder engagement strategies considering their needs and their potential positive and negative contributions.

Stake-holder	Point(s) of contact	Needs	Potential Contributions	Potential Roadblocks	Engagement Strategy
Rothamsted Research	Phil Le-Grice, Paul Harris, Deborah Beaumont	Sensor system for monitoring vegetation in pasture as an addition to the North Wyke farm platform.	Inform standard practice of sampling. Allow use of specialist equipment (GPS, quadrats). Provide access to pasture land. Provide feedback and guide the development of the project.	Lengthy ethical approval delays our ability to test sensor on livestock.	Keep Rothamsted members informed and engaged the progress through emails, calls and regular site visits. Deploying joint-decision making in experiment planning and execution. Spotlight technology improvements so they can provide support for a better output.
Sensor CDT programme managers and coordinators	Samuel McDermott, Yuqi Zang	To deliver project to collaborators, whilst improving Sensor CDT impact. To assess students.	Liaison between EPSRC and the students. Feedback on technology, planning, delivery and outreach during progress meetings. Outreach contributions. Connecting the project to other experts and resources.	Financial roadblocks due to insufficient funds which can limit number of experiments and travel days or deny purchase requests. Imposing time limitations and deadlines.	Communications through the project team for administration assistance. Weekly updates where Samuel and Yuqi engage with the progress of the work and provide feedback. Involvement on visits to farms to see the technology in action.
Sensor CDT directors	Clemens Kaminski, Lorenzo Di Michele, Tijmen Euser, Yan Yan Shery Huang, Róisín M Owens, Axel Zeitler	To ensure effective management, quality control, and overall success of the educational program. To assess success of the project.	Critical feedback on technology development. Discussing problems and solutions (through Q&A sessions).Supporting Sensor CDT administrators in steering the project.	Dissatisfaction with our technical direction and put pressure on changing the focus over a shortened time span.	Communication through weekly progress update presentations and Q&A.Project dissemination through a final report, which can give a complete overview of the extent of the work done.
University Veterinary School	Ian McCrone, Robert King	To ensure the health and safety of the animal during every procedure.	Enable the testing and mounting of sensors. Feedback on collar attachment, location and response. Convey knowledge from experience working with animals. Monitor cow behaviour and response to the sensor.	Lengthy ethical approval delays our ability to test sensor on livestock	Deploy meetings and joint-decision making on the experimental protocols to achieve the most successful testing schedule. Regularly update using email to ensure all permissions and risk assessments are in place.

University farm	Paul Kelly	To ensure the health and safety of the animal during every procedure.	Enable the testing and mounting of sensors. Feedback on collar attachment, location and response. Monitor cow behaviour and response to the sensor.	Collar mounting is constrained by the cattle schedule. Collar can be applied once a week when the animal is moved from field to housing. The collar can be removed when this event occurs again the following week. This may impact our development schedule.	Deploy meetings and joint-decision making on the experimental protocols to achieve the most successful testing schedule. Regularly update using email to ensure all permissions and risk assessments are in place. Update on new 3D renders of the device and gain his approval to ensure that the product specification is practical and safe for the animals.
CEB health and safety team	Jessica Fitzgibbon	Ensure individual risk is minimised or eliminated during group, lone and field work. Ensure safety requirements are met such that procedural complications are not met at a later date.	Ensure all students are safe when working in CEB and externally. Provide assistance with completing risk assessments. Approve risk assessments and working away forms.	Deny approval of Risk Assessment and Working Away forms. Deny access to pivotal pieces of equipment.	Contact well in advance with any requirements of approvals. Leave plenty of time for iterative changes to protocols/ risk assessments. Execute advised changes as soon as possible.
CEB Makerspace	Josh Easy, Oliver Dennison, Mark Scudder	Ensure all users are proficient in use of required equipment. Maintain a safe working environment for all users.	Provide training on required equipment. Advise on aspects of device development such as 3D printing and electronics.	Do not allow unsupervised work. Do not provide training on necessary equipment.	Request training in advance of when work required completion. Brief points of contact on our work so they are aware of our extended presence in the Makerspace. Remain in communication about when equipment is available for use and the help they could provide.
Agri-FoRwArdS CDT	Harry Rogers	Robust academic contributions to agricultural science.	Inform on current state of automated technology in the agricultural field. Guidance on implementation of computer vision into vegetation management	Disagrees with our approach and is unwilling assist.	Keep updated with project progress in teams meetings and invite to comment on our direction.

Farmer's Weekly	Oliver Mark	Generate interesting, informative and high quality articles for the magazine's readership.	Publicise the sensor to reach stakeholders in the farming community through their popular platform. Provide the group insights about the needs of the farming industry: price, availability, demand.	Publishes article which incorrectly describes the capabilities of the sensor. Portrays the technology a negative light. Is unwilling to cooperate with the requirements of CEB communications.	Open a dialogue about the value of the sensor during the interview and get his perspectives from interacting with the farming community. Provide straightforward explanations of the technology, using context appropriate terms. Convey the benefits of the sensor to the farming community.
CEB communi-cations	Hannah Dolman, Alex Wilby	Publish interesting content about CEB that publicises current work. Ensure communications with external media outlets are compliant with CEB procedures. Assure that the department is credited in their role of hosting scientific projects.	Review articles from external sources to ensure integrity about the project and tone is appropriate. Create content about the project to display on CEB social outlets. Provide feedback on DAISY outreach.	Block the publication of an external article. Cause delays in the release of external articles.	Ensure open communication and talk freely about any concerns regarding content. Receive approval on all pieces which Sensor CDT or CEB will be represented. Highlight contributions of CEB to external interviewers. Participate in their outreach for CEB channels.
University of Cambridge community	University members in our departments and colleges	Produce high quality research.	Give practical advice about the device or data components of the project.	Disagreement with approaches and directions within the project.	Engage during formal presentations and informal conversations in common areas.
Gonville and Caius College communi-cation	Declan Boyd	Publicise the activities and accomplishments of college members to engage past, present and potential members.	Enable the project to reach new members of the academic community. Publicise the interdisciplinary nature of the Sensor CDT to potential applicants and academic collaborators.	Writes a piece which does not accurately capture the project.	Provide straightforward explanations of the technology, using appropriate terms for an academic community of non-subject matter experts. Describe data and device outputs that will be of interest to academics outside of agriculture (for example development of the machine learning model).

B Appendix - Background

B.1 Daisy User Manual

DAISY

SENSING BIODIVERSITY

USER MANUAL

CONTENTS

WHAT IS DAISY?

At DAISY we understand how field biodiversity goes on to impact environmental goals as well as livestock grazing patterns, livestock rotation and field resowing. We set out to quantify four key field indicators and display these in a useful interface to allow you to understand your fields better.

Using the DAISY cow bell mounted to a cow collar, distributions of grass, clover, dung and bare soil can be monitored.

CATTLE MOUNTED

Traditional ecological surveying is labour-intensive and rarely performed on farms despite the crucial field insights that such data could provide. DAISY uses the roaming cattle to passively image and understand the field composition.

A CLASSIC DESIGN

The DAISY device utilises the iconic cow bell design allowing it to hang from a collar and capture clear pictures of the field with minimal disturbance to the cow.

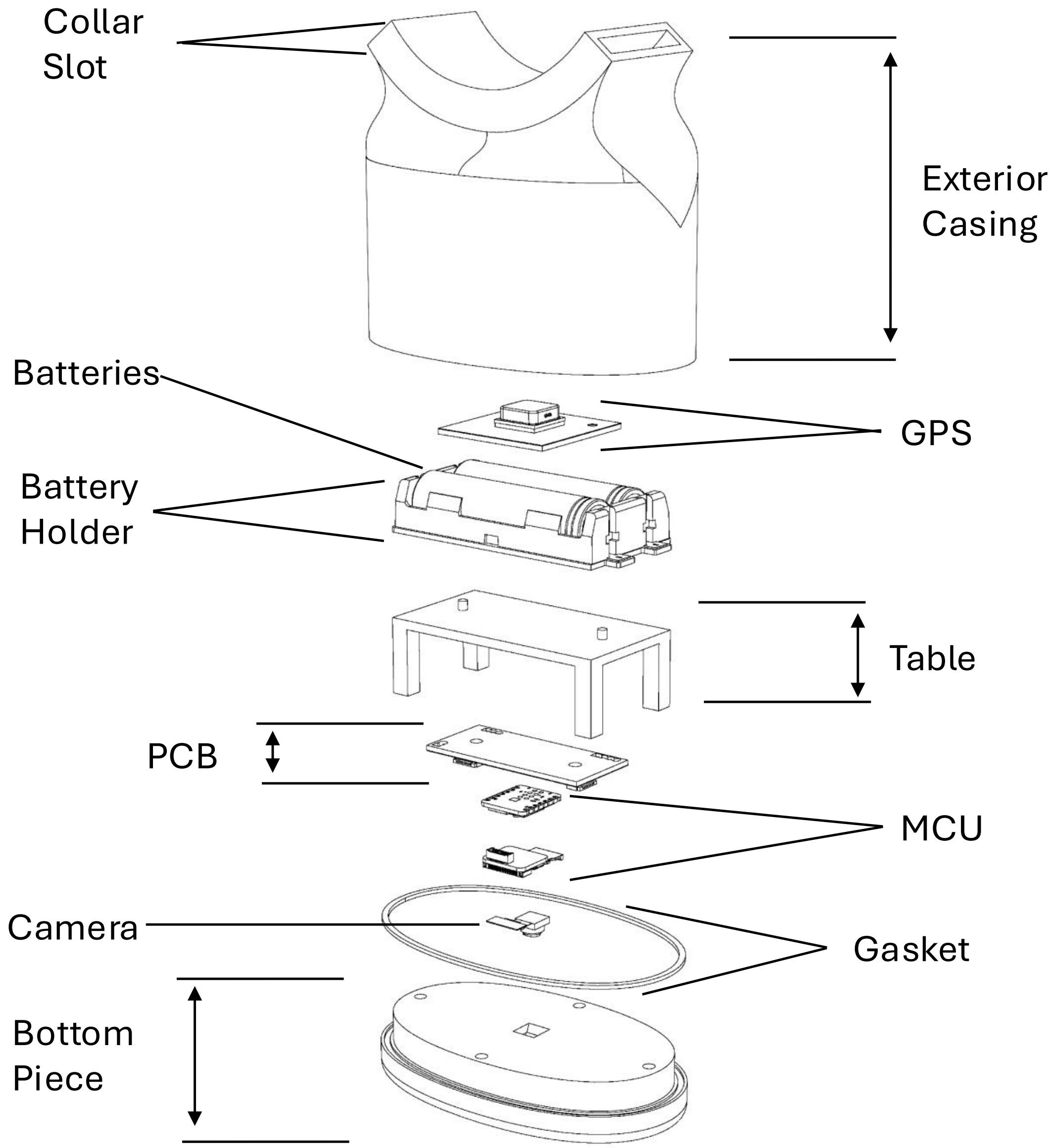
AI POWERED

Pictures are analysed by machine learning algorithms to understand the composition of your field to a high level of certainty.

CONVENIENT

The data collected from our algorithms is shared with you via an interactive interface allowing you to understand the vegetation of your field and how it maps to other field characteristics such as soil class and topography.

COMPONENTS



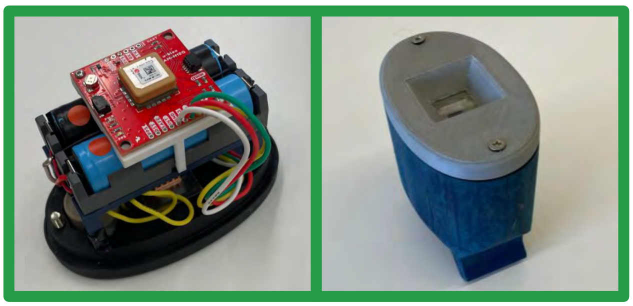
SPECIFICATIONS

Dimensions	100 cm x 120 cm x 70 cm
Weight	~ 450 g
Battery Life	~ 10 days
Charge Time	~ 1 hours
GPS Accuracy	± 1.5 m *

*As cited by u-blox for the SAM-M10Q antenna module.
N.B. This may differ experimentally.

QUICK GUIDE

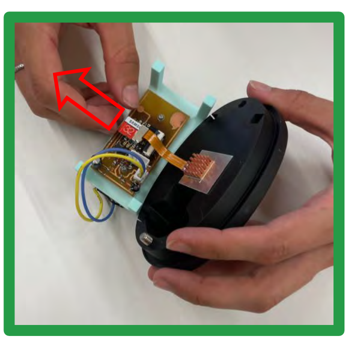
STEP 1:
CHARGE THE DEVICE



STEP 2:
ASSEMBLE THE DAISY COWBELL

STEP 3:
ATTCH TO CATTLE

STEP 4:
LEAVE TO SAMPLE FIELD



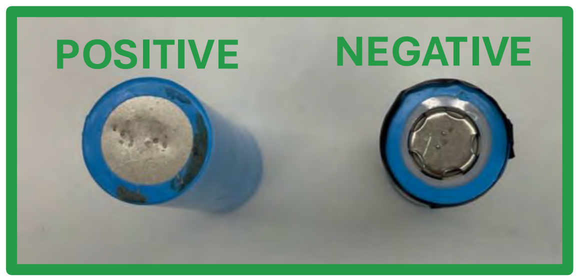
STEP 5:
DETACH AND REMOVE THE SD CARD

STEP 6:
USE OUR CUSTOM INTERFACE TO UNDERSTAND YOUR FIELD

SET UP

STEP 1: CHARGE THE DEVICE

Identify the positive end of the batteries via the attached sticker or the distinct end shapes.

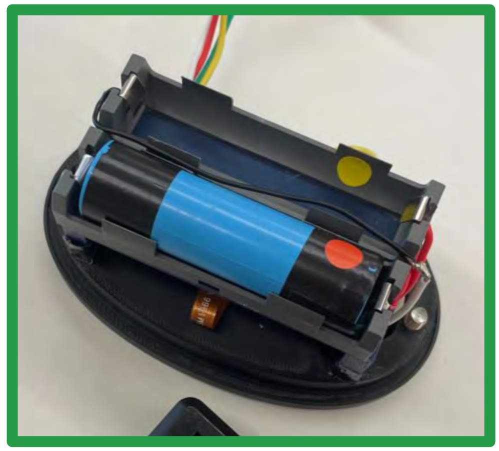


Plug the provided charger into a computer. Insert the batteries into the charger. Continue to charge until the display flashes ‘FULL’. This should take approximately 1 hour from empty.

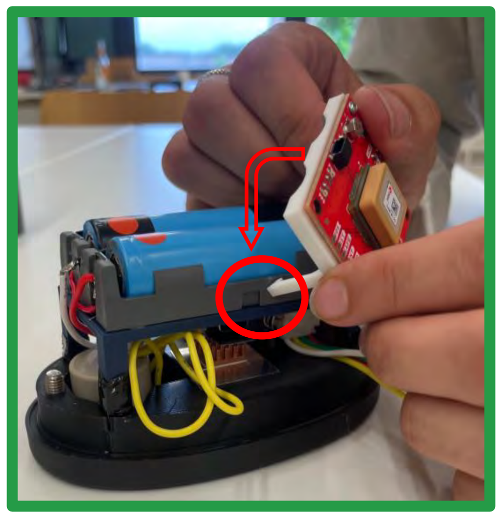
SET UP

STEP 2: ASSEMBLE THE DAISY COW BELL (INTERIOR)

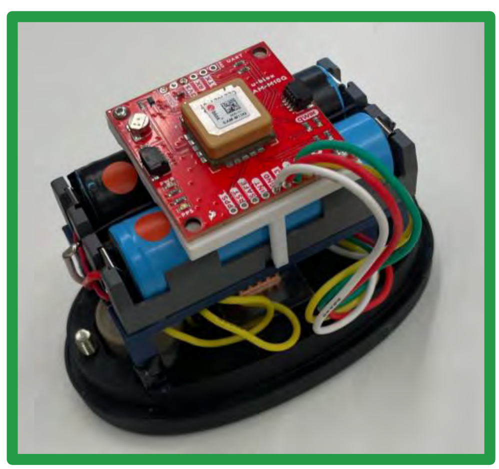
Insert the charged batteries into the battery component matching up the positive end of the battery with the sticker on the interior of the component.



Click the legs of the GPS unit into the notches in the side of the battery component.



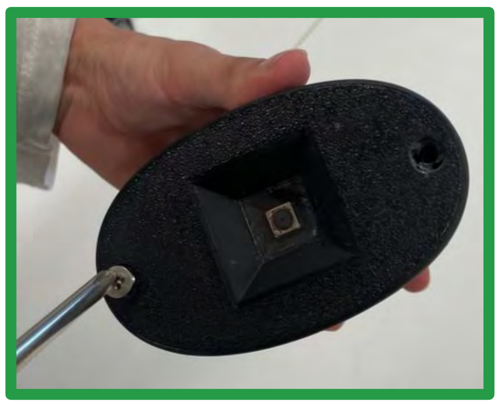
Gently tuck exposed wires underneath the battery component.



SET UP

STEP 2: ASSEMBLE THE DAISY COW BELL (EXTERIOR)

Lower the exterior casing onto the base.



