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Major Project Proposal Report on

GARUD-UAV: Land Use Classification Using Deep Learning on Upscaled UAV Images

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List of Abbreviation

AI Artificial Intelligence

GPIO General Purpose Input Output

IoT Internet of Things

ML Machine Learning

RAM Random Access Memory

OS Operating System

BRNN Bidirectional Recurrent Neural Networks

GRU Gated Recurrent Units

MIMO Multiple Input Multiple Output

SoC System-on-Chip

USB Universal Serial Bus

Wi-Fi Wireless Fidelity

NLP Natural Language Processing

TTS Text-To-Speech

API Application Programming Interface

ARM Advanced RISC Machine

RISC Reduced Instruction Set Computer

IP Internet Protocol

MCU Micro-Controller Unit

Chapter 1: Introduction

1.1 Background Theory

The rapid advancement of Unmanned Aerial Vehicles (UAVs) has transformed applications in environmental monitoring, agriculture, and urban planning by providing cost-effective and high-resolution data collection capabilities [1] [3]. Fixed-wing UAVs, in particular, offer significant advantages for land use image classification due to their extended range, longer endurance, and ability to cover large areas efficiently, making them ideal for wide-areas surveillance and mapping tasks [1]. These vehicles can capture high-resolution aerial imagery, enabling precise analysis of land use patterns critical for precision agriculture, urban development, and disaster management [3] [16]. However, challenges such as limited payload capacity, regulatory constraints, and the need for advanced image processing to achieve high-quality outputs persist, necessitating innovative design and algorithmic solutions [1][3] .

A key component of this project is the integration of Enhanced Super-Resolution Generative Adversarial Network (ESRGAN), a state-of-the-art deep learning model for single image super-resolution (SISR) introduced by Wang et al. in 2018 [19]. ESRGAN employs a Generative Adversarial Network (GAN) framework, comprising a generator that creates high-resolution images from low-resolution inputs and a discriminator that ensures realism. Noted for its ability to reconstruct realistic textures and fine details, ESRGAN is ideal for enhancing images captured by UAV-mounted cameras, such as those using Raspberry Pi modules, typically upscaling images by a factor of 4x [19]. This capability is particularly valuable for land use classification, where high-resolution imagery is essential for identifying intricate land features.

This research project aims to design and develop a fixed-wing UAV tailored for land use image classification, leveraging lightweight materials, advanced sensors, and ESRGAN for enhanced image processing to improve data accuracy and operational efficiency. By addressing design considerations such as aerodynamic efficiency, flight stability, and integration of high-resolution imaging systems, this project seeks to create a UAV capable of collecting and processing aerial imagery for accurate land use analysis [1][3] . Drawing on prior research, including deep learning applications for UAV systems and their use in precision agriculture [3], this project will optimize UAV performance for environmental monitoring tasks. The outcome is expected to contribute to UAV-based remote sensing, offering a scalable solution for land use analysis in diverse geographical contexts.

1.2 Problem Statement

Land use and land cover (LULC) classification is critical for effective environmental management, agricultural monitoring, urban planning, and disaster response. Traditionally, satellite imagery has been the primary source for such analysis; however, limitations such as low spatial resolution, infrequent data updates, atmospheric disturbances, and high operational costs restrict its applicability for high-precision, real-time monitoring [3]. In contrast, UAVs offer a flexible, cost-effective, and scalable solution for high-resolution remote sensing. Among UAV types, fixed-wing aircraft present superior advantages for surveying large geographical areas due to their extended flight duration, aerodynamic efficiency, and higher operational altitudes [1][3] .

Despite their potential, existing UAV platforms used for LULC classification are often either commercially expensive, overly complex for academic research and field adaptation, or designed around rotary-wing systems that lack the range and endurance needed for broad-area coverage [2]. Moreover, there is a lack of integrated, low-cost fixed-wing UAV solutions that combine autonomous navigation, high-resolution image acquisition, and onboard or post-processed land classification capability tailored to specific regional or environmental needs.

