

**Drone Based Data Collection for Agriculture**

**Using UAV based imaging and AI for providing high quality crop data**

1. **Executive Summary**

Crop analytics and prediction at a large scale is becoming more and more feasible. However, the available datasets to build AI models are lacking both in quality (resolution) and quantity. We plan to do the cost-benefit analysis for image based crop applications using Drones as opposed to using a satellite.

In addition to providing this vital information, we will also be able to release the dataset for the AI community to benchmark various models. More importantly, we will develop a mechanism to acquire crop data using drones with minimal human intervention. This will greatly help in estimations required by various governments, non-governmental, as well as AgriTech organizations. Indeed the PI of this project used to work with one such AgriTech company (Cropin), who are also struggling to find a good third party to provide quality data at a reasonable cost.

The final aim of this project is indeed to build up drone infrastructure and expertise to become a self-sustained company working with various organizations and researchers helping them collect reliable Agriculture datasets in a cost effective manner.

1. **Description**

Availability of high quality datasets is a major issue in most applications of Artificial Intelligence. For

Agriculture in particular, suffers from lack of clean publically available datasets in countries where data collection is challenging (South and South East Asia, Latin America, Africa).

The major reason for this is simply that data collection requires a lot of on field effort of qualified and trained professionals. Usually this involves a lot of outsourcing the work to third party and thus data quality usually suffers a great deal. Also, the costs involved in data collection are quite prohibitory to collect very large sample farms as the process usually involves a person physically going to the place to collect the data.

An obvious solution to this problem is to simplify and automate the process of data collection as far as possible to make the process more efficient and streamlined. More importantly, it will help improve the digital farming applications by providing more reliable data to train the models on.

Drones are a good candidate for this job as they are relatively easy to operate. Moreover, being at a height, they can capture multispectral data more quickly. The optimal height for flying the drones can be calibrated based on applications, where applications such as pest detection will require a much closer flyby. All this is still a topic of research and we hope to contribute to the scientific discussions with our results.

By employing embedded Machine Learning models, one could also optimize the height at which the photo needs to be taken for the model to have reasonable accuracies.

1. **Literature Review**

Remote Sensing through satellite has been traditionally used to provide predictive crop analytics[1] [2]. This makes perfect sense as satellites can cover vast amounts of land relatively inexpensively. However, drone technology has been developing rapidly, and the costs for acquiring data through drones is also reducing drastically [3] [4]. This in turn opens plethora of new use cases which could be tackled thanks to higher precision (10^4 times better resolution).

We propose to collect data using nano-drones, while determining the best parameters and Standard Operating Procedures (SOPs) to follow. Based on the new Drones Policy 2021, only nano drones (<250 gms) can be flown by anyone without a license. If the data collection has to be inexpensive, then nano-drones form a natural limit.

We also plan to compare the accuracy of UAV-collected data as compared to Satellite data. Naturally, there is a tradeoff between the accuracy and the cost involved in data collection. We wish to quantify this tradeoff to help make more informed decisions while choosing one data source over the other. While some investigation has been done in this direction [5], much is left to explore. Especially having the data in a country like India, and at large scale with inexpensive drones will help assess how well frugal solutions can perform.

1. **Business Model (Feasibility, market size, ecosystem, Risks)**
2. Feasibility

Good quality crop data at farm level is not easily available in India. This is because data collection is quite a tedious process with many layers of communication. The data quality in the end is usually as good as the person collecting it. If the data collection process itself can be automatized with drones, it will increase efficiency and improve accuracy of the data collection. We are chosing relatively inexpensive nano-drones and hope to generate good quality data even with its limited capabilities.

1. Market Size

The immediate market are the Agri-Tech companies who require regular data from different parts of the country. They typically pay 300 Rs. per plot for the data collected. This data is generally not checked for Quality and about 50% of the data is deemed unusable due to many reasons. With Drones, thanks to low operation expenses, data collection could be speeded up a lot. Indeed, if one flies a drone for 30 mins, one can easily cover 90 plots. This amounts to Rs. 27,000 for 30 minutes of flight. With few hours of flight data, one can easily recover the capital expenditure. Given that no license or training is required to fly the nano-drones, it is easy to scale up the operations without requiring trained drone pilots.

In addition to simply providing curated data, we also plan to build AI products using our collected data. This will help pitch for various government and industry projects with the unique capability of collecting drone based data as well as building AI solutions for their problems. The PI of this project recently did a 35000 US Dollar project in Nigeria which involved predicting the wheat in northern Nigeria. Our solutions becomes attractive to many thanks to our efficient data collection capability.

1. Risks

The biggest risk is of changing regulations for flying drones. While the new Drones policy 2021 did simplify a lot of bureaucracy involved in flying drones, there will continue to be more regulations as drones get newer features. Nonetheless, the nano-drones chosen for this project emphatically do not require any bureaucracy and permissions to be obtained and it seems like it is the norm in most countries now.

Another potential risk is the lack of enthusiasm amongst the farmers. It could result in non co-operation of the farmers while collecting data. The data can also help the farmers in getting more precise diagnostics of their farms. We hope to garner co-operation by showing the farmers the benefits.

Since many of the projects for agriculture come through the government, experience in connecting with state agricultural departments and ministries is crucial. We hope the distinguished faculty in UPES can help us connect with the relevant Uttarakhand officials.

1. **Financial Requirements**

We have divided the total budget needed for this project into Capital Expenditure (CAPEX) and Operational Expenditure (OPEX)

1. Budget

Table 1 – Capital Expenditure - CAPEX

|  |  |  |
| --- | --- | --- |
| ***Expertise*** | ***Quantity*** | ***Total estimated Price*** |
| Drone | 1 | 60,000 |
| Multispectral Sensor | 1 | 10,000 |
| **Total** |  | **70,000** |

Table 2 – Operational Expenditure - OPEX

|  |  |  |
| --- | --- | --- |
| ***Object*** | ***Quantity*** | ***Total estimated Price*** |
| Cloud Credits | 12 months | 17,900 |
| Travel (To and Fro) | 1000 kms | 12,000 |
| Lodging | 2 Professors – 8 days | 25,600 |
| **Total** |  | **55,500** |

**Total amount solicited: 1,25,500 INR**

**NOTE : This project aims to self sustainable. The data generated during the project alone should be able to help us recover the costs.**

1. Timeline of the project

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Sl. No.** | **Activity** |  | **Jan-**  **Apr**  **2022** | | | | **May-Aug 2022** | | | | **Sept-**  **Dec**  **2022** | | | | **Personnel** |
| **1** | Drone Preparation | P |  |  |  |  |  |  |  |  |  |  |  |  | AA, NS |
| A |  |  |  |  |  |  |  |  |  |  |  |  |
| **2** | Data Collection | P |  |  |  |  |  |  |  |  |  |  |  |  | AA, NS |
| A |  |  |  |  |  |  |  |  |  |  |  |  |
| **3** | Model Building | P |  |  |  |  |  |  |  |  |  |  |  |  | AA, NS |
| A |  |  |  |  |  |  |  |  |  |  |  |  |
| **4** | Documentation | P |  |  |  |  |  |  |  |  |  |  |  |  | AA, NS |
| A |  |  |  |  |  |  |  |  |  |  |  |  |

AA – Dr. Achal Agrawal, NS – Dr. Nitesh Singh Malan

1. **References**

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[4] Swain, K. C., Thomson, S. J., & Jayasuriya, H. P. (2010). Adoption of an unmanned helicopter for low-altitude remote sensing to estimate yield and total biomass of a rice crop. Transactions of the ASABE, 53(1), 21-27.

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