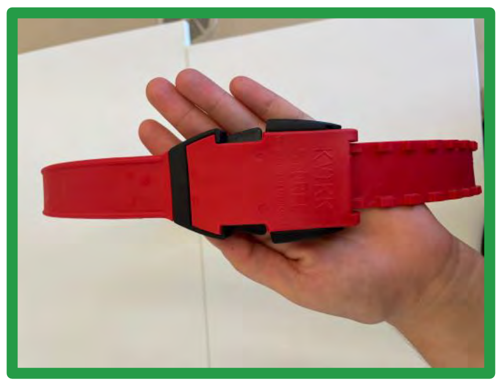
Use a Phillips head screwdriver to secure the two parts together with screws.

Keep the device upside down until you are ready to use it.

SET UP

STEP 3: ATTACH TO CATTLE

Being careful to maintain the device upside down, slide the collar through the openings in the DAISY bell.



At DAISY we recommend using a collar with a fast attach/detach system for easy removal in the case of an emergency.

Attach the collar to the cow of choice. Attachment to a cow which has been observed to be more dominant is ideal.

SET UP

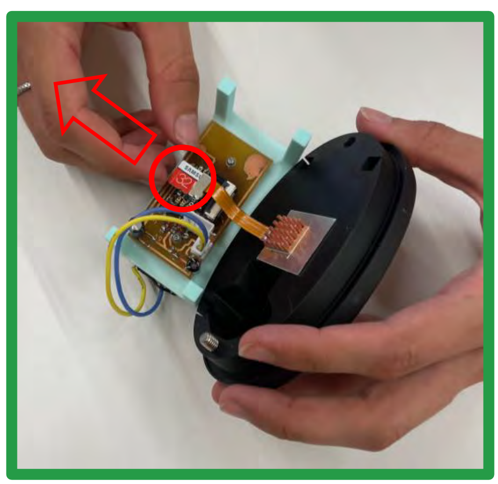
STEP 4: LEAVE DAISY TO SAMPLE THE FIELD

The DAISY collar has been designed for prolonged field sampling.

STEP 5: DETACH DAISY AND REMOVE THE SD CARD

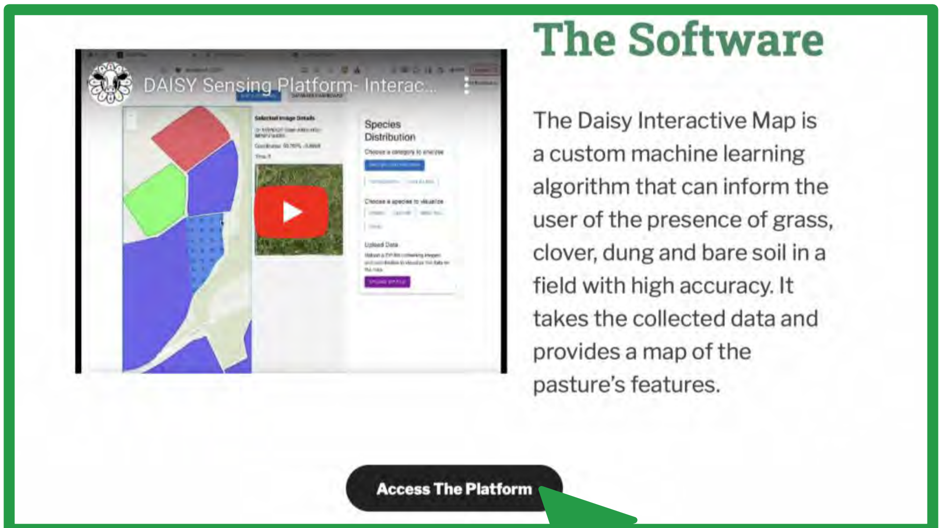
Once removed from its collar, maintain the device upside-down. Remove the screws and slide off the cover.

Lift the table from its place in the base component.
Gently remove the SD card.

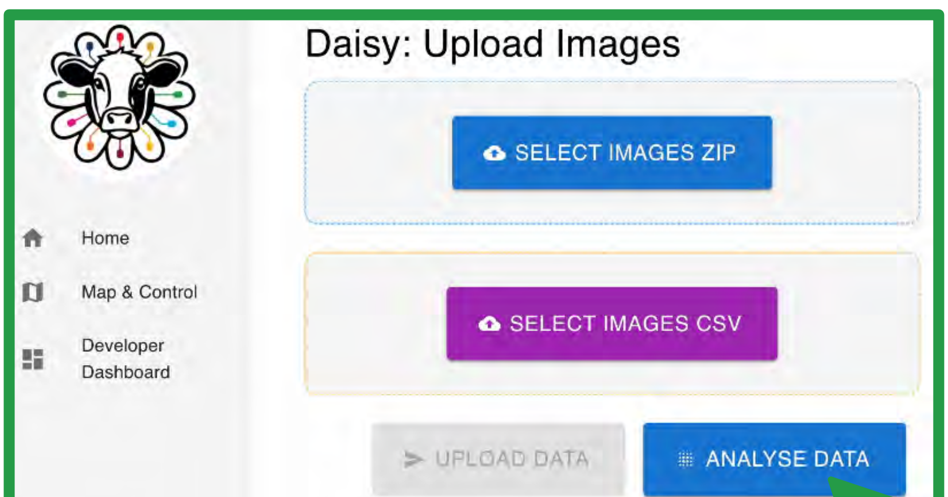


DATA ANLYSIS

STEP 1: ACCESS THE PLATFORM VIA WWW.DAISYSENSING.COM

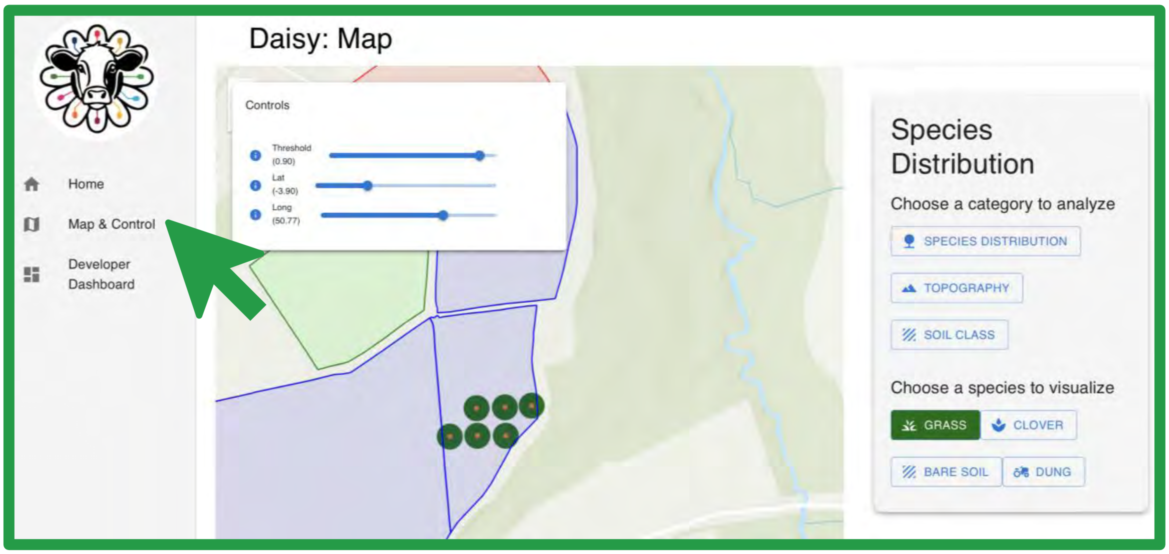


STEP 2: UPLOAD ZIP AND CSV FILES FROM THE SD CARD. UPLOAD DATA AND CLICK ANALYSE DATA.



DATA ANLYSIS

STEP 3: NAVIGATE TO 'MAP AND CONTROL' TO VISUALISE YOUR FIELD



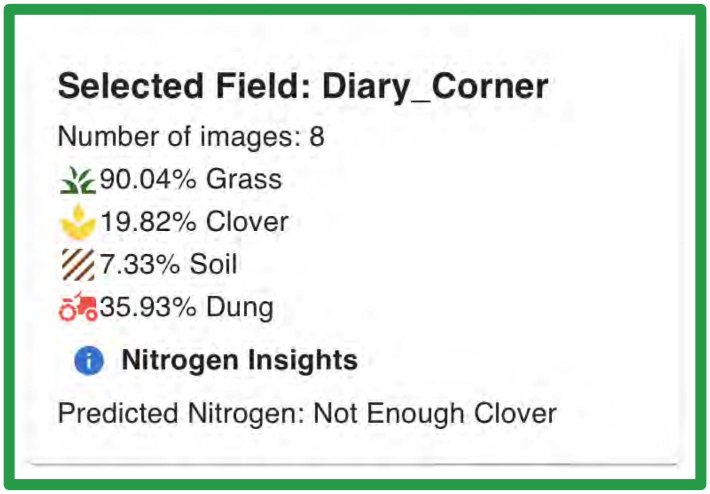
The DAISY map aids to visualize the images taken of your field. Here you may choose which type of field characteristics you would like to analyze along with which identified species you would like to visualize.

In the example, all the uploaded images contain grass as is indicated by the green circles surrounding the data points.

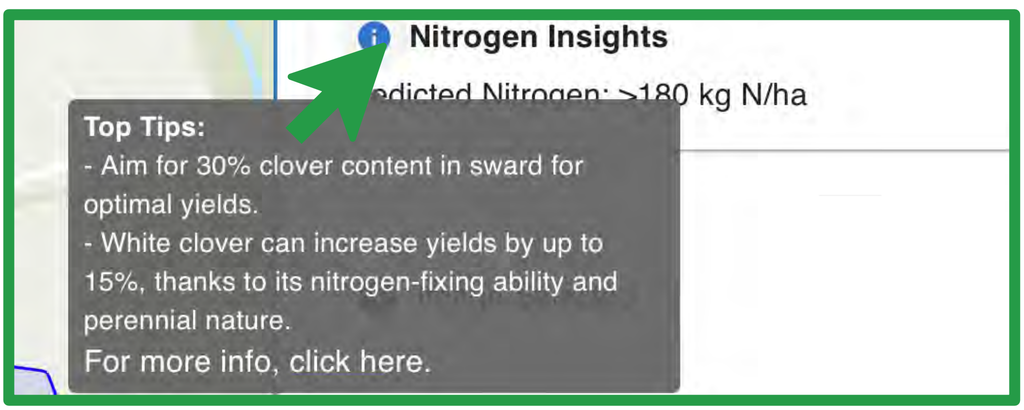
DATA ANLYSIS

STEP 4: SELECT A FIELD TO INVESTIGATE

The proportion of images in which each category has been found is summarized on the right-hand side.



When sufficient images containing clover have been captured, nitrogen insights will become available.



DATA ANLYSIS

STEP 5: SELECT AN IMAGE TO INVESTIGATE. SELECT ACTIVATE OVERLAY

To investigate how DAISY has classified an image into a specific category, select 'ACTIVATE OVERLAY'. The red overlay indicates where DAISY has predicted that this category exists in the image. The more intense the red square, the higher the probability.

In the example, the category of interest was dung.

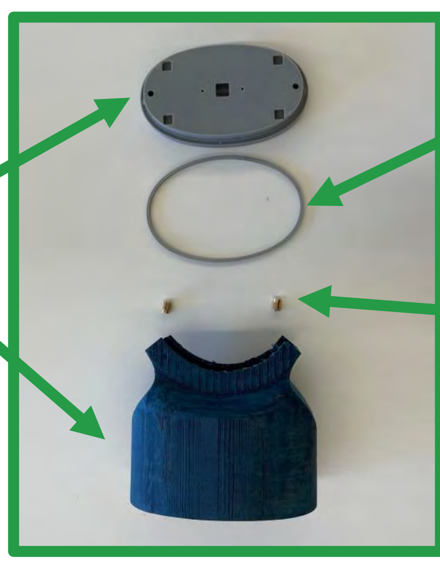
DISPOSAL

STEP 1: REMOVE COLLAR AND DETACH OUTER CASE

Remove the collar from the cow and slide off the sensor.

Collar slip:
Nylon
Recyclable

Remove the brass threaded inserts and rubber O-rings to detach the sensor casing from the collar slip.



Casing:
Nylon
Recyclable

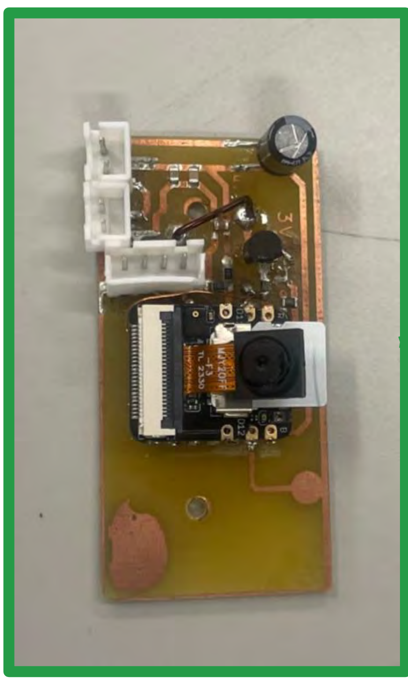
Gasket:
Rubber
Recyclable

Screws:
Brass
Recyclable

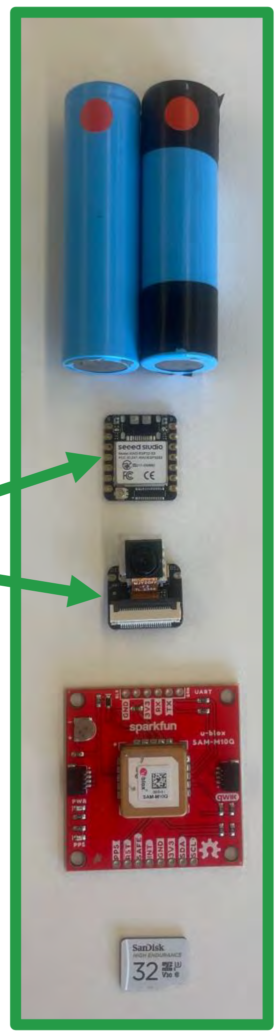
DISPOSAL

STEP 2: REMOVE AND RECYCLE ELECTRONIC COMPONENTS

Unclip the camera and SD card. Desolder the microcontroller from the printed circuit board (PCB). Remove the batteries and GPS from their fitted components
Recycle each component, along with the PCB, as E-waste.



PCB



Batteries

Microcontroller unit

Camera unit

GPS unit

SD card

DISPOSAL

GUIDELINES BY COMPONENT

Component(s)	Classification	UK Guidelines
Casing (Nylon) Collar slip (Nylon)	• Plastic waste • Non-hazardous • Recyclable UK Waste code: 17-02-03	GOV UK Plastic Waste
O-rings (Rubber)	• Consumer waste • Non-hazardous • Recyclable	Gov UK Consumer Waste
Threaded inserts (Brass)	• Metallic waste • Non-hazardous • Recyclable UK Waste code: 17-04-01	Gov UK Metallic Waste
Camera	• Category 4 E-waste: Consumer equipment • Recyclable	Gov UK E-Waste
Battery GPS Micro-controller SD card	• Category 3 E-waste: IT and telecommunications equipment • Recyclable	Gov UK E-Waste

Alternatively, repurpose your device using DAISY's open-source code. This can be found at WWW.DAISYSENSING.COM

DAISY was created as the 2024 Team Challenge Project under the Centre for Doctoral Training in Sensor Technologies and Applications for a Healthy and Sustainable Future. DAISY was created by the 2023/24 student cohort in collaboration with Rothamsted Research.

This project was funded by the EPSRC through the Centre for Doctoral Training in Sensor Technologies and Applications for a Healthy and Sustainable Future.

August 2024

B.2 Market Research

Table 15: A record of market research activities throughout the project with associated findings.

Source	Date	Industry	Main Topics
Meeting with Thomas Turner	18/06/2024	Agricultural Consultant	UK grants fail to incentivise farmers due to the time and human resources around records keeping and audits.
Farmer's Weekly Transition Talk	20/06/2024	Agricultural Broadcaster	The need for automated approaches to reduce the time and human resources around grant application was thoroughly discussed.
Meeting with Harry Rogers	27/06/2024	Academic - Agriforwards CDT	The role of academia in the future of UK farming - particularly in measuring species distribution and biodiversity assessment.
Meeting with Paul Harris	04/07/2024	Academic - Rothamsted Research	Current methods for assessing biodiversity in industry and academia. The requirement for automated approaches was highlighted.
Meeting with Deborah Beaumont	09/07/2024	Academic - Rothamsted Research	Current sampling approaches used in academia and industry.
Meeting with Paul Harris	18/07/2024	Academic - Rothamsted Research	Currently available statistical packages (in R) for Global Weighted Regression and Geospatial analysis.
Meeting with Harry Rogers	24/07/2024	Academic - Agriforwards CDT	Action items for farmers and GUI
Web searches - academic literature	12/06/2024 onwards	-	-
Web searches - commercial farming practices	12/06/2024 onwards	-	-
Web searches - Government subsidies	12/06/2024 onwards	-	-
Web searches - Veterinary practices	12/06/2024 onwards	-	-

B.3 Creating Value

Product Milestone 2: Creating Value

This document demonstrates each point of value that can be delivered and developed throughout the project. These points of value are grouped into 6 themes. **This document should inform and drive the direction of engineering decisions towards established points of value. In this way we will be able to keep all workstreams aligned to achieve the most impactful product.**

Theme 1: Image Collection Specifications

Camera resolution

MVP: sufficient to differentiate between grass, broad-leaved plants and bare soil, such that the ML model can classify them reliably.