Therefore, there exists a critical need to develop a custom-built, fixed-wing UAV system optimized for land use image classification—one that is affordable, reliable, and capable of autonomous operation in varied field conditions. This research project addresses that need by designing and implementing a fixed-wing UAV equipped with geo-referenced imaging systems and an image-processing pipeline to enable accurate and efficient land use classification.

1.3 Objectives

1. To design and build a fixed-wing UAV equipped with a lightweight camera system capable of capturing aerial image.
2. To improve the quality of captured aerial images through image upscaling techniques for enhanced clarity and detail.
3. To perform deep learning based land use classification using the upscaled high-resolution aerial imagery.

Chapter 2: Literature Review

The rapid development of Unmanned Aerial Vehicles (UAVs) has significantly impacted remote sensing, particularly in Land Use and Land Cover (LULC) classification. UAVs can capture high-resolution imagery, which is ideal for extracting fine-grained spatial details. However, challenges such as varying resolution, atmospheric distortion, and inconsistent lighting can affect the quality of the images. The application of deep learning techniques, particularly convolutional neural networks (CNNs), in enhancing UAV imagery via image upscaling is a promising direction, as seen in the proposed Gaurad-UAV model.

High-resolution data is crucial for accurate land use classification. Traditional satellite-based imagery often suffers from resolution constraints and longer revisit times. UAVs overcome these issues by offering greater spatial resolution and flexible data acquisition. Studies such as [5] [11] have successfully demonstrated the use of UAV imagery for detailed classification of urban and agricultural landscapes. In [5], Bui et al. employed a CNN model combined with UAV images and digital surface models (DSMs) to achieve a high overall classification accuracy of over 91% in urban mapping tasks. Deep learning models, especially transfer learning-based CNNs, have proven highly effective for LULC classification. Naushad et al. [11] used models like VGG16 and Wide Residual Networks (WRNs) to classify complex land use categories with an accuracy exceeding 98%, highlighting the capability of deep features to capture subtle variations in land cover types. Image upscaling, or single-image super-resolution (SISR), has emerged as a key pre-processing step to improve classification performance. Tuna et al. [18] applied CNN-based super-resolution methods to remote sensing images, showing improved visual quality and feature detectability, which in turn enhanced classification outcomes. This process helps generate higher-resolution approximations of low-resolution images, mitigating the effects of noise and data sparsity in UAV captures.

The Gaurad-UAV framework is proposed as a comprehensive approach that leverages deep CNNs for image upscaling before land use classification. While specific architectural and experimental details are yet to be broadly published, the conceptual foundation aligns well with existing literature. By enhancing image resolution, Gaurad-UAV aims to improve the feature quality available to classification models, thereby increasing accuracy and robustness in heterogeneous environments.

In summary, the integration of UAV imagery with deep learning and image super-resolution techniques presents a strong foundation for enhanced LULC classification. Gaurad-UAV, as a deep learning-powered image enhancement pipeline, contributes meaningfully to this domain by addressing the challenge of limited image resolution in high-precision mapping applications.

Chapter 3: Related Theory

3.1 Hardware

3.1.1 FLYSKY with Receiver

Figure 3.1. FLYSKY with Receiver

Flysky is a trusted name in the RC hobby community, renowned for producing cost-effective and dependable radio control systems. Their receivers, such as the FS-iA6B, FS-BS6, and FGr4S, are designed to work seamlessly with Flysky transmitters like the FS-i6X, FS-GT5, and Noble NB4. These receivers operate on the 2.4GHz frequency using the AFHDS 2A or AFHDS 3 protocols, offering robust signal stability and low-latency performance. Key features include support for iBUS and PPM protocols, enabling up to 18 channels for complex setups, as well as telemetry for real-time data like battery voltage. Models like the FS-BS6 include built-in gyro stabilization and failsafe functions, enhancing control for RC cars and boats. Flysky receivers are praised for their affordability and compatibility, making them a popular choice for hobbyists across skill levels.

