ESTIMATION AND ANALYSIS OF LANDSLIDE OCCURRENCE BY COMBINING GEOGRAPHICAL AND ATMOSPHERICAL STUDY USING UNET MODEL

Major Project report submitted in partial fulfillment of the Requirements for the Award of the Degree of

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Submitted by

K. V. VISHNU VARDHAN	198W1A0529
V.H.S.S KAUSHIK	198W1A0561

Under the Guidance of

Dr. K.L. Sailaja, M.Tech, Ph.D

Assistant Professor

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

VR SIDDHARTHA ENGINEERING COLLEGE

Autonomous and Approved by AICTE, NAAC A+, NBA Accredited

Affiliated to Jawaharlal Nehru Technological University, Kakinada

Vijayawada 520007

2023

VELAGAPUDI RAMAKRISHNA SIDDHARTHA ENGINEERING COLLEGE

(Autonomous, Accredited with 'A+' grade by NAAC)

Department of Computer Science and Engineering

CERTIFICATE

This is to certify that the MAJOR project course report entitled **"ESTIMATION AND ANALYSIS OF LANDSLIDE OCCURRENCE BY COMBINING GEOGRAPHICAL AND ATMOSPHERICAL STUDY USING UNET MODEL"** being submitted by

K.V. VISHNU VARDHAN(**198W1A0529**)

V.H.S.S KAUSHIK(**198W1A0561**)

in partial fulfillment for the award of the Degree of Bachelor of Technology in Computer Science and Engineering to the Jawaharlal Nehru Technological University, Kakinada is a record of bonafide work carried out during the period from 2022 - 2023.

Dr. K.L. Sailaja, M.Tech, Ph.D
Assistant Professor & Guide

Dr. D. Rajeswara Rao, M.Tech, Ph.D
Professor & HOD, CSE

DECLARATION

We hereby declare that the Major project entitled "ESTIMATION AND ANALYSIS OF LANDSLIDE OCCURRENCE BY COMBINING GEOGRAPHICAL AND ATMOSPHERICAL STUDY USING UNET MODEL" submitted for the B.Tech Degree is our original work and the dissertation has not formed the basis for the award of any degree, associateship, fellowship or any other similar titles.

Place: Vijayawada | K. V. Vishnu Vardhan (198W1A0529)

Date: | V.H.S.S Kaushik (198W1A0561)

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Place: Vijayawada K. V. Vishnu Vardhan (198W1A0529)

Date: V.H.S.S Kaushik (198W1A0561)

Abstract

Landslides have a significant impact on society, resulting in damage to the environment, economic and agricultural losses, and social disruptions. Therefore, the early prediction of landslides is crucial. Remote sensing techniques are becoming increasingly important in landslide monitoring and prediction, as they can help reduce the risks associated with such events. One such method involves using data from the Sentinel-2 satellite to detect landslides. This technique involves analyzing changes in the current system and identifying triggering events such as rainfall or deforestation. To predict landslides, various factors are considered, including Digital Elevation Model from sentinel-2 imagery using the Stereo Correlation technique, Slope of the land is also analyzed to determine deformation-induced landslides. Other parameters such as NDVI and NIR are used to identify barren and deforested areas, while aerosol, water vapor, and NDMI are considered to detect rainfall-induced landslides. Geological data is used to identify the underlying geological conditions causing the landslides. An enhanced U-Net model is used for training purposes and detect the forth coming landslides. The results of the prediction with specific regional data can be used to estimate the area at risk of landslides.

Keywords: Landslide prediction, Remote sensing, Sentinel-2, Digital Elevation Model, U-Net model.

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Chapter 1

INTRODUCTION

Landslides are the movement of rock, soil, or debris down a slope. They can occur naturally or as a result of human activities. There are several types of landslides, including rockfalls, debris flows, landslides, and mudflows. Landslides are caused by a combination of several factors, including Geology, Topography, Climate, Human activities and certain types of rock and soil are more prone to landslides than others. For example, weak and saturated soils, as well as rock layers that are easily weathered, can make a slope more prone to landslides.