Next steps: Improve the reliability and accuracy with which grass, broad-leaved plants and bare soil can be classified.

Best case scenario: Classification of plants of academic and commercial interest. Sufficient to determine the presence of species as outlined by the Government subsidies described in the Product Development Plan.

Field of view

MVP: rough estimate for the field of view attached to each image. This can be done in whichever ways the device and/or data teams deem most appropriate. E.g. fix camera height to achieve known field of view and only allow pictures to be taken while the cow is in the "correct" position. Alternatively, reject inappropriate images in post-processing.

Next steps: reduce uncertainty in field of view estimation for more accurate estimation of sampled area via "quadrat" (image) sampling.

Best case scenario: uniform field of view between each image with high spatial resolution. Highly accurate estimation of total sampled area.

Theme 2: Power Mangement

Battery life

MVP: Battery life of 3-4 weeks. Preserving battery for 4 weeks is the limiting factor and restricts the sampling approach.

Next steps: Battery life of 4 weeks whilst accommodating the determined optimal sampling approach to ensure statistical significance.

Best case scenario: Enhanced battery life due to the integration of a renewable power source i.e., solar panel. Any sampling approach can be supported.

Image coverage

MVP: Images are taken as often as possible within power capacity constraints i.e., 15 minutes - the same time slot used by Rothamsted sensors. The GPS location is checked to ensure to meet the non-overlapping conditions for random sampling.

Next steps: Integrate a method to measure the distance between device and ground to maintain a constant field of view and ensure consistency and accuracy of data.

Best case scenario: The camera is activated when the GPS location changes and only if the camera field of view respects the specified parameters i.e., at a specific height. Several images are taken at each location and the most appropriate ones are selected in the pre-processing step. This is done to ensure statistically significant coverage of the area of the field occupied by the cattle.

Theme 3: Data processing

Data transmission

MVP: Data collection by SD card. Data undergoes processing once every 4 weeks when the cows are brought in.

Next Step: Continuous data transmission via Bluetooth, WiFi and cellular for real-time monitoring of the sensor function i.e., detect any malfunction.

Best Case scenario: Continuous data transmission, continuous data processing and real-time update of the GUI.

Model development and translatability

MVP: Identification of key vegetation types for UK fields (grass and clover).

Next step: identification of all pertinent UK vegetation types (outlined in Product Development Plan, section 4).

Best case scenario: Easily accessible model that can identify vegetation species that are important for monitoring in developing areas and inaccessible geographic locations. Uptake by scientists around the world who want to adopt the technology and alter the model for the plants of interest in their location. Open-source data creates large-scale vegetation maps.

Classification ability

MVP = x,y location (GPS) and classification into Yes/No based on presence or absence of species of interest.

Next step = x,y,z where z is the magnitude - the spatial analysis is performed in segmented pictures where each “quadrat” is divided in “subquadrats” and subsequently analyse for the presence of each species. This results in a more accurate % coverage.

Best case scenario = x,y,z_1, z_2 (z_2 is another characteristic i.e., growth stage, dead).

Data Granularity

MVP (aimed at Rothamsted): Raw data available for data manipulation by Rothamsted researchers. This will include all the images acquired in each sample period with specified time and location. Additionally, a % coverage score for the selected species will be presented.

Next steps: Raw data for Rothamsted researchers + graphical-user interface (GUI) with heat maps where each box represents an area that has been sampled. This will allow to infer qualitative conclusions and identify agricultural properties.

Best case scenario: Ideal data granularity depends on the end-user.

Academics would require raw data to interpret as they see fit. The pairing of GPS coordinates with raw data will allow vegetation patterns to be overlayed with other location-based data generated at Rothamsted. This will allow interpretation of soil health, grazing, plant biodiversity and distribution and inorganic fertilisers etc. as described in the Product Development Plan.

Farmers require data for a specific purpose rather than exploratory means. For example, for record keeping, communication with DEFRA, demonstrating compliance with subsidies and schemes outlined in the Product Development Plan. The way in which such results are presented is largely dependent on the form of data we can collect and the data processing procedures we achieve.

Theme 4: Practical implementations

Attachment location/method

MVP: attachment to the collars provided by Rothamsted Research with little/no control over camera height as the cow moves and grazes. Inappropriate images discarded in the pre-processing step.

Next step: attachment to a commercially available collar or a custom collar produced by the *Device workstream* in a way which fixes the field of view of the camera.

Best case scenario: A fully custom attachment method which allows us to fix the camera reliably. Potential "plug and play" approach which allows attachment of different types of sensors (such as VOCs, etc...).

Device protection

MVP: ensure all components of the sensor system are protected from environmental conditions i.e., weather, cow behaviour. In particular, the camera lens is protected from damage and dirt to ensure maximum image quality.

Next steps: aluminium 3D printed case and commercially produced PCB.

Best case scenario: camera cleansing and camera protection mechanical components.

Area of interest coverage

MVP: A camera is attached to 3-5 cows. Statistical tests are used to determine whether these cows have sampled the field sufficiently to make statistically significant inferences.

Next steps: Understanding of the non-sampled regions of the field. Devising a sampling approach which allows assumptions on the non-sampled regions to be made which inform the data output from these regions. Consideration of additional camera sensors per herd.

Best case scenario: Validation of the system's results by sufficiently recent manual surveys or accurate aerial images. Optimised number of sensors per sample region/herd.

Theme 5: Data output and statistical analysis

As demonstrated, within each theme that defines the value of our product, there are multiple individual points that can be optimised to achieve "the best-case scenario". All these themes and subpoints converge to effect on our data output. This is the ultimate point of value that our product provides for end users and the reason why we are working to optimise the individual components of our system. Each point of optimisation within engineering decisions affects the extent to which the sampling strategy can develop. In turn, these impact the quality of statistical inferences that can be made.

Sampling approach

MVP: collect as much data as possible in any way. Just doing this and sharing the data publicly will be accepted by the academic community and will be useful.

Next Steps: Fix the field of view to an unknown value by mounting the camera strategically so that it remains at a somewhat fixed distance above the ground.

Best case scenario: A calibration can be done which allows to estimate the size of a fixed field of view.

Statistical analysis (dependent on sampling approach)

MVP: The distribution of each species is studied using simple visualisation techniques i.e., graphs and mapping to detect either an even or a random distribution. (Tufte 1997, Carr 1999). For example a heat map made to our own specification

Next Steps: Compare the obtained findings to existing data sets to examine spatial dependence i.e., topography, soil moisture, distance from the edge (shade). Use geographical weighted regression (GWR) to represent any spatial variation and explore any potential relationship between these variables. Use species distribution models (SDM) to predict the distribution of a species across geographic space and time using environmental data.

Best Case Scenario: Random sampling is successfully achieved allowing any statistical models to be run

Data Visualisation and Graphical-User-Interface

MVP: No data visualisation is specified in the MVP document.

Next step: Heat maps are produced for the GUI. Simple statistical tests and graphs can be presented to allow end-users to easily interpret the data and draw statistical conclusions on the distribution of species of interest.

Best case scenario: Aerial images of the field can be taken and overlayed with the close-up cow images at each sampled coordinate. This allows to create a digital twin platform to visualise the sampled field.

Additionally, the GUI will include interactive maps to allow the user to select plant species and visualise their distribution or select a specific area of the field for statistical tests. This will enable to visualise the trends for each plant species or in each field subsection.

Theme 6: Public outreach

Outreach

MVP: The project will be presented to the public during CEB Open Day and promoted through the social media pages of the CDT and of each of our colleges if the college communication teams are contacted. Additionally, a social media account will be created to do regular updates on the progress of this project.

Next step: Reach out to local news media outlets, university newspapers and technology societies.

Best case scenario: Research dissemination through scientific publications.

C Appendix - Science and Technology: System Requirements

C.1 Data Granularity

M4 Data Granularity

The level of data manipulation which we output to end users increases with the value which we can provide. Here we describe the increasing levels of data granularity as guided by the M2 document. Each level of granularity builds upon the previous, with everything available at MVP level also being available for the next steps and so on.

MVP:

The MVP is aimed at Rothamsted and is concerned with presenting data in its **raw** form. Therefore, we will provide the **raw images** that were taken by the sensor system and an **Excel workbook** with the data that is created. This document will be in alignment with the current platform used in the North Wyke Farm. This will include:

- The **GPS information** of each photograph;
- The **date and time** at which the photograph was taken;
- The **binary species classification** (Yes/No) obtained from the machine learning algorithm for each photograph.

Photograph_ID	Date	Time	GPS coordinates	Lolium perenne	Trifolium repens	Bare ground	Dung
	dd/mm/yyyy	hh:mm	xx.xxxx N, xx.xxxx E	Yes/No	Yes/No	Yes/No	Yes/No

Rothamsted and other research institutes which decide to take up the technology can use and manipulate the data as they see fit.

Next steps:

The next achievable steps involve taking raw data which **does not require a specific sampling approach** and presenting it in ways that allow **patterns** in the field to be observed. This involves a **heat map made to our specifications** based on vegetation classifications as well as using geographically weighted regression (**GWR**) to make heat maps of our data paired with other data available about the field (for example, soil properties and elevation). Additionally, we can overlay the images we collect with a macro **aerial image** which allows the production of a **digital twin platform**.

Best case scenario:

The best-case scenario provides a user interface which enables **toggling between different types of analysis, some of which require random sampling.** This would enable a range of user types to explore the data in the way which is most valuable to them, along with allowing the download of raw data. Some of the enhanced analysis types would provide information on **spatial dependence** and **anisotropy** via a **range of statistical analysis approaches**.

By ensuring that the analysis strategies align with the information required by DEFRA when performing audits, farmers can easily use the data outputs to keep robust records for applying to subsidies.

D Appendix - Science and Technology: Device

D.1 Alternations from Initial MVP

During the development of the device, several changes from the initial KWAs were implemented, including:

- Multiple devices were installed to increase the field coverage. This provides valuable insights on cows' movement to find the optimal number of devices required per herd or field.
- The device intelligence was upgraded via the use of a GPS module that provides information on location, date and time to easily track cattle movement over time.
- A tilt switch was implemented to ensure that the device is only turned on when it is in the correct orientation to prevent the imaging of subjects other than the ground and optimise the device power management.
- The USB interface to recharge the lithium batteries was removed to reduce the number of water ingress points and ensure robustness in the field. The batteries will need to be replaced by the user, hence also eliminating the device downtime associated with recharging.
- The data output was modified to include a ZIP file containing a CSV which can be easily uploaded in the provided web platform. This represents a more structured, convenient and user-friendly way to handle the collected data.

Overall, the alterations from the initial MVP have contributed to the development of a user-friendly device with enhanced functionality and an improved user experience.

D.2 Energy Consumption Per Sample

As longevity is one of the device's most important key performance indicators (KPIs), we compiled an extensive power management report to ensure our battery life targets were met. As part of this process, the minimum estimated energy consumption per sample for each component was calculated, as detailed below. In reality, more power is consumed than expected due to numerous factors, including routing resistance, transistor leakage current and non-ideal voltage regulation.

D.2.1 Microcontroller (MCU)

We estimated that the MCU should consume roughly 0.01246mAh every five minutes, with the clock frequency set to 80 MHz), as shown in Table 16.

Phase	Current (mA)	Time (s)	Energy (mAh)
Modem-Sleep	16.2 (40 MHz) 28.4 (80 MHz) [35]	1.5	0.00675 (40 MHz) 0.01180 (80MHz)
Deep-Sleep	0.008 [35]	298.5	0.00066
Total	-	300	0.01246

Table 16: Estimated energy consumed by the SEEED Studio XIAO ESP32-S3 Sense across one five-minute sampling period at different clock frequencies, assuming that all peripheral clocks are disabled and operations are applied to 32-bit variables using only one core.

D.2.2 Camera

Meanwhile, we estimated that the camera should consume roughly 0.00372mAh every five minutes, assuming that an image can be taken in one-fifteenth of a second, as shown in Table 17.

Phase	Current (mA)	Time (s)	Energy (mAh)
Recording (15 FPS)	110 (Typ) 140 (Max) [36]	0.067	0.00205 (Typ) 0.00261 (Max)
Standby	0.02 (Typ) 0.05 (Max) [36]	≈ 300	0.00167 (Typ) 0.00417 (Max)
Total	-	300	0.00372 (Typ) 0.00678 (Max)

Table 17: Estimated energy consumed by the OV5640 camera across one five-minute sampling period.

D.2.3 GPS Module

As shown in Table 18, the SAM-M10Q GPS module should consume 0.00663mAh every five minutes, assuming a hot start (which should apply every time after the first boot) and hardware backup mode.

Phase	Current (mA)	Time (s)	Energy (mAh)
Acquisition	12 (I_{VCC}), 2.3 (I_{V_IO}) 14.3 ($I_{VCC} + I_{V\_IO}$) [37]	1 (Hot Start) 23 (Cold Start) [37]	0.00397 (Hot Start) 0.0913 (Cold Start)
Sleep	0.032 (I_{V_BACKUP}) 0.046 ($I_{VCC} + I_{V\_IO}$) [37]	299 (Hot Start) 277 (Cold Start)	0.00266 (Hot Start, I_{V_BACKUP}) 0.00382 (Hot Start, $I_{VCC} + I_{V\_IO}$)
Total	-	300	0.00663 (Hot Start, I_{V_BACKUP}) 0.00779 (Hot Start, $I_{VCC} + I_{V\_IO}$)

Table 18: Estimated energy consumed by the SAM-M10Q GPS module across one five-minute sampling period using the GPS+GAL+GLO configuration.

D.2.4 Accelerometer

As shown in Table 19, the accelerometer's energy consumption per cycle is dominated by its sleep mode, instead of its turn-on time and current draw during readings. We estimated that, assuming that the sampling period is equal to the LIS2DH12's turn-on time and that the output data rate (ODR) equals 1 Hz, it should consume 0.0426nAh every five minutes.

Mode	Current (μA)	Time (ms)	Energy (nAh)
Normal	11 (50 Hz) 2 (1 Hz) [68]	1.6 [68]	0.00489 (50 Hz) 0.000889 (1 Hz)
Low-Power	6 (50 Hz) [68]	1 [68]	0.00167
Sleep	0.5 [68]	≈ 300	0.0417
Total	-	300	0.0466 (Normal, 50 Hz) 0.0426 (Normal, 1 Hz)

Table 19: Estimated energy consumed by the LIS2DH12 accelerometer across one five-minute sampling period with an output data rate (ODR) of either 50 Hz or 1 Hz.

D.3 PCB Pseudo-Circuit Diagram

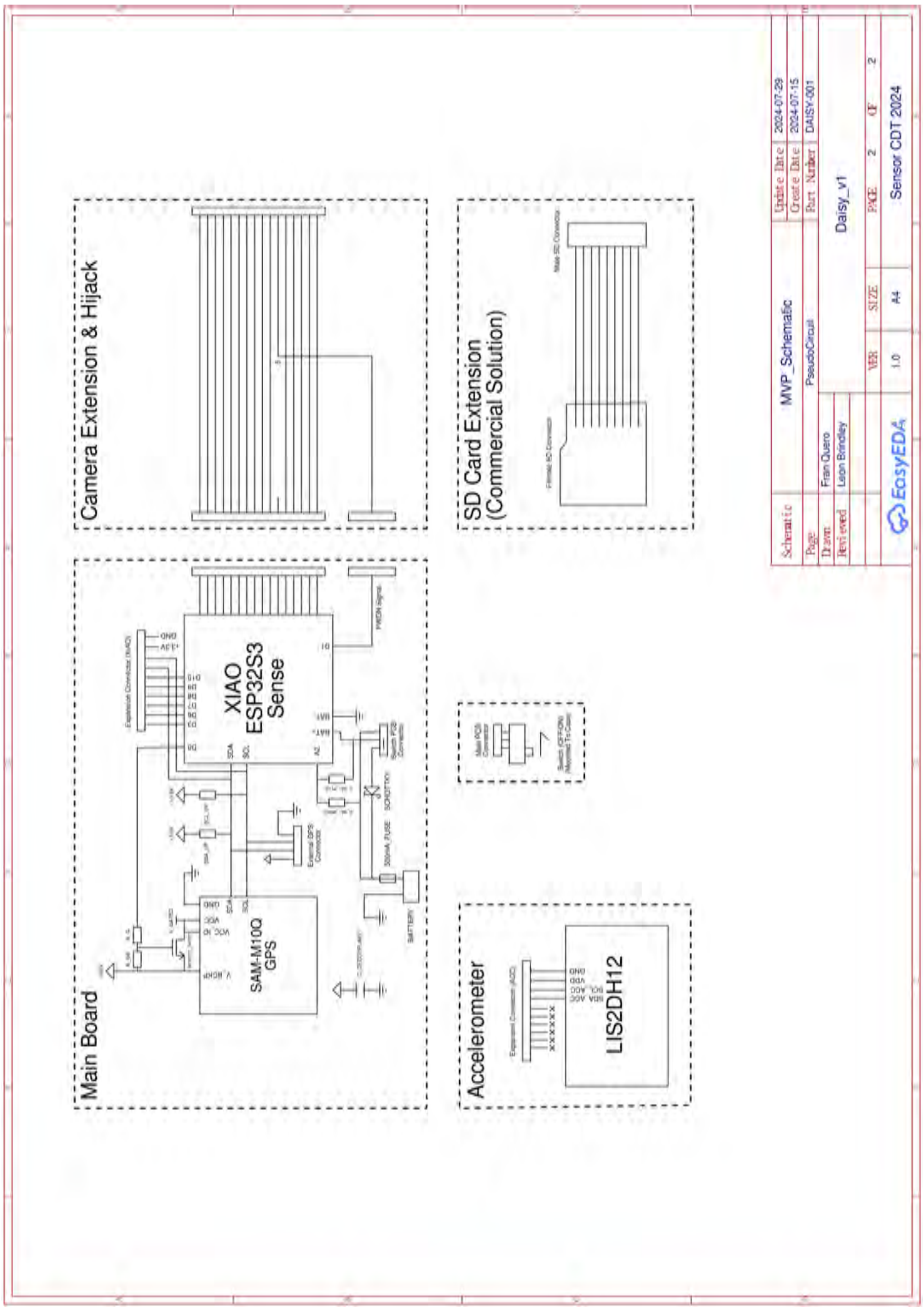


Figure 56: EasyEDA PCB pseudo-circuit diagram for our minimum viable product (MVP).