3.1.2 30A ESC Skywalker

Figure 3.2. 30A ESC Skywalker

The 30A Skywalker ESC (Electronic Speed Controller) is a device designed to control the speed, direction, and braking of a brushless motor. Rated for a maximum continuous current of 30 amps, it is ideal for medium-sized electric drones and RC aircraft. It takes signals from the receiver or flight controller and converts them into three-phase power for the motor, allowing smooth acceleration and precise speed control. The ESC also includes safety features like overheating and overcurrent protection.

3.1.3 Flight Stabilizer (NXE4 EVO)

Figure 3.3. NXE4 EVO Flight Stabilizer

The NXE4 EVO Flight Stabilizer is an advanced control system used in RC aircraft and drones to maintain stability during flight. It uses onboard sensors such as gyroscopes and accelerometers to detect orientation and movement, and then automatically adjusts control surfaces or motor speeds to correct any deviations. This improves flight performance, especially in windy or unstable conditions, and enables smoother operation for both beginners and experienced pilots. It's essential for autonomous or semi-autonomous flight control.

3.1.4 1000KV Brushless Motor

Figure 3.4. 1000KV Brushless Motor

A 1000KV brushless motor is a high-efficiency electric motor that rotates at 1000 revolutions per minute per volt applied. It is commonly used in drones, RC aircraft, and electric vehicles due to its power-to-weight ratio, reliability, and minimal maintenance needs. Unlike brushed motors, brushless motors have no internal contact between the rotor and stator, reducing wear and increasing lifespan. The motor typically has three wires for connection to an ESC and is paired with a propeller or gear mechanism for motion output.

3.1.5 MG996 Metal Gear Servo

Figure 3.5. MG996 Metal Gear Servo

The MG996 is a high-torque, metal gear servo motor used for precise angular movement in robotics, RC vehicles, and automation systems. Its durable metal gear construction offers increased torque and strength compared to plastic gear servos, making it suitable for demanding applications. Controlled by a PWM signal, it can rotate to specific angles between 0° and 180°, making it ideal for steering mechanisms, robotic arms, or flaps in RC aircraft. It comes with a standard 3-wire connector for power, ground, and signal.

3.1.6 2200mAh 3S LiPo Battery

Figure 3.6. 2200mAh 3S LiPo Battery

The 2200mAh 3S LiPo (Lithium Polymer) battery is a high-capacity, lightweight power source commonly used in RC models, drones, and portable electronics. With three cells in series, it delivers a nominal voltage of 11.1V and a high discharge rate to support power-hungry components like motors and servos. Its 2200mAh capacity provides moderate runtime, making it ideal for short to medium-duration flights or robotic operations. The battery typically features a discharge plug (like XT60) and a balance connector for safe charging.

3.1.7 Buck Module Voltage Regulator

Figure 3.7. Buck Module Voltage Regulator

A buck module voltage regulator is a DC-DC converter that steps down higher input voltage to a lower, stable output voltage. It is commonly used in embedded electronics to power microcontrollers, sensors, and other 5V or 3.3V devices from higher-voltage sources like LiPo batteries. The module includes components such as an inductor, capacitor, and adjustable potentiometer to maintain a consistent output. Its compact size and efficiency make it essential for battery-powered projects to protect components from over-voltage.

3.1.8 Raspberry Pi 4 Model B

Figure 3.8. Raspberry Pi 4 model B

The Raspberry Pi is a credit card-sized single-board computer capable of running a full Linux OS and performing various computing tasks. When paired with a USB camera, it can capture images and video for applications like computer vision, surveillance, and robotics. The HDMI cable allows video output to a monitor or display, enabling real-time viewing or debugging. This setup is ideal for lightweight, portable embedded systems where processing power, camera input, and display output are all required.