The slope of the land can effect the likelihood of a landslide. Steep slopes are more prone to landslides than gentle slopes. Heavy rainfall, snowmelt, and drought can cause landslides by changing the water content of the soil and rock. Human activities can also contribute to landslides, such as deforestation, mining, and urban development. These activities can change the natural drainage patterns and increase the weight on the slope, making it more prone to landslides.

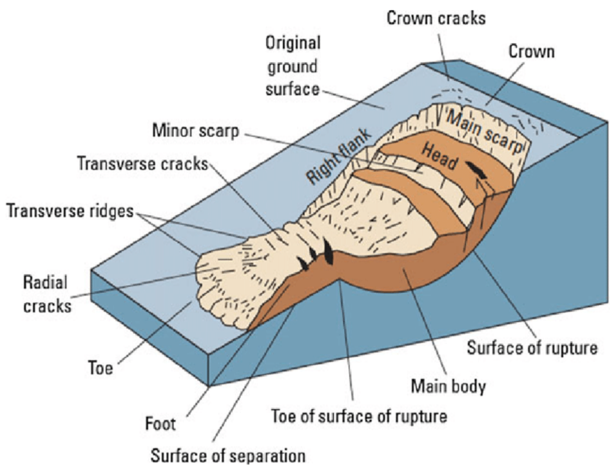

Figure 1.1: Landslide Nomenclature [1]

Landslides can be triggered by an earthquake, volcanic activity, or other seismic events. It is important to note that landslides can happen suddenly, without warning, and can be extremely dangerous [1]. Early warning systems, risk assessments, and proper land-use planning can help to reduce the risk of landslides and protect people and property. An idealized slump-earth flow is depicted in Figure 1.1, demonstrating the commonly adopted nomenclature used for designating the various elements of a landslide.

1.1 Basic Concepts

DInSAR

The deformation of the Earth's surface may be measured with millimeter-level accuracy using the remote sensing method known as Differential Interferometric Synthetic Aperture Radar (DInSAR) [2]. Using the phase difference between Radar pictures of the same site acquired at several periods, it is possible to identify slight variations in the surface height. For monitoring and forecasting natural hazards including landslides, subsidence, and volcanic activity, DInSAR has proven to be an invaluable tool. It is also helpful for identifying ground movement brought on by human operations like mining and oil production. Correcting for atmospheric impacts is essential for obtaining precise measurements, as failure to do so can lead to inaccurate results. The precision of DInSAR observations may be increased by utilizing a variety of methods, including the use of numerous interferograms and atmospheric models. For a more full view of ground deformation, DInSAR is frequently employed in combination with other remote sensing methods, such as GPS and satellite imaging. Combining data from many sources can assist to increase the precision and dependability of DInSAR measurements.

U-Net

For image segmentation tasks, U-Net is a well-liked deep-learning architecture. It was released in 2015 and is frequently used for biomedical image segmentation tasks including tissue and cell segmentation. Convolutional neural networks are used in U-Net's encoder-decoder architecture to extract features from the input picture and create a segmented output. Because it utilizes skip connections, U-Net has a special ability that enables it to blend low-level and high-level characteristics to achieve incredibly precise segmentation results. The symmetric design of U-Net features expansive and contracting paths [3]. While the expanding route creates the segmentation map and the contracting path collects the image's context. To overcome its drawbacks, U-Net has undergone a number of changes and enhancements. Attention U-Net, Residual U-Net, Dense U-Net, and Recurrent U-Net are a few of the variations of UNet.

SAR (Synthetic Aperture Radar)

A sort of Radar technology called SAR (Synthetic Aperture Radar) is used to take high-definition pictures of the surface of the Earth. SAR employs a synthetic aperture, which is formed by the mobility of the platform holding the radar instrument (such as a satellite or an airplane), in contrast to conventional radar systems, which use a single antenna to broadcast and receive signals. SAR operates by sending out microwave waves and detecting the signals that are backscattered by the surface [4]. Distinct kinds of surfaces will produce distinct backscattered signals, which are utilized to construct a picture of the surface. SAR is a form of active remote sensing, which means it sends out a signal and then measures the response. This makes SAR a helpful tool for recording the Earth's surface in all weather circumstances since it enables it to work independently of sunlight and penetrate clouds. SAR can be used in conjunction with other remote sensing methods to get additional data about the Earth's surface, such as optical and thermal imaging. This can deepen our comprehension of intricate environmental processes and guide our management of natural resources.