D.4 PCB Schematic

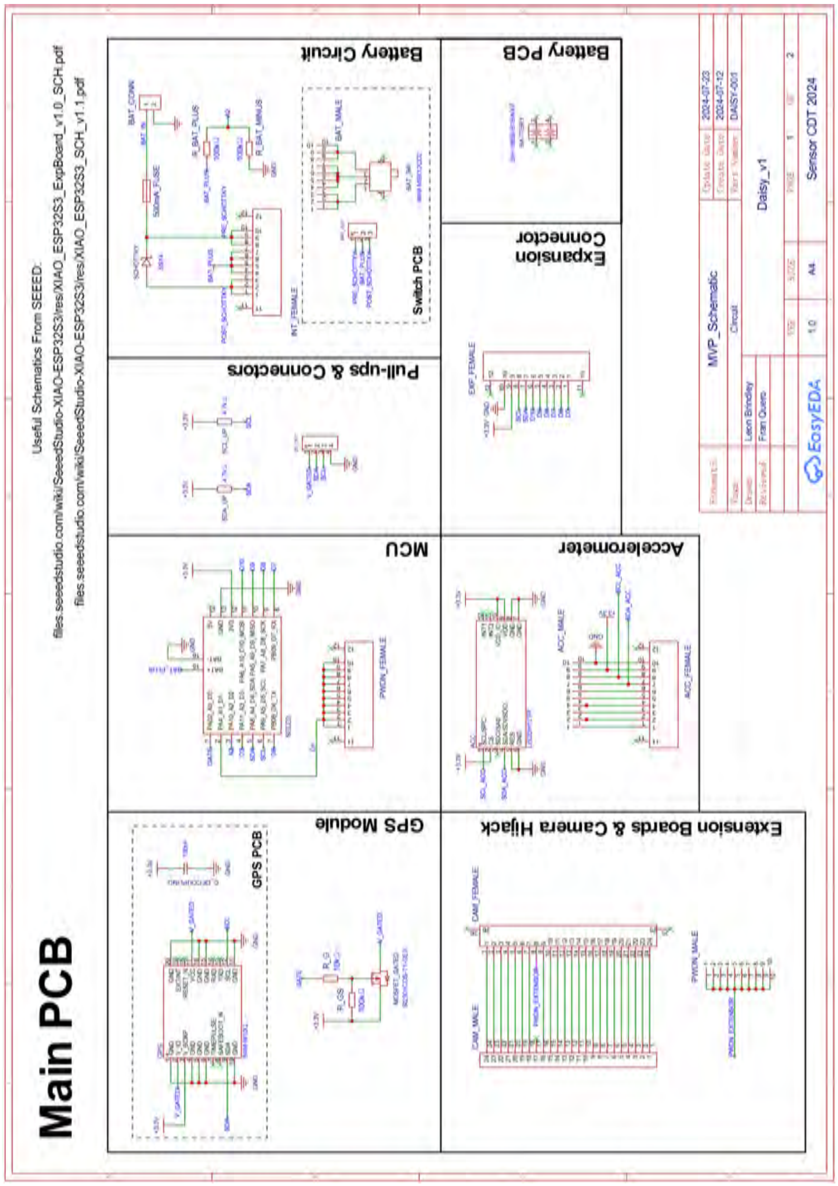


Figure 57: EasyEDA PCB schematic for our minimum viable product (MVP).

D.5 PCB Layout

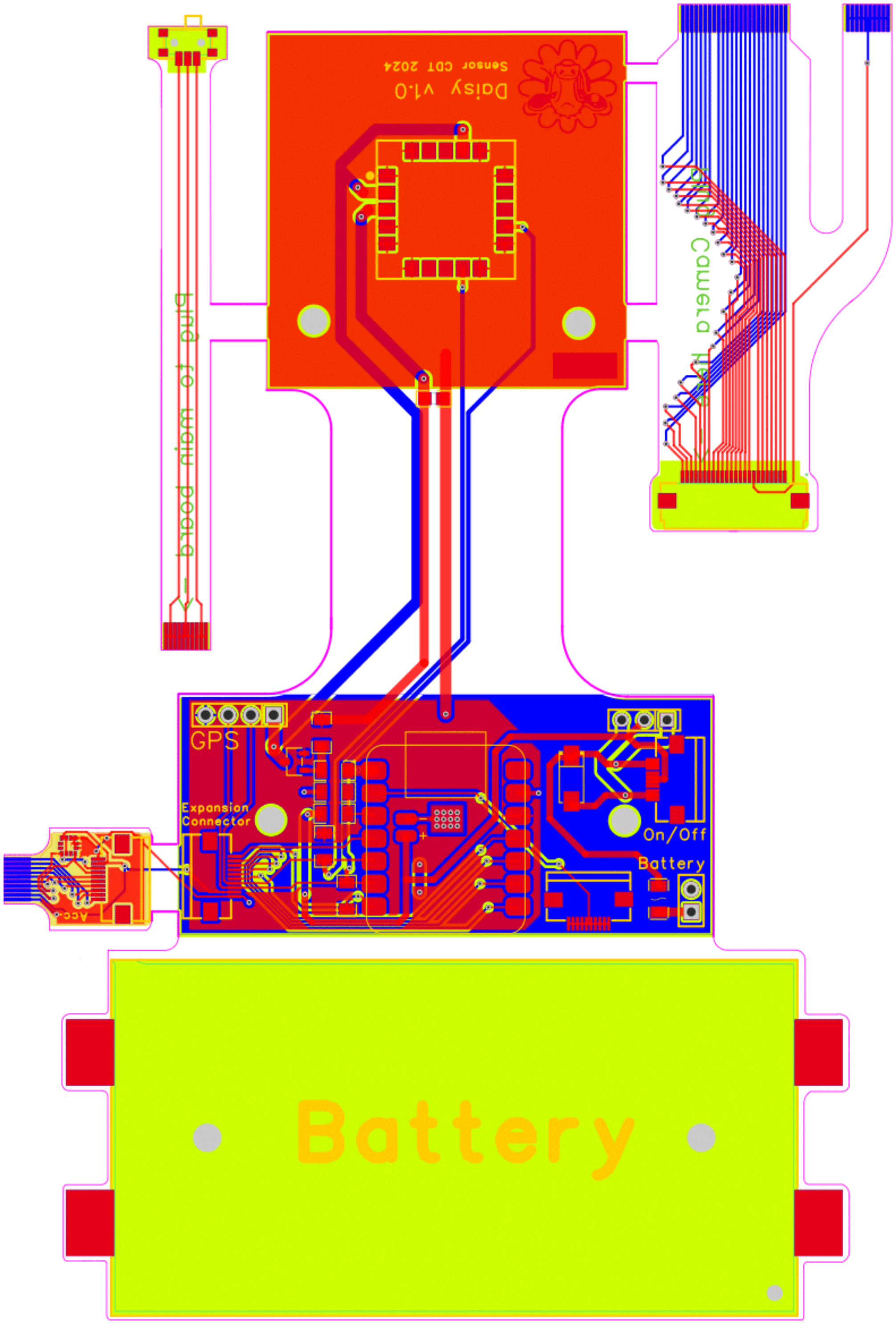


Figure 58: EasyEDA PCB layout for our minimum viable product (MVP).

D.6 PCB 3D Render

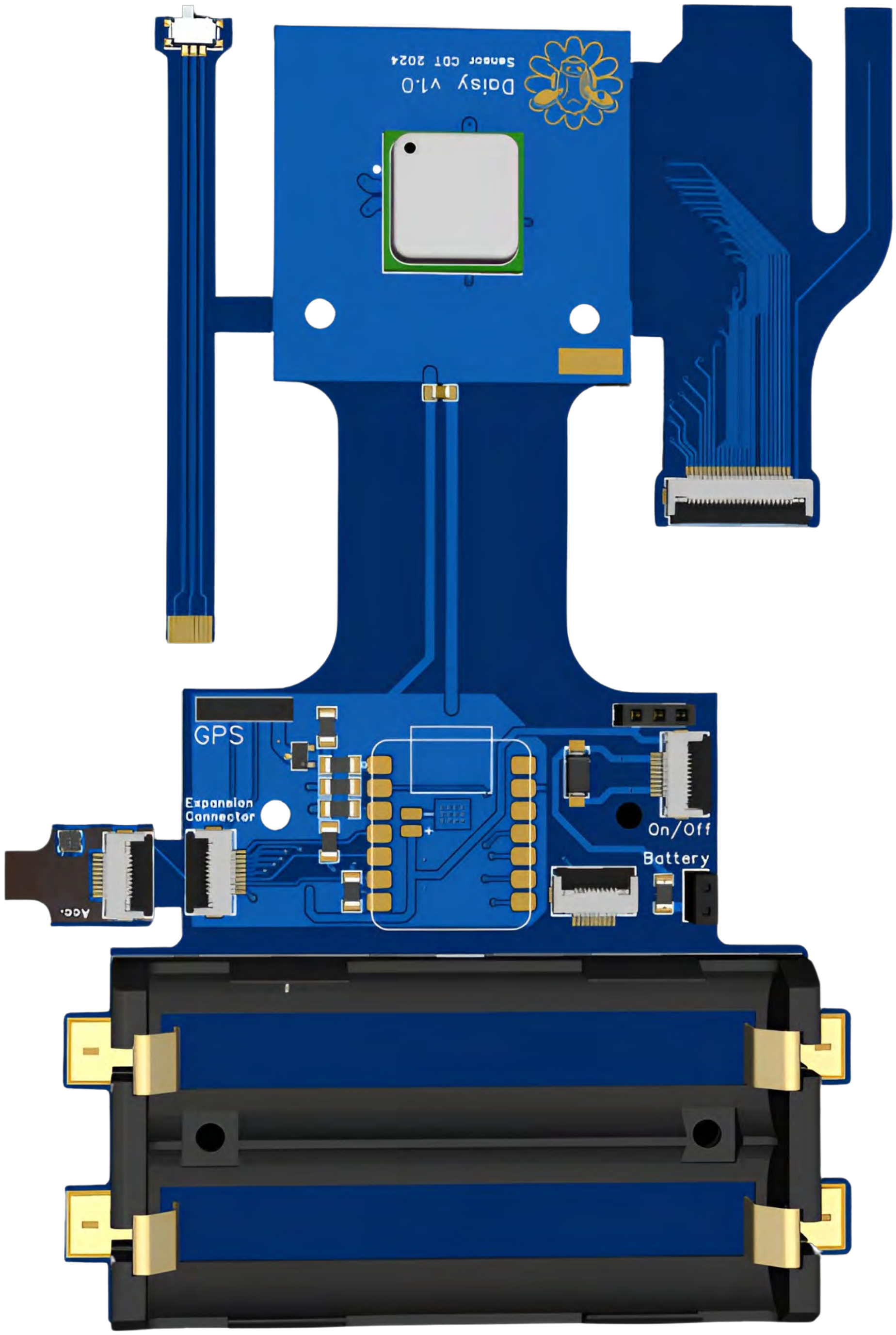


Figure 59: EasyEDA 3D render for our minimum viable product (MVP).

D.7 Custom XIAO ESP32S3 Sense Variant

To explore the possibility of overcoming the limitations of the XIAO development board, especially the inability to control the power pins to the camera, we created a custom board based on the XIAO schematics.

Figure 60 shows a render of this design. Figure 61 shows the complete rigid PCB, including all of the SMD components and the camera. After re-working two minor routing errors, the design successfully captured high-quality images and saved them to a microSD card.

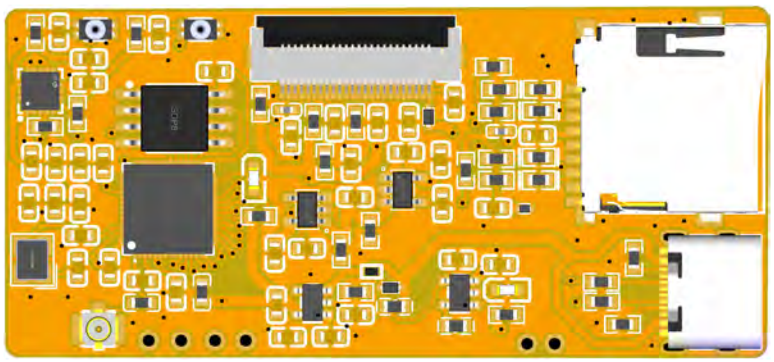


Figure 60: EasyEDA 3D render with new components to replace the XIAO ESP32S3 Sense.

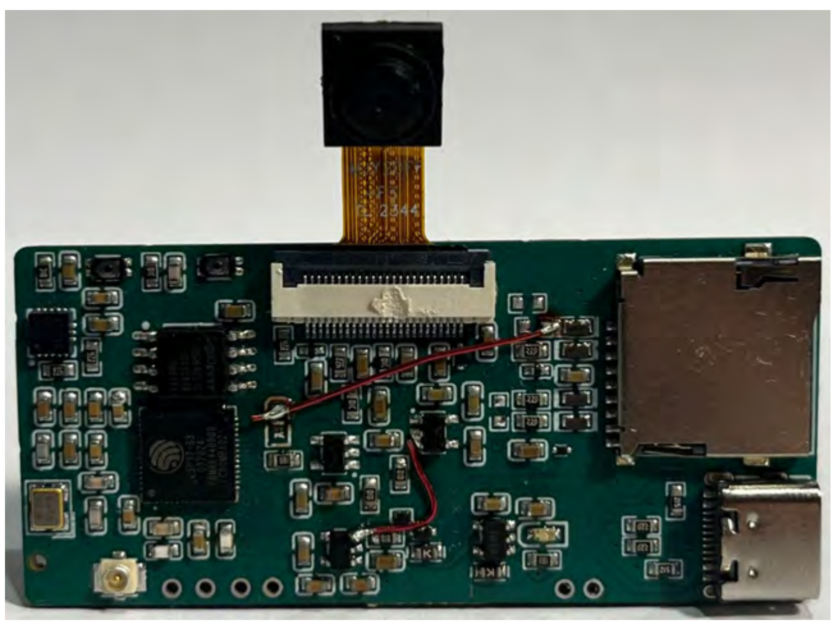


Figure 61: Custom Variant of XIAO development board.

D.8 Bill of Materials (BOM)

Item	Unit Price	Quantity	Total Price	Source
SanDisk High Endurance 32GB microSD Card	£9.49	1	£9.49	Amazon
microSD Male-to-Female Extension Cable	£11.88	1	£11.88	Amazon
USB Type-C Male-to-Female Extension Cable	£14.80	1	£14.80	Amazon
OV5640 Autofocus Camera (72° Lens)	£30.98	1	£30.98	Amazon
Flexible Two-Layer Printed Circuit Board	£26.50	1	£26.50	JLCPCB
Seeed XIAO ESP32S3 Sense	£13.00	1	£13.00	DigiKey
Quick-Release Cattle Collars	£11.40	1	£11.40	Shearwell
M3 Brass Threaded Inserts	£0.167	4	£0.668	RS
M4 Brass Threaded Inserts	£0.175	4	£0.70	RS
M3 Stainless Steel Machine Screws	£0.0877	4	£0.3508	RS
M4 Stainless Steel Machine Screws	£0.1411	4	£0.5644	RS
RS PRO 18650 2.6Ah Rechargeable Batteries	£8.76	2	£17.52	RS
2mm Acrylic for Exterior Casing	$/cm^2$	cm^2	£	Sheet Plastics

Table 20: The complete bill of materials (BOM) per cattle-mounted device (where all prices include VAT). Note that the M3/M4 inserts and screws come in packs of 100.

D.9 List of Required Arduino Libraries

To compile our code, these libraries must be included through the Arduino IDE's Library Manager. Furthermore, the board should be set to 'XIAO_ESP32S3', the correct COM port must be selected and Espressif's ESP32 board package should be installed under File->Preferences.

- SD
- OV5640 Auto Focus for ESP32 Camera
- SparkFun LIS2DH12 Arduino Library
- SparkFun LIS3DH Arduino Library
- SparkFun u-blox GNSS v3

(a) Original (b) Strength 5 (c) Strength 6 (d) Strength 7 (e) Strength 8

Figure 62: Example of determining motion blur strength augmentation parameter.(a) Original image. (b) Strength: 5. Accepted, because it is significantly different from the original image. (c) Strength: 6. Rejected, because it looks similar to strength 5 (b) and strength 7 (d). (d) Strength 7. Accepted, because it is significantly different from strength 5 (b). (e) Strength 8. Rejected, because the motion blur is too intensive. The clover feature is lost.