3.2 Software Overview

3.2.1 ESRGAN for Image Super-Resolution

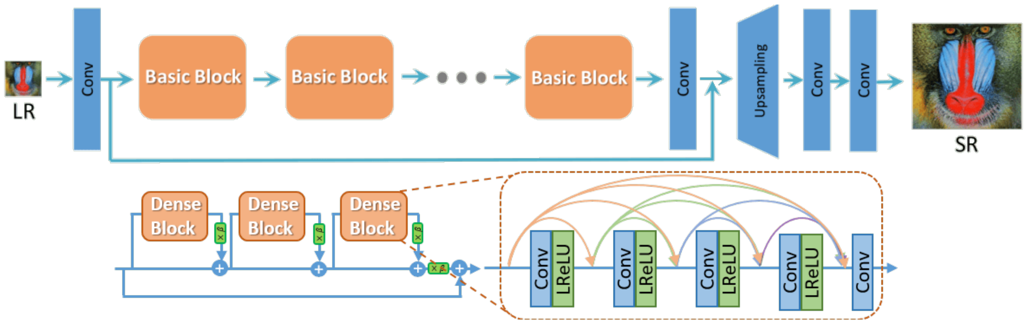


Figure 3.9. ESRGAN Architecture with Residual-in-Residual Dense Blocks (RRDB)

ESRGAN introduced by Wang *et al.* in 2018 [19], improves upon SRGAN by employing a deep generator built from Residual-in-Residual Dense Blocks (RRDB) without batch normalization. Each RRDB combines multiple convolutional layers, local dense connections, and global residual links to capture complex image features. The generator upsamples low-resolution inputs (e.g. 820×616 pixels) by a factor of 4× to high-resolution outputs (e.g. 3280×2464 pixels). The discriminator is relativistic, estimating the probability that a real image is more realistic than a generated one, which enhances stability and visual fidelity. ESRGAN further integrates a perceptual loss based on high-level VGG features computed before ReLU activations, preserving fine textures and brightness consistency. This design enables ESRGAN to produce photorealistic details, as demonstrated by its victory in the PIRM2018 SR Challenge [19].

In our UAV system, images captured onboard with a Raspberry Pi USB Camera are retrieved post-flight. ESRGAN runs on a ground PC to upscale extracted frames, recovering critical details (e.g. building outlines, vegetation patterns) necessary for accurate land use classification in the Kathmandu region.

3.2.2 Comparison of Super-Resolution Models

We compare ESRGAN with earlier SR approaches:

Model	Year	Architecture	Strengths	Weaknesses
SRCNN	2014	3-layer CNN	Simple, fast	Overly smooth outputs [6]
FSRCNN	2016	CNN + deconv	Efficient, higher PSNR [6]	Limited texture detail
EDSR	2017	Deep ResNet	High PSNR, faster [10]	Less perceptual quality
ESRGAN	2018	GAN + RRDB	Realistic textures, sharp edges [19]	Computationally intensive

Table 3.1. Comparison of Super-Resolution Models

3.2.3 Land Use Classification

Land use classification from UAV imagery entails categorizing pixels or patches into classes such as forest, agriculture, water, and urban. Common approaches include:

- **Convolutional Neural Networks (CNNs)**: End-to-end models (e.g. U-Net, ResNet, EfficientNet) that learn spatial hierarchies directly from upscaled images [4].
- **Random Forest (RF)**: Ensemble of decision trees trained on raw pixels or derived indices, robust to overfitting and effective for moderate datasets [4][6].
- **Support Vector Machine (SVM)**: Kernel-based classifier suitable for moderate-sized, well-separated classes [4][6].

A hybrid approach often combines CNN feature extractors with RF or SVM classifiers, leveraging deep networks for hierarchical feature learning and traditional ML for robust classification when labeled data is limited.

3.2.4 Software

The software pipeline integrates the following tools and libraries:

- **OpenCV**: For image/frame extraction, filtering, and geometric transformations [12].
- **NumPy & SciPy**: Core numerical and array operations for preprocessing.
- **scikit-learn**: Implements RF and SVM classifiers, data splitting, scaling, and evaluation utilities [15].

- **TensorFlow & PyTorch**: Deep learning frameworks for ESRGAN and CNN implementation. PyTorch (BasicSR toolkit) eases experimentation [14], while TensorFlow (TF-Hub ESRGAN) supports scalable deployment [17].
- **GDAL/Rasterio**: For handling geo-referenced imagery and aligning with regional GIS data [8].