E Appendix - Science and Technology: Data

E.1 Image Augmentation

E.1.1 Image Augmentation Parameters

The parameters used for each argumentation method are shown in Table 21. For rotation, the parameter is in degrees. Only degrees that are multiples of 90 degrees were used to prevent the requirement to fill in empty pixels. For mirroring, the parameter is the direction of the mirroring (horizontal mirror or vertical mirror). For brightness change, the parameter is in values added or subtracted from the original pixel value in HSV colour space. For motion blur, parameter 1 is the kernel size of the blur matrix (ie, the magnitude of the blur). Parameter 2 is the direction of the blur in degrees. For Gaussian noise, the parameter is the standard deviation of the Gaussian noise (ie, the magnitude of the noise).

Table 21: List of augmentation parameters for each augmentation method used.

Augmentation Method	**Parameter 1**	**Parameter 2**
Rotation	90, 180, 270	NA
Mirroring	horiz, vertical	NA
Brightness Change	±50, ±75, ±100	NA
Motion Blur	3, 5, 7	0, 90, 180, 270
Gaussian Noise	0.6, 0.7, 0.8	NA

E.1.2 Image Augmentation Parameter Determination

As mentioned in §7.1.5, the image augmentation is qualitatively determined. The criterion for these parameters is that the resulting image should, at the same time, look significantly different from the original image and from images that had applied the same augmentation method but with different parameters. Figure 62 shows an example on how the parameters were determined.

E.1.3 Image Augmentation Examples

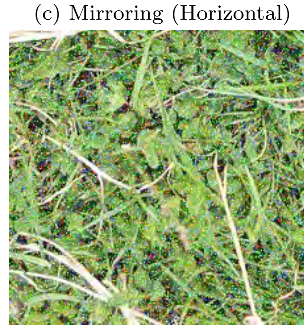
(a) Original

(b) Rotation (90 Degree)

(c) Mirroring (Horizontal)

(d) Brightness Change (+75)

(e) Motion Blur (Intensity: 7, Direction: 90 Degree)



(f) Gussian Noise (Intensity: 0.8)

E.2 Machine Learning Model Experiments

E.2.1 Experiment 1

Parameter	Values
Learning Rate	1e-3, 1e-4, 1e-5, 1e-6, 1e-7
Extra Perceptron?	TRUE, FALSE
# Outer Layers Fine-Tuned	AlexNet: [1..8]
	DenseNet121: [1..9]
	iNaturalist: [1..5]
	InceptionV3: [1..13]
	PlantNet: [1..5]
	ResNet50: [1..5]
	VGG16: [1..7]

Table 22: Experiment 1 model parameters (most combinations tried).

Model Name	Accuracy	F1 Score	Learning Rate	Perceptron?	# Layers Fine-Tune
inaturalist	95.0%	94.6%	0.0001	FALSE	5
densenet121	95.1%	94.5%	0.0001	TRUE	7
inaturalist	94.7%	94.1%	0.0001	TRUE	4
inaturalist	94.6%	94.0%	0.0001	TRUE	3
inaturalist	94.6%	94.0%	0.0001	FALSE	3
densenet121	94.8%	93.9%	0.0001	FALSE	7
densenet121	94.6%	93.7%	0.0001	TRUE	9
inaturalist	94.5%	93.7%	0.0001	FALSE	2
inaturalist	94.5%	93.6%	1e-05	TRUE	4
inaturalist	94.5%	93.5%	0.001	FALSE	2
densenet121	94.3%	93.4%	0.0001	TRUE	6
inaturalist	94.4%	93.3%	0.0001	TRUE	2
inaturalist	94.3%	93.3%	0.0001	FALSE	4
plantnet	94.2%	93.3%	0.0001	FALSE	3
inaturalist	94.3%	93.3%	1e-05	FALSE	3
inaturalist	94.2%	93.2%	1e-05	TRUE	5
plantnet	94.2%	93.2%	1e-05	FALSE	3
plantnet	94.1%	93.2%	0.0001	TRUE	3
inaturalist	94.4%	93.2%	1e-05	TRUE	2
densenet121	94.0%	93.2%	0.0001	TRUE	5
inceptionv3	94.1%	93.1%	0.0001	TRUE	10
plantnet	93.9%	93.1%	0.0001	FALSE	4
densenet121	94.1%	93.1%	1e-05	FALSE	6
inceptionv3	94.0%	93.1%	0.0001	TRUE	12
vgg16	93.8%	93.1%	0.0001	TRUE	6
resnet	94.0%	93.1%	0.0001	TRUE	3
resnet	94.2%	93.1%	0.0001	TRUE	5
vgg16	93.9%	93.0%	1e-05	FALSE	7
inaturalist	94.0%	93.0%	1e-05	FALSE	5
densenet121	94.1%	93.0%	0.0001	FALSE	8

resnet	93.8%	93.0%	0.0001	FALSE	5
plantnet	94.0%	93.0%	0.0001	FALSE	5
inaturalist	94.1%	93.0%	1e-05	TRUE	3
inceptionv3	94.0%	93.0%	0.0001	FALSE	11
densenet121	93.9%	93.0%	0.0001	FALSE	5
plantnet	93.7%	93.0%	1e-05	FALSE	5
inaturalist	93.8%	92.9%	1e-05	FALSE	4
plantnet	93.8%	92.9%	1e-05	FALSE	2
resnet	93.8%	92.9%	0.0001	FALSE	3
densenet121	94.0%	92.9%	0.001	TRUE	7
densenet121	93.9%	92.8%	0.0001	TRUE	4
resnet	93.8%	92.8%	0.0001	FALSE	4
vgg16	93.9%	92.8%	1e-05	FALSE	6
inceptionv3	94.0%	92.7%	0.0001	TRUE	13
inaturalist	93.8%	92.7%	1e-06	TRUE	3
inceptionv3	93.8%	92.7%	0.0001	FALSE	12
inceptionv3	93.0%	92.7%	0.0001	FALSE	8
inaturalist	93.8%	92.7%	0.0001	TRUE	5
densenet121	93.8%	92.7%	0.001	TRUE	6
plantnet	93.7%	92.7%	1e-05	TRUE	4
inceptionv3	94.0%	92.7%	0.0001	FALSE	13
densenet121	93.8%	92.7%	0.0001	FALSE	9
densenet121	94.0%	92.7%	0.0001	TRUE	8
plantnet	93.9%	92.7%	0.0001	TRUE	5
vgg16	93.6%	92.7%	1e-05	TRUE	6
inceptionv3	93.5%	92.7%	0.0001	FALSE	10
densenet121	93.8%	92.7%	0.001	FALSE	8
densenet121	93.7%	92.6%	1e-05	TRUE	7
densenet121	93.7%	92.6%	0.0001	FALSE	4
densenet121	93.4%	92.6%	0.001	TRUE	8
plantnet	93.6%	92.6%	1e-05	TRUE	2
plantnet	93.7%	92.6%	1e-05	TRUE	5
densenet121	93.6%	92.6%	1e-05	TRUE	4
vgg16	93.3%	92.5%	0.0001	FALSE	6
resnet	93.8%	92.5%	0.0001	TRUE	4
vgg16	93.5%	92.5%	0.0001	FALSE	7
resnet	93.6%	92.5%	1e-05	FALSE	3
densenet121	93.6%	92.5%	0.0001	TRUE	3
inceptionv3	93.7%	92.5%	0.0001	TRUE	11
vgg16	93.6%	92.5%	1e-05	TRUE	7
densenet121	93.4%	92.5%	0.001	TRUE	9
densenet121	93.6%	92.4%	1e-05	TRUE	5
plantnet	93.4%	92.4%	0.001	TRUE	5
densenet121	93.3%	92.4%	0.001	TRUE	3
inaturalist	93.7%	92.4%	0.001	TRUE	2
densenet121	93.3%	92.4%	1e-05	FALSE	4
inaturalist	93.7%	92.4%	1e-05	FALSE	2
plantnet	93.3%	92.4%	0.001	FALSE	3

densenet121	93.3%	92.3%	1e-05	FALSE	5
densenet121	93.2%	92.3%	0.001	FALSE	9
densenet121	93.3%	92.3%	1e-05	FALSE	3
plantnet	93.4%	92.3%	0.001	FALSE	2
vgg16	93.1%	92.3%	1e-05	FALSE	5
resnet	93.5%	92.3%	1e-05	TRUE	2
resnet	93.1%	92.3%	0.001	FALSE	3
resnet	93.3%	92.3%	0.001	TRUE	2
plantnet	93.6%	92.2%	1e-05	FALSE	4
densenet121	93.3%	92.2%	1e-05	TRUE	3
vgg16	93.4%	92.2%	1e-05	TRUE	5
plantnet	93.2%	92.2%	0.0001	TRUE	2
inaturalist	93.3%	92.2%	0.001	TRUE	5
densenet121	93.3%	92.2%	0.0001	FALSE	3
densenet121	93.3%	92.2%	1e-05	TRUE	8
resnet	93.2%	92.2%	1e-05	FALSE	4
inceptionv3	93.1%	92.1%	0.0001	TRUE	8
densenet121	93.3%	92.1%	1e-05	FALSE	8
resnet	93.3%	92.1%	1e-05	TRUE	3
resnet	93.2%	92.1%	1e-05	FALSE	5
resnet	93.3%	92.1%	0.0001	TRUE	2
plantnet	93.3%	92.1%	1e-05	TRUE	3
resnet	93.1%	92.1%	1e-05	FALSE	2
plantnet	92.9%	92.1%	0.001	TRUE	2
vgg16	93.1%	92.0%	0.0001	FALSE	5
densenet121	93.2%	92.0%	1e-05	FALSE	9
inceptionv3	93.2%	92.0%	0.0001	FALSE	9
vgg16	93.0%	92.0%	0.0001	TRUE	5
resnet	93.2%	92.0%	1e-05	TRUE	4
densenet121	93.5%	92.0%	0.001	FALSE	7
inaturalist	93.2%	92.0%	1e-06	FALSE	4
densenet121	93.3%	92.0%	0.001	FALSE	3
densenet121	93.2%	92.0%	1e-05	FALSE	7
vgg16	93.0%	92.0%	1e-05	TRUE	4
densenet121	93.1%	91.9%	1e-05	TRUE	6
resnet	93.1%	91.9%	1e-05	TRUE	5
inaturalist	92.8%	91.9%	0.001	FALSE	4
densenet121	93.1%	91.8%	0.001	TRUE	5
plantnet	93.3%	91.8%	0.0001	FALSE	2
resnet	92.9%	91.8%	0.001	FALSE	4
resnet	93.1%	91.8%	0.001	FALSE	2
plantnet	92.8%	91.8%	0.0001	TRUE	4
densenet121	93.1%	91.8%	0.001	TRUE	4
inceptionv3	93.5%	91.8%	0.001	FALSE	7
resnet	92.8%	91.8%	1e-06	TRUE	4
inceptionv3	92.7%	91.7%	0.0001	FALSE	7
densenet121	93.1%	91.7%	0.0001	FALSE	6
vgg16	92.6%	91.7%	1e-05	TRUE	2

alexnet	92.9%	91.7%	0.0001	TRUE	7
densenet121	92.8%	91.7%	1e-05	TRUE	9
vgg16	92.9%	91.7%	1e-05	FALSE	4
resnet	92.7%	91.7%	1e-06	TRUE	5
inaturalist	93.0%	91.6%	1e-06	FALSE	5
inaturalist	92.8%	91.6%	1e-06	TRUE	4
vgg16	92.7%	91.6%	0.0001	TRUE	7
inceptionv3	92.8%	91.6%	0.001	TRUE	12
inceptionv3	92.8%	91.6%	0.001	TRUE	7
inceptionv3	93.0%	91.6%	1e-05	FALSE	11
inceptionv3	92.7%	91.5%	1e-05	TRUE	9
alexnet	92.6%	91.5%	0.0001	FALSE	6
vgg16	92.7%	91.5%	0.0001	FALSE	4
inceptionv3	92.8%	91.5%	0.0001	TRUE	9
plantnet	92.8%	91.5%	0.001	FALSE	5
inaturalist	92.7%	91.5%	1e-06	TRUE	5
vgg16	92.5%	91.5%	0.001	TRUE	2
alexnet	92.9%	91.4%	1e-05	TRUE	7
alexnet	92.9%	91.4%	0.0001	TRUE	5
inceptionv3	92.9%	91.4%	1e-05	FALSE	8
inaturalist	92.8%	91.4%	0.001	FALSE	5
vgg16	92.9%	91.4%	1e-06	FALSE	7
resnet	92.6%	91.4%	0.001	TRUE	3
inceptionv3	92.8%	91.4%	1e-05	FALSE	10
vgg16	92.6%	91.4%	0.0001	TRUE	3
vgg16	92.3%	91.4%	0.0001	FALSE	3
vgg16	92.3%	91.3%	0.001	FALSE	1
vgg16	92.4%	91.3%	1e-05	FALSE	3
inceptionv3	92.5%	91.3%	1e-05	TRUE	12
inaturalist	92.7%	91.3%	1e-06	TRUE	2
plantnet	92.8%	91.3%	0.0001	TRUE	1
inceptionv3	92.5%	91.3%	1e-05	TRUE	13
alexnet	92.7%	91.3%	0.0001	FALSE	7
inceptionv3	92.6%	91.3%	1e-05	FALSE	12
inceptionv3	92.5%	91.3%	0.001	TRUE	11
vgg16	92.6%	91.2%	0.0001	TRUE	4
resnet	92.3%	91.2%	0.001	TRUE	5
densenet121	92.5%	91.2%	0.001	FALSE	5
inaturalist	91.8%	91.2%	0.001	FALSE	3
vgg16	92.6%	91.2%	0.0001	TRUE	2
inaturalist	92.8%	91.2%	1e-06	FALSE	3
alexnet	92.5%	91.2%	1e-05	FALSE	8
inaturalist	92.3%	91.1%	0.001	TRUE	3
inceptionv3	92.3%	91.1%	1e-05	TRUE	10
plantnet	92.2%	91.1%	0.001	FALSE	4
vgg16	92.5%	91.1%	1e-06	FALSE	6
inceptionv3	92.3%	91.1%	0.001	FALSE	11
resnet	92.2%	91.1%	0.0001	FALSE	2

vgg16	92.1%	91.1%	1e-05	TRUE	3
vgg16	92.4%	91.1%	0.0001	TRUE	1
inceptionv3	92.3%	91.1%	0.0001	TRUE	3
inceptionv3	92.6%	91.1%	0.001	FALSE	13
alexnet	92.3%	91.0%	0.001	TRUE	5
resnet	92.3%	91.0%	1e-06	TRUE	3
inaturalist	92.8%	91.0%	0.0001	TRUE	1
inaturalist	92.2%	91.0%	0.001	TRUE	4
inceptionv3	92.1%	91.0%	0.001	FALSE	8
vgg16	92.3%	91.0%	1e-06	TRUE	7
inceptionv3	92.4%	91.0%	1e-05	TRUE	11
alexnet	92.3%	91.0%	1e-05	FALSE	6
inceptionv3	92.4%	91.0%	0.0001	TRUE	4
inceptionv3	92.1%	90.9%	0.001	TRUE	8
inceptionv3	92.3%	90.9%	0.0001	TRUE	7
alexnet	92.4%	90.9%	0.0001	FALSE	5
alexnet	92.5%	90.9%	1e-05	TRUE	5
alexnet	92.3%	90.9%	0.0001	FALSE	8
plantnet	92.3%	90.9%	0.001	TRUE	1
inceptionv3	92.5%	90.9%	1e-05	FALSE	13
inceptionv3	92.3%	90.9%	0.001	TRUE	9
resnet	92.2%	90.9%	0.001	TRUE	4
vgg16	92.1%	90.9%	0.001	FALSE	3
vgg16	92.0%	90.9%	0.001	TRUE	5
inceptionv3	92.1%	90.9%	0.001	FALSE	9
inceptionv3	92.3%	90.9%	1e-05	FALSE	9
alexnet	92.3%	90.8%	1e-05	TRUE	8
resnet	92.3%	90.8%	1e-06	FALSE	5
inceptionv3	92.1%	90.8%	1e-05	TRUE	8
inceptionv3	92.2%	90.8%	0.001	TRUE	6
alexnet	92.5%	90.7%	0.0001	TRUE	6
inceptionv3	92.1%	90.7%	0.0001	TRUE	6
inceptionv3	92.0%	90.7%	0.001	FALSE	12
inaturalist	92.6%	90.7%	1e-06	FALSE	2
inaturalist	92.2%	90.7%	0.001	TRUE	1
vgg16	92.2%	90.7%	0.001	TRUE	1
resnet	91.9%	90.7%	1e-06	FALSE	4
vgg16	92.1%	90.7%	1e-06	FALSE	5
inceptionv3	92.3%	90.6%	0.0001	FALSE	6
inceptionv3	92.2%	90.6%	1e-05	TRUE	7
vgg16	92.0%	90.6%	1e-05	FALSE	2
alexnet	92.3%	90.6%	0.001	TRUE	2
alexnet	92.1%	90.6%	0.0001	TRUE	8
inceptionv3	92.3%	90.6%	1e-05	FALSE	7
inceptionv3	92.3%	90.6%	0.001	FALSE	5
alexnet	92.1%	90.5%	1e-05	TRUE	6
plantnet	92.1%	90.5%	1e-06	FALSE	4
alexnet	92.1%	90.5%	1e-05	FALSE	5

inceptionv3	92.1%	90.4%	1e-05	FALSE	4
resnet	91.9%	90.4%	1e-06	FALSE	3
inceptionv3	91.8%	90.4%	0.001	TRUE	3
resnet	92.0%	90.4%	1e-06	TRUE	2
inceptionv3	92.2%	90.4%	1e-05	FALSE	5
alexnet	92.0%	90.3%	1e-05	FALSE	7
resnet	91.9%	90.3%	1e-06	FALSE	2
densenet121	91.5%	90.3%	0.001	FALSE	4
alexnet	91.9%	90.3%	0.0001	FALSE	2
alexnet	92.0%	90.3%	1e-05	TRUE	4
inceptionv3	92.2%	90.3%	1e-05	FALSE	3
plantnet	92.0%	90.3%	1e-06	FALSE	5
inceptionv3	92.0%	90.3%	1e-05	FALSE	6
inceptionv3	91.7%	90.3%	0.001	FALSE	3
alexnet	92.1%	90.2%	1e-05	FALSE	4
inceptionv3	91.7%	90.2%	0.0001	TRUE	5
inceptionv3	91.8%	90.2%	0.001	FALSE	4
resnet	91.8%	90.2%	0.001	FALSE	5
alexnet	91.8%	90.2%	0.0001	TRUE	2
alexnet	92.1%	90.2%	0.001	TRUE	1
plantnet	91.3%	90.1%	1e-06	TRUE	4
plantnet	91.9%	90.1%	0.001	FALSE	1
plantnet	91.6%	90.1%	1e-06	TRUE	3
plantnet	91.8%	90.1%	1e-06	TRUE	5
inceptionv3	91.7%	90.1%	0.001	TRUE	5
vgg16	91.6%	90.1%	0.0001	FALSE	2
vgg16	91.2%	90.1%	0.001	FALSE	5
inceptionv3	91.8%	90.1%	0.0001	FALSE	5
resnet	91.5%	90.0%	0.001	TRUE	1
plantnet	91.5%	90.0%	0.001	TRUE	3
plantnet	91.4%	90.0%	0.001	TRUE	4
inceptionv3	91.3%	90.0%	0.001	FALSE	6
alexnet	91.7%	90.0%	0.0001	TRUE	3
resnet	91.7%	90.0%	0.0001	TRUE	1
vgg16	91.5%	89.9%	1e-06	TRUE	6
densenet121	91.5%	89.9%	0.0001	TRUE	2
alexnet	91.6%	89.9%	1e-06	TRUE	7
densenet121	91.6%	89.9%	0.0001	TRUE	1
alexnet	91.7%	89.9%	1e-05	TRUE	3
inceptionv3	91.8%	89.9%	0.001	TRUE	4
vgg16	91.3%	89.9%	0.001	FALSE	6
vgg16	91.4%	89.8%	1e-06	TRUE	4
alexnet	91.9%	89.8%	0.0001	TRUE	1
plantnet	91.6%	89.8%	1e-06	FALSE	3
alexnet	91.3%	89.8%	0.001	TRUE	4
inaturalist	91.8%	89.8%	0.001	FALSE	1
inceptionv3	91.5%	89.8%	0.0001	FALSE	3
vgg16	91.3%	89.7%	1e-06	TRUE	5

densenet121	91.0%	89.7%	0.001	FALSE	6
alexnet	91.6%	89.7%	0.0001	FALSE	3
densenet121	91.7%	89.7%	0.001	TRUE	2
plantnet	91.3%	89.7%	1e-05	TRUE	1
inceptionv3	91.3%	89.7%	0.001	TRUE	13
alexnet	91.4%	89.7%	0.0001	TRUE	4
vgg16	91.4%	89.7%	0.001	TRUE	3
vgg16	91.7%	89.6%	0.001	FALSE	2
vgg16	91.3%	89.6%	1e-05	TRUE	1
alexnet	91.5%	89.6%	1e-05	TRUE	1
inceptionv3	91.4%	89.6%	1e-05	TRUE	2
inceptionv3	91.3%	89.6%	0.001	FALSE	2
alexnet	91.5%	89.6%	1e-06	TRUE	8
alexnet	91.6%	89.6%	1e-05	TRUE	2
inceptionv3	91.2%	89.6%	0.0001	FALSE	4
alexnet	91.7%	89.6%	1e-05	FALSE	3
alexnet	91.6%	89.6%	0.0001	FALSE	4
densenet121	91.4%	89.5%	1e-06	FALSE	8
vgg16	91.3%	89.5%	1e-06	FALSE	4
vgg16	91.2%	89.5%	0.0001	FALSE	1
plantnet	91.1%	89.5%	0.0001	FALSE	1
inceptionv3	91.5%	89.5%	0.0001	FALSE	2
inceptionv3	91.4%	89.5%	0.0001	TRUE	2
inceptionv3	91.4%	89.5%	0.001	TRUE	10
inceptionv3	91.2%	89.5%	1e-05	TRUE	4
inceptionv3	91.2%	89.4%	1e-05	TRUE	5
alexnet	91.3%	89.4%	0.001	FALSE	1
inceptionv3	91.3%	89.4%	1e-05	TRUE	6
resnet	91.1%	89.4%	0.001	FALSE	1
densenet121	90.9%	89.3%	0.001	FALSE	2
inaturalist	91.5%	89.3%	1e-05	TRUE	1
inceptionv3	91.4%	89.3%	1e-05	FALSE	2
vgg16	90.6%	89.3%	0.001	FALSE	7
alexnet	91.2%	89.2%	1e-06	FALSE	7
alexnet	91.3%	89.2%	0.0001	FALSE	1
alexnet	91.3%	89.2%	1e-05	FALSE	2
densenet121	91.0%	89.1%	1e-06	TRUE	6
inaturalist	91.4%	89.1%	0.0001	FALSE	1
alexnet	91.2%	89.1%	1e-06	TRUE	5
alexnet	90.9%	89.1%	0.001	TRUE	3
densenet121	90.8%	89.1%	1e-06	FALSE	5
alexnet	90.9%	89.0%	1e-06	TRUE	6
alexnet	91.1%	89.0%	0.001	FALSE	3
inceptionv3	89.9%	89.0%	0.001	FALSE	10
alexnet	91.0%	89.0%	1e-06	FALSE	5
plantnet	91.1%	89.0%	1e-06	FALSE	2
alexnet	91.1%	88.9%	1e-06	FALSE	6
densenet121	90.8%	88.9%	1e-06	TRUE	9

vgg16	90.4%	88.9%	0.001	TRUE	4
alexnet	91.1%	88.9%	1e-06	TRUE	4
alexnet	90.8%	88.9%	0.001	TRUE	6
densenet121	90.6%	88.8%	0.001	FALSE	1
inceptionv3	90.8%	88.8%	1e-06	FALSE	12
inceptionv3	91.0%	88.8%	1e-05	TRUE	3
resnet	90.7%	88.7%	0.0001	FALSE	1
vgg16	90.6%	88.7%	1e-06	TRUE	3
alexnet	90.6%	88.7%	0.001	FALSE	4
alexnet	90.7%	88.7%	1e-06	FALSE	8
densenet121	90.5%	88.6%	1e-06	FALSE	7
inceptionv3	90.6%	88.6%	1e-06	FALSE	10
resnet	90.6%	88.6%	1e-05	TRUE	1
vgg16	90.4%	88.5%	0.001	TRUE	6
inceptionv3	90.3%	88.5%	0.001	TRUE	2
densenet121	90.6%	88.4%	0.0001	FALSE	2
densenet121	90.5%	88.4%	1e-05	TRUE	1
inceptionv3	90.5%	88.3%	1e-06	FALSE	13
densenet121	90.6%	88.3%	1e-06	FALSE	9
vgg16	90.6%	88.3%	1e-06	FALSE	3
alexnet	90.7%	88.3%	0.001	FALSE	5
inceptionv3	90.2%	88.1%	1e-06	FALSE	11
densenet121	90.5%	88.1%	1e-05	TRUE	2
densenet121	90.3%	88.1%	0.001	TRUE	1
inceptionv3	90.1%	88.0%	1e-06	FALSE	9
inceptionv3	90.2%	88.0%	1e-06	FALSE	8
densenet121	90.3%	88.0%	0.0001	FALSE	1
inceptionv3	89.9%	87.7%	0.001	TRUE	1
alexnet	90.2%	87.6%	1e-06	TRUE	3
densenet121	89.8%	87.6%	1e-06	FALSE	6
vgg16	89.7%	87.5%	0.001	FALSE	4
alexnet	89.3%	87.5%	0.001	FALSE	6
alexnet	90.1%	87.5%	1e-06	FALSE	4
densenet121	90.1%	87.5%	1e-06	TRUE	5
inceptionv3	89.7%	87.2%	0.001	FALSE	1
inaturalist	89.7%	86.9%	1e-05	FALSE	1
densenet121	89.1%	86.7%	1e-06	FALSE	4
alexnet	89.6%	86.6%	1e-06	FALSE	3
alexnet	89.9%	86.6%	0.001	FALSE	2
alexnet	89.4%	86.4%	1e-06	TRUE	2
inceptionv3	89.0%	86.3%	1e-06	FALSE	6
inceptionv3	88.9%	86.2%	1e-06	FALSE	7
inceptionv3	89.4%	86.1%	0.0001	TRUE	1
inceptionv3	88.9%	85.9%	1e-06	FALSE	4
inceptionv3	88.7%	85.9%	1e-06	FALSE	5
inceptionv3	88.9%	85.8%	1e-06	FALSE	3
vgg16	89.1%	85.5%	1e-06	FALSE	2
alexnet	88.8%	85.4%	1e-06	FALSE	2

alexnet	89.0%	85.4%	1e-05	FALSE	1
inceptionv3	88.3%	85.2%	1e-05	TRUE	1
inceptionv3	88.7%	85.1%	0.0001	FALSE	1
alexnet	87.8%	84.7%	0.001	TRUE	8
densenet121	88.4%	84.6%	1e-06	TRUE	3
inaturalist	88.6%	84.3%	1e-06	TRUE	1
densenet121	87.7%	84.2%	1e-06	FALSE	3
alexnet	86.8%	84.1%	0.001	FALSE	7
vgg16	88.4%	84.0%	1e-05	FALSE	1
inceptionv3	87.2%	82.5%	1e-06	FALSE	2
alexnet	84.9%	81.8%	0.001	TRUE	7
alexnet	87.0%	81.2%	1e-06	TRUE	1
resnet	84.2%	79.8%	1e-07	FALSE	4
resnet	80.1%	76.8%	1e-07	FALSE	5
inaturalist	81.0%	76.0%	1e-07	FALSE	5
resnet	84.1%	75.6%	1e-07	FALSE	2
alexnet	83.2%	75.1%	1e-07	TRUE	7
vgg16	83.7%	75.0%	1e-06	TRUE	1
plantnet	77.8%	74.6%	1e-07	FALSE	5
inaturalist	71.7%	72.9%	1e-07	FALSE	4
vgg16	80.5%	72.6%	0.001	TRUE	7
alexnet	82.4%	71.4%	1e-07	FALSE	8
alexnet	80.3%	70.7%	1e-07	FALSE	6
plantnet	73.5%	70.1%	1e-07	FALSE	3
inaturalist	77.8%	70.0%	1e-07	FALSE	2
resnet	82.9%	68.5%	1e-07	FALSE	3
inceptionv3	75.3%	67.0%	1e-07	FALSE	6
inceptionv3	69.3%	65.9%	1e-07	FALSE	3
inceptionv3	76.5%	65.5%	1e-07	FALSE	12
alexnet	80.0%	65.3%	1e-07	FALSE	7
alexnet	79.4%	65.3%	1e-07	FALSE	5
inceptionv3	60.9%	64.8%	1e-07	FALSE	7
inceptionv3	75.4%	64.5%	1e-07	FALSE	13
inceptionv3	62.7%	62.0%	1e-07	FALSE	2
alexnet	77.1%	61.5%	1e-07	FALSE	4
alexnet	71.3%	61.2%	1e-07	FALSE	3
densenet121	73.0%	61.0%	1e-07	FALSE	9
vgg16	77.4%	60.8%	1e-07	FALSE	6
vgg16	76.8%	60.7%	1e-07	FALSE	5
inaturalist	67.3%	59.9%	1e-07	FALSE	3
inceptionv3	61.9%	59.8%	1e-07	TRUE	10
inaturalist	76.5%	59.7%	1e-07	TRUE	4
vgg16	76.1%	59.6%	1e-07	FALSE	4
vgg16	75.3%	59.2%	1e-07	TRUE	4
inceptionv3	66.5%	59.2%	1e-07	FALSE	9
densenet121	58.2%	58.9%	1e-07	FALSE	7
alexnet	77.0%	58.3%	1e-06	FALSE	1
inceptionv3	74.1%	57.9%	1e-07	FALSE	5

inaturalist	77.9%	57.7%	1e-07	TRUE	5
inceptionv3	68.8%	57.5%	1e-07	FALSE	8
alexnet	66.7%	57.3%	1e-07	TRUE	1
densenet121	70.1%	56.5%	1e-07	TRUE	4
vgg16	74.4%	56.0%	1e-07	FALSE	2
vgg16	74.1%	54.0%	1e-07	FALSE	7
alexnet	78.0%	53.7%	1e-07	TRUE	5
inceptionv3	64.3%	53.1%	1e-07	TRUE	6
plantnet	74.9%	52.7%	1e-07	TRUE	2
densenet121	76.4%	52.4%	1e-06	TRUE	8
inceptionv3	69.1%	52.0%	1e-07	FALSE	11
inceptionv3	71.3%	51.8%	1e-07	TRUE	8
alexnet	69.1%	51.7%	1e-07	TRUE	6
densenet121	56.7%	51.6%	1e-07	FALSE	8
alexnet	76.5%	51.6%	1e-07	TRUE	2
vgg16	73.7%	51.4%	1e-07	TRUE	7
vgg16	75.1%	51.0%	1e-07	TRUE	2
inceptionv3	70.3%	51.0%	1e-07	FALSE	10
plantnet	76.4%	50.5%	1e-06	TRUE	2
inceptionv3	56.5%	50.4%	1e-07	TRUE	9
inceptionv3	73.5%	50.3%	1e-07	FALSE	4
alexnet	75.1%	49.8%	1e-07	TRUE	8
inaturalist	72.6%	49.5%	1e-06	FALSE	1
inaturalist	76.5%	49.3%	1e-07	TRUE	3
plantnet	72.1%	48.9%	1e-07	FALSE	4
densenet121	71.4%	48.5%	1e-07	TRUE	7
plantnet	58.0%	48.4%	1e-07	FALSE	2
plantnet	73.2%	48.0%	1e-05	FALSE	1
densenet121	63.5%	47.7%	1e-06	FALSE	2
densenet121	60.7%	47.5%	1e-06	FALSE	1
alexnet	75.6%	46.9%	1e-07	TRUE	3
vgg16	72.7%	46.0%	1e-07	TRUE	6
vgg16	72.9%	45.2%	1e-06	TRUE	2
vgg16	67.5%	44.7%	1e-06	FALSE	1
inceptionv3	64.7%	44.5%	1e-07	TRUE	1
inceptionv3	63.7%	43.5%	1e-07	TRUE	3
alexnet	51.7%	42.7%	1e-07	FALSE	1
alexnet	70.5%	42.7%	1e-07	FALSE	2
plantnet	62.3%	42.5%	1e-06	FALSE	1
vgg16	65.2%	42.4%	1e-07	TRUE	3
vgg16	71.5%	42.4%	1e-07	FALSE	3
inceptionv3	57.6%	42.1%	1e-06	FALSE	1
resnet	63.2%	41.1%	1e-07	TRUE	4
alexnet	58.7%	41.1%	1e-07	TRUE	4
densenet121	66.4%	41.0%	1e-07	FALSE	4
plantnet	56.3%	40.6%	1e-07	TRUE	3
inceptionv3	66.3%	40.0%	1e-07	TRUE	4
densenet121	71.8%	39.9%	1e-06	TRUE	7

resnet	61.0%	39.7%	1e-07	TRUE	3
densenet121	57.2%	38.5%	1e-07	TRUE	6
inceptionv3	71.5%	38.2%	1e-07	TRUE	12
resnet	70.7%	37.3%	1e-07	TRUE	2
densenet121	68.6%	36.9%	1e-07	TRUE	8
inceptionv3	59.3%	36.8%	1e-07	TRUE	13
densenet121	62.2%	36.6%	1e-07	FALSE	6
inceptionv3	65.8%	36.0%	1e-07	TRUE	5
plantnet	69.0%	35.8%	1e-07	TRUE	5
inceptionv3	70.8%	35.5%	1e-07	TRUE	7
densenet121	69.5%	35.2%	1e-07	TRUE	5
inceptionv3	60.2%	35.1%	1e-07	TRUE	2
plantnet	72.0%	35.0%	1e-07	TRUE	1
inaturalist	70.3%	34.7%	1e-07	TRUE	2
plantnet	67.9%	34.6%	1e-07	TRUE	4
resnet	64.8%	34.4%	1e-07	TRUE	1
densenet121	67.8%	34.0%	1e-07	TRUE	9
inceptionv3	69.8%	33.8%	1e-06	TRUE	12
densenet121	51.5%	33.8%	1e-07	FALSE	5
inceptionv3	49.4%	33.5%	1e-07	FALSE	1
inceptionv3	66.1%	33.1%	1e-07	TRUE	11
densenet121	68.9%	32.4%	1e-05	FALSE	1
densenet121	55.6%	32.4%	1e-07	FALSE	3
resnet	69.5%	31.3%	1e-07	TRUE	5
densenet121	68.3%	30.9%	1e-05	FALSE	2
densenet121	65.8%	30.1%	1e-07	TRUE	3
inceptionv3	69.1%	30.0%	1e-06	TRUE	4
resnet	65.8%	29.9%	1e-06	FALSE	1
resnet	68.6%	29.7%	1e-05	FALSE	1
inaturalist	40.8%	29.3%	1e-07	FALSE	1
resnet	55.8%	29.0%	1e-07	FALSE	1
densenet121	51.2%	28.7%	1e-07	FALSE	2
inceptionv3	68.5%	27.7%	1e-06	TRUE	8
densenet121	66.8%	27.2%	1e-07	TRUE	2
inceptionv3	68.2%	26.3%	1e-06	TRUE	7
inaturalist	66.8%	26.0%	1e-07	TRUE	1
inceptionv3	68.2%	25.9%	1e-06	TRUE	13
densenet121	68.1%	25.7%	1e-06	TRUE	4
densenet121	45.4%	25.5%	1e-07	TRUE	1
inceptionv3	68.1%	25.4%	1e-06	TRUE	10
vgg16	63.2%	24.6%	1e-07	TRUE	1
densenet121	47.0%	22.7%	1e-07	FALSE	1
inceptionv3	67.4%	21.8%	1e-06	TRUE	6
inceptionv3	67.3%	21.6%	1e-06	TRUE	3
inceptionv3	67.3%	21.4%	1e-06	TRUE	2
inceptionv3	67.3%	21.3%	1e-06	TRUE	11
inceptionv3	67.3%	21.1%	1e-06	TRUE	5
densenet121	67.3%	21.1%	1e-06	TRUE	2

plantnet	67.3%	21.1%	1e-06	TRUE	1
inceptionv3	67.3%	21.1%	1e-06	TRUE	9
alexnet	67.3%	21.1%	0.001	FALSE	8
resnet	67.3%	21.1%	1e-06	TRUE	1
inceptionv3	67.3%	21.1%	1e-06	TRUE	1
densenet121	67.3%	21.1%	1e-06	TRUE	1
inceptionv3	67.2%	21.1%	1e-05	FALSE	1
vgg16	46.4%	20.4%	1e-07	FALSE	1
plantnet	55.7%	18.9%	1e-07	FALSE	1
vgg16	57.5%	13.1%	1e-07	TRUE	5

Table 23: Experiment 1 model performances and parameters.