3.2.5 Dataset

1. Kathmandu Land Use Datasets

Region-specific datasets used for land use classification in Kathmandu:

- **Nepal National Land Cover Dataset**: Annual land-cover maps (2000–2022) from Landsat imagery via Google Earth Engine, covering forests, agriculture, water, and built-up areas [7].
- **Kathmandu City Land Use Shapefiles**: Urban land use polygons (residential, commercial, parks) for Kathmandu Metropolitan City (2011) from ICIMOD [9].
- **OpenStreetMap Polygons**: Land-use tags for Kathmandu accessible through the Humanitarian Data Exchange [13].

2. Image Super-Resolution Datasets

Datasets used to train and evaluate ESRGAN and other super-resolution models:

- **DIV2K**: A large-scale dataset designed for image super-resolution, consisting of 1000 high-resolution images and their corresponding low-resolution counterparts. Suitable for training deep SR models.
- **Set5 and Set14**: Benchmark datasets commonly used for evaluating the performance of super-resolution models. While smaller in size, they are widely adopted for quantitative comparisons.

These datasets provide essential ground truth for training and validating both our land use classification pipeline and image super-resolution models.

Chapter 4: Feasibility Study

4.1 Technical Feasibility

4.1.1 Hardware Availability and Requirements

- **UAV Hardware:** Raspberry Pi 4 with a camera module for capturing aerial imagery.
- **ESRGAN Processing:** Ground PC with GPU or cloud-based services (e.g., Google Colab) for super-resolution.
- **Flight Components:** Motors, ESCs, batteries, and flight controllers, readily available in local electronics stores in Kathmandu.

4.1.2 Software Tools and Implementation

- **ESRGAN Super-Resolution:** Implemented using PyTorch or TensorFlow with open-source pretrained models.
- **Land Use Classification:** Utilizes scikit-learn (SVM, RF) and CNNs using PyTorch or TensorFlow.
- **Image Processing:** Managed with OpenCV, NumPy, and GDAL/Rasterio for geospatial tasks.

4.1.3 UAV Design and Development Tools

- **Design:** AeroToolbox and similar open-source tools for wing loading, CG calculation, and thrust analysis.
- **Build Materials:** Depron sheets used for lightweight UAV frame construction, available locally.

4.1.4 Time Feasibility

- **Design, Assembly, and Software Development:** UAV frame design, hardware integration, and implementation of the image processing/classification pipeline will take around 3 months.

- **Testing and Validation:** Field testing of UAV and validation of outputs will require 2–3 weeks.
- **Data Collection and Model Training:** Capturing aerial imagery, labeling datasets, and training/testing models with ESRGAN-upscaled images will take 2.5–3.5 months.

Total Estimated Time: Approximately 6–7 months.

4.2 Economic Feasibility

- **Cost-Effective Setup:** Low-cost components like Raspberry Pi, camera modules, depron, and UAV parts are affordable and readily available in Kathmandu (e.g., local stores or Daraz).
- **Free Software and Compute Resources:** Software tools such as PyTorch, TensorFlow, OpenCV, and cloud services like Google Colab are free, minimizing development cost.

Market Potential and Conclusion: This project provides a scalable, low-cost solution for high-resolution land-use classification using UAV imagery and super-resolution techniques. Its modular structure and reliance on open-source software and affordable components make it both technically and economically viable. With applications in urban planning, smart agriculture, and environmental monitoring, the system shows strong commercialization potential. Future upgrades like onboard inference, real-time telemetry, and satellite data integration can further enhance its market value.