E.2.2 Experiment 2

Parameter	Values
Learning Rate	1e-4, 1e-5
Dropout Probability	0 (Blank), 0.1, 0.3, 0.5
Regularisation Weight Decay	None (Blank), 0.01, 0.0015, 1e-5

Table 24: Experiment 2 model parameters (most combinations tried).

Model Name	Accuracy	F1 Score	Learning Rate	Dropout Probability	Regularisation Weight Decay
inaturalist	92.2%	92.2%	0.0001	0.1	1e-05
densenet121	92.3%	92.1%	0.0001	0.3	1e-05
inaturalist	91.8%	91.9%	0.0001	0.3	
densenet121	92.1%	91.8%	0.0001	0.3	0.01
densenet121	91.7%	91.6%	0.0001	0.1	1e-05
densenet121	91.8%	91.6%	0.0001	0.3	
resnet	91.8%	91.5%	0.0001	0.3	
inaturalist	91.7%	91.5%	0.0001		1e-05
inaturalist	91.9%	91.4%	0.0001	0.3	1e-05
plantnet	91.8%	91.3%	0.0001	0.3	
plantnet	91.6%	91.3%	0.0001	0.3	1e-05
inceptionv3	91.2%	91.2%	0.0001	0.3	0.01
resnet	91.5%	91.2%	0.0001	0.3	0.0015
densenet121	91.6%	91.2%	0.0001	0.1	0.01
inaturalist	91.5%	91.1%	1e-05	0.1	
densenet121	91.6%	91.0%	0.0001	0.5	0.01
inaturalist	91.5%	91.0%	1e-05	0.3	0.0015
alexnet	91.2%	91.0%	0.0001		0.0015
alexnet	91.3%	91.0%	1e-05	0.5	
alexnet	91.1%	91.0%	0.0001	0.1	0.0015
densenet121	91.2%	90.9%	1e-05	0.3	1e-05

densenet121	91.4%	90.9%	0.0001		
inaturalist	91.2%	90.9%	1e-05		1e-05
densenet121	91.2%	90.9%	0.0001	0.5	1e-05
inaturalist	91.2%	90.9%	1e-05		
densenet121	91.6%	90.8%	0.0001		0.0015
inaturalist	91.5%	90.8%	0.0001		
densenet121	91.2%	90.7%	1e-05	0.5	0.0015
densenet121	91.1%	90.7%	0.0001	0.1	
inaturalist	91.2%	90.7%	0.0001	0.5	
inceptionv3	90.8%	90.7%	0.0001	0.3	0.0015
plantnet	91.0%	90.6%	0.0001		1e-05
resnet	90.8%	90.6%	0.0001	0.5	
inaturalist	90.9%	90.5%	1e-05	0.1	0.0015
inceptionv3	91.4%	90.5%	0.0001		
densenet121	91.1%	90.5%	0.0001		0.01
plantnet	91.0%	90.5%	0.0001	0.1	1e-05
alexnet	90.7%	90.5%	0.0001	0.1	1e-05
alexnet	91.0%	90.5%	1e-05	0.5	0.0015
plantnet	91.0%	90.4%	0.0001	0.5	
vgg16	90.6%	90.4%	1e-05	0.3	
vgg16	90.6%	90.3%	0.0001		0.01
densenet121	90.9%	90.3%	0.0001		1e-05
densenet121	91.0%	90.3%	0.0001	0.5	
resnet	90.8%	90.3%	0.0001	0.1	
alexnet	91.0%	90.3%	1e-05	0.1	1e-05
resnet	90.5%	90.3%	1e-05	0.5	
inaturalist	90.7%	90.3%	0.0001	0.3	0.0015
vgg16	90.6%	90.3%	0.0001		1e-05
densenet121	91.0%	90.3%	0.0001	0.5	0.0015
inaturalist	90.6%	90.2%	1e-05	0.1	0.01
resnet	90.6%	90.2%	0.0001	0.5	1e-05
inaturalist	90.5%	90.2%	1e-05	0.3	1e-05
resnet	90.5%	90.2%	1e-05	0.1	
vgg16	90.7%	90.1%	0.0001		0.0015
vgg16	90.4%	90.1%	0.0001	0.1	
vgg16	90.6%	90.1%	1e-05	0.1	0.0015
alexnet	90.8%	90.1%	1e-05	0.3	0.01
vgg16	90.6%	90.1%	1e-05	0.5	0.01
densenet121	90.8%	90.1%	1e-05	0.3	0.01
alexnet	90.6%	90.0%	1e-05		1e-05
densenet121	90.8%	90.0%	1e-05	0.5	0.01
inaturalist	90.4%	90.0%	1e-05	0.1	1e-05
inceptionv3	90.4%	90.0%	0.0001		0.01
alexnet	90.6%	90.0%	1e-05	0.3	
inceptionv3	91.0%	90.0%	0.0001	0.1	
inaturalist	90.6%	90.0%	0.0001	0.5	0.0015
vgg16	90.5%	90.0%	0.0001	0.1	0.0015
densenet121	90.7%	90.0%	1e-05	0.1	0.01

plantnet	90.3%	90.0%	0.0001	0.1	0.0015
plantnet	90.9%	90.0%	1e-05	0.1	0.0015
plantnet	90.8%	90.0%	1e-05	0.5	0.0015
resnet	90.6%	90.0%	0.0001	0.3	0.01
inaturalist	90.7%	90.0%	1e-05	0.5	
plantnet	90.5%	89.9%	0.0001		
inceptionv3	90.8%	89.9%	0.0001	0.3	1e-05
inaturalist	90.5%	89.9%	1e-05		0.0015
resnet	90.4%	89.9%	1e-05	0.3	0.01
inceptionv3	90.7%	89.8%	0.0001	0.1	0.0015
inceptionv3	90.4%	89.8%	1e-05	0.1	0.0015
plantnet	90.6%	89.8%	0.0001	0.5	0.0015
vgg16	90.0%	89.8%	0.0001	0.3	0.01
plantnet	90.5%	89.8%	1e-05	0.3	
resnet	90.5%	89.8%	1e-05		0.0015
vgg16	90.5%	89.8%	1e-05	0.1	1e-05
vgg16	90.2%	89.8%	1e-05	0.1	
resnet	90.4%	89.8%	0.0001	0.3	1e-05
inaturalist	90.5%	89.7%	0.0001	0.1	
inceptionv3	90.6%	89.7%	0.0001	0.3	
plantnet	90.4%	89.7%	1e-05	0.5	
densenet121	90.5%	89.7%	1e-05		0.01
densenet121	90.4%	89.7%	1e-05	0.3	0.0015
resnet	90.3%	89.7%	0.0001	0.1	1e-05
resnet	90.4%	89.7%	1e-05	0.1	0.0015
inaturalist	90.3%	89.7%	1e-05	0.5	1e-05
resnet	90.3%	89.7%	0.0001		
alexnet	90.3%	89.7%	0.0001	0.5	
inceptionv3	90.5%	89.6%	1e-05		1e-05
alexnet	90.2%	89.6%	0.0001	0.3	1e-05
vgg16	90.3%	89.5%	1e-05	0.3	0.0015
inaturalist	90.1%	89.5%	1e-05	0.5	0.0015
plantnet	90.3%	89.5%	1e-05	0.3	0.01
plantnet	90.3%	89.5%	1e-05		
resnet	90.1%	89.5%	1e-05	0.5	0.0015
inceptionv3	90.4%	89.5%	1e-05	0.3	0.0015
vgg16	90.2%	89.5%	1e-05	0.5	
densenet121	90.3%	89.5%	0.0001	0.1	0.0015
plantnet	90.4%	89.5%	1e-05		1e-05
resnet	89.9%	89.5%	1e-05	0.3	1e-05
inceptionv3	90.3%	89.5%	0.0001	0.5	1e-05
resnet	90.5%	89.5%	0.0001	0.5	0.01
inceptionv3	90.0%	89.5%	0.0001	0.1	1e-05
inaturalist	90.4%	89.5%	0.0001	0.1	0.0015
inceptionv3	90.3%	89.5%	1e-05	0.5	0.0015
alexnet	90.2%	89.4%	1e-05	0.3	0.0015
vgg16	90.0%	89.4%	0.0001	0.3	0.0015
inaturalist	89.9%	89.4%	1e-05	0.3	

inceptionv3	90.2%	89.4%	0.0001		1e-05
plantnet	90.2%	89.4%	1e-05		0.0015
inaturalist	90.0%	89.4%	0.0001	0.5	1e-05
alexnet	90.2%	89.4%	0.0001	0.3	
inceptionv3	90.3%	89.4%	0.0001	0.5	
resnet	90.1%	89.3%	1e-05	0.3	
alexnet	90.1%	89.3%	1e-05	0.3	1e-05
vgg16	89.9%	89.3%	0.0001	0.5	0.0015
resnet	90.1%	89.3%	1e-05	0.5	1e-05
plantnet	90.2%	89.3%	1e-05	0.5	1e-05
plantnet	90.1%	89.3%	1e-05	0.3	0.0015
alexnet	89.8%	89.3%	0.0001		
inceptionv3	90.0%	89.3%	1e-05		0.01
alexnet	90.1%	89.3%	0.0001	0.5	0.0015
resnet	89.9%	89.3%	1e-05	0.1	1e-05
inaturalist	90.2%	89.2%	1e-05	0.5	0.01
vgg16	89.7%	89.2%	0.0001	0.3	
vgg16	90.0%	89.2%	1e-05	0.5	1e-05
densenet121	90.0%	89.2%	1e-05		
inaturalist	90.0%	89.2%	0.0001		0.0015
densenet121	90.1%	89.2%	1e-05	0.5	1e-05
inceptionv3	89.2%	89.2%	0.0001	0.1	0.01
alexnet	89.4%	89.2%	0.0001	0.3	0.01
alexnet	89.6%	89.2%	0.0001	0.3	0.0015
alexnet	89.5%	89.2%	0.0001	0.5	1e-05
alexnet	90.0%	89.1%	1e-05		
plantnet	90.0%	89.1%	0.0001		0.0015
plantnet	89.9%	89.1%	0.0001	0.3	0.01
plantnet	90.2%	89.1%	1e-05	0.3	1e-05
resnet	90.1%	89.1%	1e-05		0.01
inaturalist	90.0%	89.1%	1e-05	0.3	0.01
densenet121	89.9%	89.1%	1e-05	0.5	
vgg16	89.6%	89.1%	0.0001	0.1	1e-05
alexnet	90.1%	89.0%	1e-05	0.1	
resnet	89.7%	89.0%	1e-05	0.3	0.0015
densenet121	89.9%	89.0%	1e-05	0.3	
vgg16	89.8%	89.0%	1e-05		
resnet	89.8%	89.0%	0.0001	0.1	0.0015
vgg16	89.9%	89.0%	1e-05	0.3	1e-05
inceptionv3	90.0%	89.0%	1e-05	0.1	1e-05
deepverge	89.7%	89.0%	0.0001	0.5	
inceptionv3	89.7%	88.9%	1e-05	0.5	0.01
alexnet	90.0%	88.9%	1e-05	0.5	1e-05
resnet	89.8%	88.9%	1e-05		
alexnet	89.8%	88.9%	1e-05		0.0015
densenet121	89.8%	88.9%	1e-05	0.1	1e-05
resnet	89.6%	88.8%	1e-05	0.1	0.01
plantnet	89.7%	88.8%	1e-05	0.1	0.01

deepverge	89.2%	88.7%	1e-05	0.5	1e-05
alexnet	89.7%	88.7%	1e-05		0.01
deepverge	88.8%	88.7%	1e-05		1e-05
inaturalist	89.8%	88.7%	1e-05		0.01
plantnet	89.9%	88.7%	1e-05		0.01
resnet	89.5%	88.7%	0.0001	0.1	0.01
alexnet	89.3%	88.6%	0.0001	0.1	
deepverge	89.4%	88.6%	0.0001	0.5	
densenet121	89.7%	88.6%	1e-05		1e-05
resnet	89.5%	88.6%	0.0001	0.5	0.0015
vgg16	89.5%	88.6%	1e-05	0.3	0.01
resnet	89.7%	88.6%	1e-05	0.5	0.01
vgg16	89.5%	88.6%	1e-05		1e-05
inceptionv3	89.8%	88.6%	1e-05	0.3	
alexnet	89.8%	88.6%	1e-05	0.5	0.01
inceptionv3	89.8%	88.6%	1e-05	0.1	
inceptionv3	89.4%	88.5%	1e-05	0.5	1e-05
vgg16	89.5%	88.5%	0.0001	0.5	1e-05
alexnet	89.1%	88.5%	0.0001	0.1	0.01
deepverge	89.2%	88.5%	1e-05	0.5	
inaturalist	89.7%	88.5%	0.0001	0.3	0.01
inceptionv3	89.3%	88.5%	0.0001		0.0015
densenet121	89.7%	88.5%	1e-05	0.1	
vgg16	89.2%	88.5%	0.0001		
inceptionv3	89.6%	88.5%	1e-05		0.0015
inceptionv3	89.7%	88.5%	1e-05	0.3	1e-05
resnet	89.4%	88.4%	1e-05		1e-05
inceptionv3	89.7%	88.4%	0.0001	0.5	0.0015
deepverge	88.8%	88.4%	0.0001	0.3	
plantnet	89.6%	88.4%	1e-05	0.1	
deepverge	89.0%	88.4%	1e-05	0.1	1e-05
plantnet	89.4%	88.4%	1e-05	0.5	0.01
vgg16	89.4%	88.4%	0.0001	0.5	0.01
deepverge	88.7%	88.4%	0.0001	0.3	1e-05
resnet	89.1%	88.3%	0.0001		1e-05
vgg16	89.4%	88.3%	1e-05	0.5	0.0015
resnet	89.5%	88.2%	0.0001		0.0015
plantnet	89.2%	88.2%	0.0001	0.5	1e-05
vgg16	89.3%	88.1%	1e-05		0.01
deepverge	88.5%	88.1%	1e-05	0.3	
vgg16	89.4%	88.1%	1e-05	0.1	0.01
vgg16	89.1%	88.0%	0.0001	0.1	0.01
densenet121	89.1%	88.0%	1e-05		0.0015
densenet121	89.3%	87.9%	0.0001	0.3	0.0015
plantnet	89.5%	87.9%	0.0001	0.1	
plantnet	89.2%	87.9%	0.0001	0.5	0.01
vgg16	89.0%	87.9%	1e-05		0.0015
vgg16	89.1%	87.8%	0.0001	0.3	1e-05

alexnet	88.7%	87.8%	0.0001		1e-05
deepverge	88.2%	87.8%	0.0001	0.5	1e-05
inaturalist	89.1%	87.7%	0.0001	0.5	0.01
inceptionv3	89.0%	87.7%	1e-05	0.1	0.01
densenet121	89.1%	87.6%	1e-05	0.1	0.0015
plantnet	89.0%	87.6%	1e-05	0.1	1e-05
inceptionv3	88.8%	87.6%	1e-05		
plantnet	89.4%	87.6%	0.0001	0.3	0.0015
alexnet	89.2%	87.4%	1e-05	0.1	0.0015
deepverge	87.7%	87.3%	0.0001	0.1	1e-05
vgg16	88.5%	87.2%	0.0001	0.5	
alexnet	88.5%	87.1%	0.0001		0.01
deepverge	87.4%	87.1%	0.0001	0.3	
deepverge	88.1%	86.8%	1e-05		0.0015
inceptionv3	88.8%	86.8%	0.0001	0.5	0.01
deepverge	87.4%	86.7%	1e-05	0.5	0.0015
resnet	88.4%	86.7%	0.0001		0.01
inceptionv3	88.1%	86.6%	1e-05	0.5	
alexnet	88.4%	86.6%	1e-05	0.1	0.01
deepverge	87.5%	86.4%	0.0001	0.1	
deepverge	87.4%	86.4%	0.0001	0.5	1e-05
inceptionv3	87.9%	86.4%	1e-05	0.3	0.01
deepverge	87.6%	86.2%	1e-05	0.1	0.0015
alexnet	88.1%	86.2%	0.0001	0.5	0.01
inaturalist	87.9%	86.1%	0.0001	0.1	0.01
deepverge	87.1%	86.1%	1e-05	0.3	1e-05
deepverge	87.3%	85.8%	0.0001	0.3	1e-05
inaturalist	87.7%	85.7%	0.0001		0.01
deepverge	86.6%	85.4%	0.0001	0.3	0.0015
deepverge	86.5%	85.4%	0.0001		
plantnet	88.0%	85.3%	0.0001	0.1	0.01
deepverge	86.2%	85.2%	0.0001		1e-05
deepverge	86.6%	85.2%	1e-05	0.3	0.0015
deepverge	86.5%	85.0%	0.0001	0.1	1e-05
deepverge	86.5%	84.9%	1e-05		
deepverge	86.3%	84.7%	1e-05	0.1	
deepverge	86.3%	84.4%	0.0001		0.0015
plantnet	87.2%	84.4%	0.0001		0.01
deepverge	85.9%	84.3%	0.0001	0.1	
deepverge	86.1%	84.2%	0.0001		
deepverge	85.6%	83.8%	0.0001		1e-05
deepverge	85.0%	83.7%	0.0001	0.5	0.0015
deepverge	85.2%	83.5%	0.0001	0.1	0.0015
simplecnn	80.1%	79.6%	0.0001	0.1	0.01
simplecnn	79.2%	77.5%	0.0001	0.5	1e-05
simplecnn	76.8%	77.5%	0.0001	0.3	1e-05
simplecnn	78.7%	77.0%	0.0001	0.3	
simplecnn	79.7%	76.6%	1e-05		1e-05

simplecnn	78.5%	76.6%	0.0001	0.5	0.0015
simplecnn	77.1%	76.5%	0.0001	0.3	0.0015
simplecnn	78.8%	75.4%	0.0001	0.1	1e-05
simplecnn	78.4%	75.2%	0.0001		
simplecnn	75.6%	75.1%	0.0001	0.5	0.01
simplecnn	75.3%	75.1%	0.0001	0.5	
simplecnn	79.1%	74.5%	0.0001		1e-05
simplecnn	77.4%	74.2%	0.0001	0.1	0.0015
simplecnn	78.6%	73.8%	0.0001	0.1	
simplecnn	78.2%	73.5%	1e-05		0.0015
simplecnn	78.2%	73.4%	1e-05	0.3	0.0015
simplecnn	78.8%	73.3%	1e-05	0.3	
deepverge	80.3%	73.1%	1e-05	0.3	0.01
deepverge	79.5%	73.1%	1e-05	0.1	0.01
simplecnn	78.5%	72.3%	1e-05	0.1	0.0015
simplecnn	77.4%	72.0%	0.0001		0.0015
simplecnn	77.7%	71.5%	1e-05	0.1	1e-05
simplecnn	78.2%	71.3%	1e-05	0.3	0.01
deepverge	79.3%	70.2%	1e-05		0.01
simplecnn	77.9%	70.1%	1e-05	0.3	1e-05
simplecnn	76.9%	69.4%	1e-05	0.1	
simplecnn	77.9%	69.3%	1e-05	0.1	0.01
simplecnn	75.5%	68.4%	1e-05		0.01
simplecnn	77.6%	68.1%	1e-05		
simplecnn	76.9%	67.6%	1e-05	0.5	
simplecnn	76.8%	67.6%	1e-05	0.5	0.01
simplecnn	75.2%	67.2%	0.0001		0.01
simplecnn	76.5%	66.0%	1e-05	0.5	0.0015
simplecnn	76.9%	66.0%	1e-05	0.5	1e-05
deepverge	76.3%	65.7%	0.0001		0.01
simplecnn	74.9%	63.4%	0.0001	0.3	0.01
deepverge	75.2%	63.4%	0.0001	0.1	0.01
deepverge	76.1%	62.4%	1e-05	0.5	0.01
deepverge	75.0%	61.2%	0.0001	0.3	0.01
deepverge	74.5%	60.1%	0.0001	0.5	0.01

Table 25: Experiment 2 model performances and parameters.

E.2.3 Experiment 3

Parameter	Values
Learning Rate	1e-3, 1e-4
Dropout Probability	0 (Blank), 0.1, 0.3, 0.5
Regularisation Weight Decay	None (Blank), 0.01, 0.0015, 1e-5
Voting Perceptron Size	Small (0), Medium (1), Large (2)
# Base Models	[2..7]

Table 26: Experiment 3 model parameters (most combinations tried).

Accuracy	F1 Score	Learning Rate	Dropout Probability	Weight Decay	Size	# Base Models
93.0%	93.0%	0.001	0.3	0.01	3	5
93.0%	93.0%	0.001	0.1	0.0015	2	6
92.8%	93.0%	0.001	0.3		2	5
93.0%	93.0%	0.0001	0.1		2	5
93.0%	92.9%	0.001		1e-05	2	5
93.0%	92.9%	0.001	0.1		2	6
92.8%	92.8%	0.001			2	5
92.8%	92.8%	0.001	0.1	1e-05	2	5
92.7%	92.8%	0.001	0.3	0.0015	2	5
92.7%	92.8%	0.001			1	7
92.8%	92.7%	0.001			2	6
92.8%	92.7%	0.001		1e-05	2	6
92.7%	92.7%	0.001			2	2
92.7%	92.7%	0.001	0.1	1e-05	2	6
92.7%	92.6%	0.001	0.1	0.01	2	5
92.7%	92.6%	0.0001	0.1	1e-05	2	5
92.7%	92.6%	0.0001	0.1	0.01	2	6
92.7%	92.6%	0.001			2	7
92.7%	92.6%	0.001		0.0015	2	5
92.6%	92.6%	0.001	0.1		2	5
92.6%	92.6%	0.0001			2	5
92.6%	92.5%	0.001	0.3	1e-05	2	6
92.5%	92.5%	0.001			2	6
92.6%	92.5%	0.0001			2	5
92.5%	92.5%	0.0001			2	4
92.6%	92.5%	0.0001	0.1	0.0015	2	5
92.6%	92.5%	0.0001			0	6
92.5%	92.4%	0.001	0.3	0.0015	2	6
92.6%	92.4%	0.001		0.0015	2	6
92.6%	92.4%	0.0001			2	3
92.5%	92.4%	0.001			0	5
92.6%	92.4%	0.0001			2	6
92.5%	92.4%	0.001			0	3
92.4%	92.4%	0.001			1	5

92.3%	92.3%	0.001			2	3
92.5%	92.3%	0.0001			0	4
92.7%	92.3%	0.0001			0	7
92.4%	92.3%	0.0001		0.0015	2	5
92.5%	92.3%	0.001	0.1	0.0015	2	5
92.4%	92.3%	0.0001		1e-05	2	5
92.4%	92.3%	0.001	0.5	0.01	2	5
92.4%	92.2%	0.0001			1	5
92.4%	92.2%	0.001			0	4
92.3%	92.2%	0.001			1	4
92.5%	92.2%	0.0001			1	2
92.3%	92.2%	0.001			2	5
92.4%	92.2%	0.0001	0.1	0.01	2	5
92.3%	92.2%	0.0001		0.0015	2	6
92.3%	92.2%	0.001			1	3
92.2%	92.1%	0.001			2	4
92.4%	92.1%	0.001			0	7
92.3%	92.1%	0.001			0	2
92.2%	92.1%	0.001			1	6
92.3%	92.1%	0.0001		0.01	2	5
92.2%	92.1%	0.0001	0.3		2	5
92.2%	92.1%	0.0001	0.3	1e-05	2	6
92.2%	92.0%	0.001			1	2
92.2%	92.0%	0.0001	0.3	1e-05	2	5
92.2%	92.0%	0.0001			1	7
92.2%	92.0%	0.001	0.3		2	6
92.0%	91.9%	0.001	0.3	1e-05	2	5
92.2%	91.8%	0.0001			0	3
92.1%	91.8%	0.001		0.01	2	5
91.2%	91.8%	0.001	0.5	1e-05	2	5
92.1%	91.8%	0.001		0.01	2	6
92.0%	91.8%	0.0001	0.1	1e-05	2	6
92.0%	91.7%	0.0001			1	4
92.0%	91.7%	0.001	0.1	0.01	2	6
91.5%	91.7%	0.001	0.3	0.01	2	6
91.8%	91.7%	0.0001	0.3		2	6
91.9%	91.7%	0.0001			2	6
90.9%	91.6%	0.001	0.5	0.0015	2	6
91.9%	91.6%	0.001			0	6
92.0%	91.6%	0.0001	0.3	0.0015	2	6
91.9%	91.6%	0.0001			0	2
92.0%	91.6%	0.0001			2	7
92.0%	91.5%	0.0001	0.1	0.0015	2	6
90.9%	91.5%	0.001	0.5	1e-05	2	6
91.9%	91.5%	0.0001			0	5
91.8%	91.4%	0.0001			1	3
91.8%	91.4%	0.0001			2	2
91.9%	91.4%	0.0001	0.3	0.01	2	6

91.5%	91.3%	0.0001	0.1		2	6
91.7%	91.3%	0.0001			1	6
91.6%	91.2%	0.0001		1e-05	2	6
91.7%	91.1%	0.0001		0.01	2	6
90.0%	91.1%	0.001	0.5		2	5
89.9%	91.0%	0.001	0.5		2	6
90.9%	90.7%	0.0001	0.3	0.0015	2	5
89.6%	90.6%	0.001	0.5	0.01	2	6
90.3%	90.3%	0.0001	0.3	0.01	2	5
90.9%	90.2%	0.0001	0.5		2	6
89.1%	89.9%	0.001	0.5	0.0015	2	5
89.3%	89.0%	0.0001	0.5	1e-05	2	5
88.5%	88.1%	0.0001	0.5		2	5
86.9%	87.2%	0.0001	0.5	1e-05	2	6
88.3%	86.9%	0.0001	0.5	0.01	2	6
87.7%	86.5%	0.0001	0.5	0.0015	2	6
86.1%	82.8%	0.0001	0.5	0.0015	2	5
74.6%	60.2%	0.0001	0.5	0.01	2	5

Table 27: Experiment 3 model performances and parameters.

F Appendix - Testing and Validation

F.1 Handheld Device for Data Validation

F.1.1 Requirements

This apparatus (figure 41) was developed to facilitate the acquisition of images for the validation of the model. Similar to a trundle wheel, it was designed to be easily positioned and provide a stable platform from which to acquire an image. The requirements for this apparatus, were:

- Take and store photographs with the same resolution and quality as those taken by the device.
- Capture the same field of view as the device camera.
- Ensure the camera oriented perpendicular to the ground.
- Ensure no extraneous features of the apparatus or the users are in the field of view.
- Allow the user to check the photograph after it is taken to ensure focus, sharpness and exposure are satisfactory.
- Include an index in the filename so that the images can be tagged with exact location (obtained via separate GPS system).
- The apparatus should be easily dismantled and assembled for ease of transportation.

F.1.2 Design and Build

The main frame was constructed of 22 mm aluminimum tube. This was fixed with 6mm bolts to a standard bicycle front fork with a 27 inch wheel. The tube was bent in a pipe bender so that the frame was parallel to the ground at approximately the height that the device would hang on a average sized Cow.

A USB version of the same model of device camera (OV 5640 with auto-focus 72 degree field of view) mounted in a custom 3-D printed frame fixed to the centre of the frame.

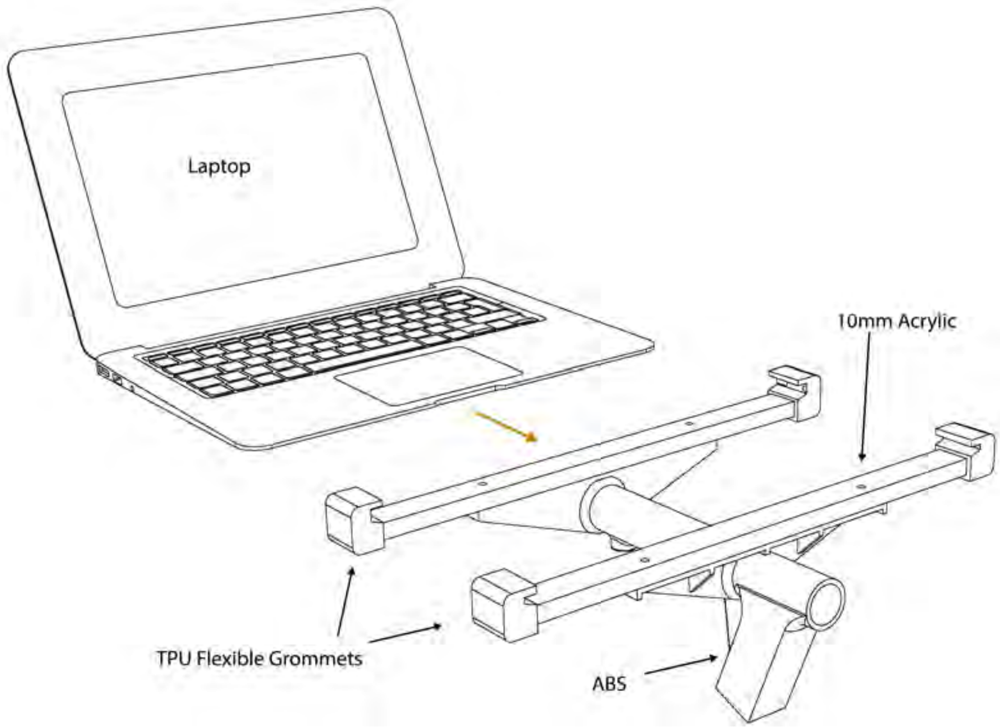


Figure 64: Bracket for laptop and stabiliser

A custom bracket (figure 64) was fabricated from FDM printed ABS and laser cut acrylic. Flexible TPU grommets were designed and printed to secure the laptop. The underside of the bracket includes a square slot to hold a stabiliser which was fabricated from 20mm aluminium extrusion profile. This is inserted into the slot before use and allows the user to rest the apparatus in the ground when taking the picture. It can then be removed for transportation.

The camera was powered and controlled by a laptop, connected via a USB cable, running a custom python program. Pictures are be taken with a press of the space bar. This picture is saved with a filename appended with an incrementing index to ensure that each filename is unique. The photo with the filename overlaid is displayed to the user a few seconds after taking. If the photo is of satisfactory quality the filename is manually recorded with the GPS location.

G Appendix - Images of Group Decision Approach

In accordance with the collaborative nature of the project and the principles covered in the Project Management course at the beginning of the Summer, group decisions were taken after discussions with clearly defined goals and actionable items resulted from them. The use of visual presentations, mindmaps and post-it notes facilitated communication and ensured all voices were heard throughout the process.

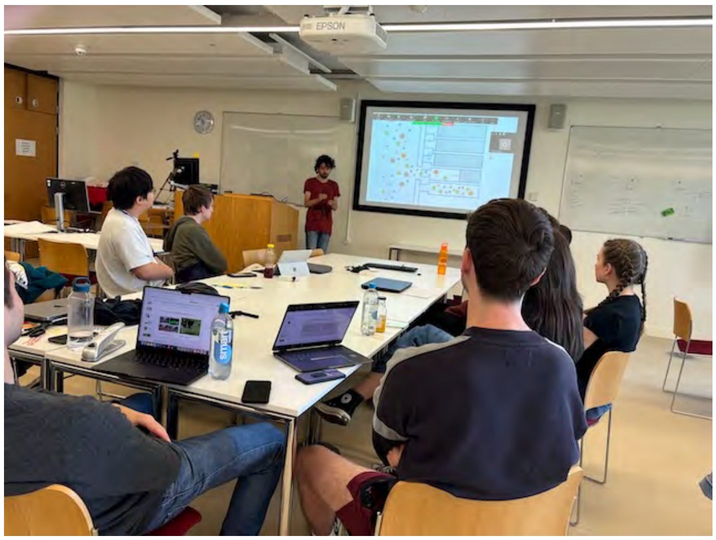


Figure 65: Flash talks delivered by different team members with 24 potential project ideas.

Figure 66: Team members voting on their favourite project ideas and stretch goals.

Figure 67: Brainstorming tasks for the product, hardware and software elements of the project using post-it notes.