Chapter 5: Methodology

5.1 System Block Diagram

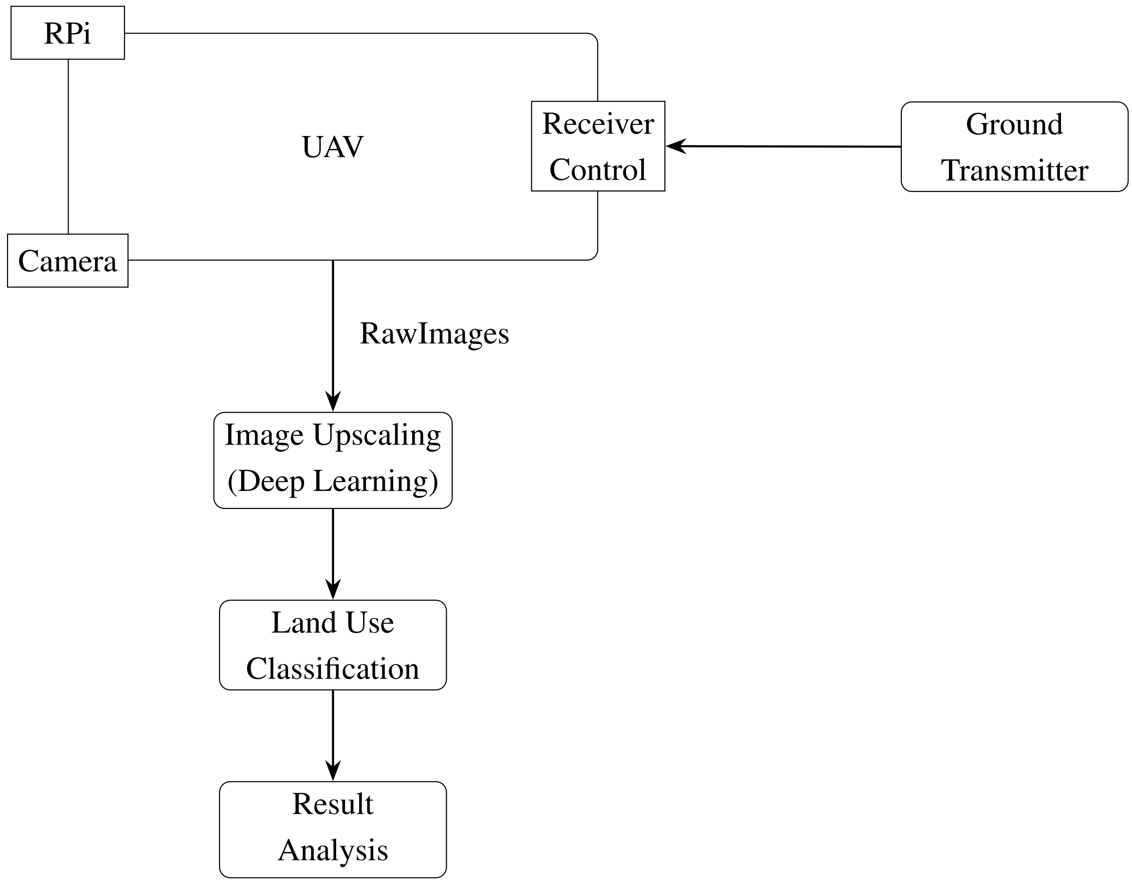


Figure 5.0: System Block Diagram of UAV System

5.1.1 System Description

The system consists of a fixed-wing UAV platform equipped with essential components for flight and data collection. The UAV includes:

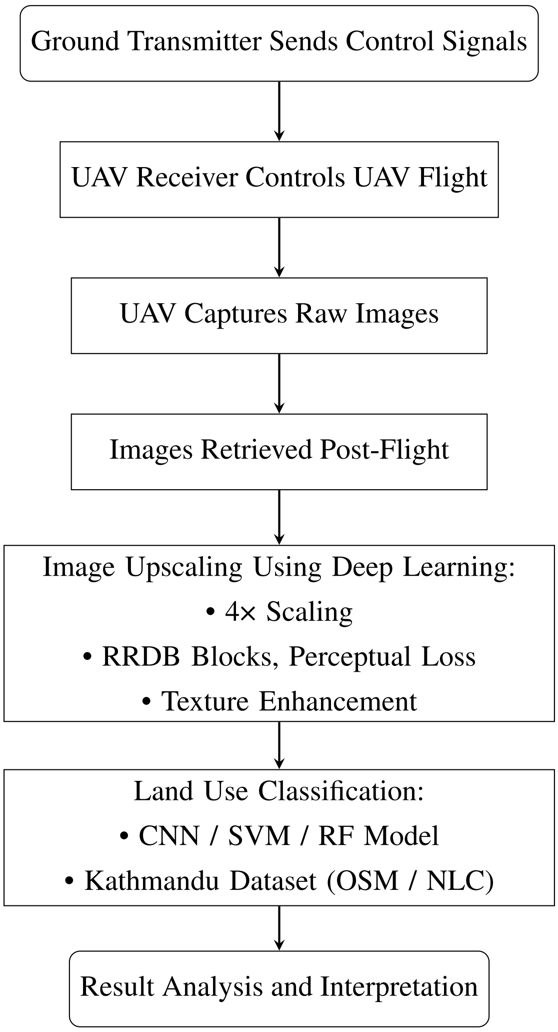
- **ESC (Electronic Speed Controller):** Regulates the speed of the motor driving the propeller.
- **Propeller:** Provides thrust for UAV flight.
- **4 Servos:** Control the movement of aerodynamic surfaces like ailerons, elevator, and rudder for flight maneuverability.

- **Battery:** Powers the entire onboard system.
- **UAV Receiver:** Receives control signals from the ground-based transmitter.
- **Raspberry Pi + Camera Module:** Captures aerial images during flight.

The ground transmitter sends flight control commands to the UAV receiver. The Raspberry Pi processes input from the onboard camera and stores captured images.

These images are then passed to the image upscaling module using deep learning methods, enhancing the resolution and clarity. The upscaled images are further processed through a classification model to identify land use categories. Finally, the results from the classification are analyzed for insights, contributing to high-resolution land use mapping from UAV-acquired data.

5.2 Flowchart



Chapter 6: Expected Output

- **Development of a Functional Fixed-Wing UAV:** A fixed-wing unmanned aerial vehicle will be designed and developed, equipped with essential components including a camera module and a receiver, to enable autonomous aerial image capturing during flight.
- **Generation of High-Resolution Aerial Images:** The captured low-resolution images will be processed using deep learning-based image upscaling techniques to generate high-resolution outputs suitable for detailed analysis.
- **Implementation of Land Use Classification:** The upscaled images will be used to perform land use classification by applying a trained deep learning-based classification model to accurately distinguish various land cover types.

Gantt Chart

Cost Estimation

Electronics & Core Components

Item	Quantity	Cost (NRs)
FLYSKY Receiver	1	8000
30A ESC Skywalker	1	2000
Flight Stabilizer (NXE4 EVO)	1	4500
1000KV Brushless Motor	1	800
MG996 Metal Gear Servo	4	3040
2200mAh 3S LiPo Battery	1	3150
Buck Module Voltage Regulator	1	550
Raspberry Pi 4B with USB Camera and HDMI Cable	1	0
Total		**22040**

Table 6.1. Electronics and Core Components for Fixed-Wing UAV

Frame & Construction Materials

Item	Quantity	Cost (NRs)
Depron Sheet(1000*600 mm)	4	10 000
Aluminum Motor Mount (L-shape)	1	150
Push Rod (1m)	2	400
Total		**10550**

Table 6.2. Frame and Construction Materials for Fixed-Wing UAV

Miscellaneous Accessories

Item	Quantity	Cost (NRs)
Hot Glue Gun Stick	10	200
Duct/Binding Tape	3 rolls	300
XT60 Connector Pair	2	500
3-Pin Orange Connector Pair	4	60
Servo Wire Cable (5m)	1	75
Propeller (7x5 inch)	4	300
Bullet Propeller Holder Adapter	1	170
Jumper Wire (MM, MF, FF, each 5)	15	30
Total		**1635**

Table 6.3. Miscellaneous Accessories for Fixed-Wing UAV

Grand Total

Category	Cost (NRs)
Electronics and Core Components	22 040
Frame and Construction Materials	10 550
Miscellaneous Accessories	1635
Grand Total	**34225**

Table 6.4. Grand Total Cost for Fixed-Wing UAV

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