Digital Elevation Model

Digital Elevation Model is referred to as DEM. It is a digital visualization of a specific area's topography, usually in the form of a 3D surface or a collection of contour lines. It may be used for a range of purposes, including terrain analysis, topographic mapping, and hydrological modeling, and is often obtained from LIDAR or stereo aerial data. Digital Elevation Models (DEMs) are used in many different disciplines, including the following: Cartography and Geographic Information Systems (GIS) are used to produce comprehensive topographic maps, display 3D terrain, and conduct spatial analysis [5]. To accurately simulate the topography of a site for planning and design purposes, calculate the volume of earthworks, and construct drainage systems are all aspects of civil engineering and land development. DEMs may be created from a variety of data sources, including Radar, Light Detection And Ranging (LiDAR), and satellite images. Choosing the best data source is essential for producing an accurate DEM since each data source has benefits and limitations of its own. The spatial sampling interval, or DEM resolution, establishes the degree of precision and complexity of the terrain representation. Higher-resolution DEMs offer more precise information but need more resources and processing time. Depending on the data source utilized, DEM resolution might also change.

1.2 Motivation

The main motive of this study is to mitigate the detrimental impact of landslides on both human and environmental well-being. Residents living in hilly and sloped regions are particularly vulnerable to landslides. Early identification of potential landslides through remote sensing methods can help prevent these incidents. By detecting regions at risk of landslides and alerting the government, necessary emergency measures can be taken to ensure the safety of local communities.

1.3 Problem Statement

Landslides pose a significant threat to both the environment and human life, and the current approach to managing this risk involves evacuating nearby individuals only after a landslide has already begun. If we can predict landslides in advance, we can potentially reduce the damage and save numerous lives. This study uses the Stereo correlation technique and deep learning methodologies to forecast impending landslides caused by factors such as land deformation, rainfall, geological conditions and atmospheric changes, utilizing data obtained from the Sentinel-2 satellite.

1.4 Objectives

The Objectives include:

1. To impart equipped techniques in early detection of landslide occurrence and prevent human loss.

2. To detect the landslides caused due to rainfall, land deformations, and geological features.

3. To provide an efficient methodology for generation of considered sentinel-2 band combinations.

4. To calculate the geographical area for the region where the landslide is going to occur.

1.5 Scope

1. Landslide detection and it's characteristics evaluation using remote sensing techniques only.

2. This study involves prediction using the data collected by the sentinel-2 satellite alone.

1.6 Applications

1. It can be used by the government to get prepared for the forth-coming landslide.

2. It can be used by rescue teams to evacuate people prior to landslides, reducing human loss.

3. It can be used by tourist organizations and travel agencies to plan accordingly for people's safety.
4. It can be used to analyze the intensiveness of the landslide and record them for research study purposes.
5. It can also be used by NGOs to prevent the pollution of rivers due to landslides.

1.7 Advantages

1. It helps to prevent human loss.
2. It helps in continuous monitoring of the lanslide susceptible regions.
3. It also helps in taking preventive measures for avoiding it.
4. It helps in prevailing social, economic, and environmental damage caused due to landslides.
5. It helps in preventing the blockage of rivers due to landslides.
6. It helps in preventing infrastructure, forest, and agricultural loss.

Chapter 2

LITERATURE REVIEW

This chapter contains a comprehensive list of research papers that were examined. Our primary focus was on identifying the various approaches mentioned in these papers to gain insights into the current technologies. Specifically, we studied the techniques used for model development and training.

2.1 Landslide detection using deep learning and object-based image analysis

Omid Ghorbanzadeh et al [6] proposed a novel approach for landslide detection using pixel-based deep learning methods applied to Sentinel-2 satellite imagery. The method classifies each pixel as either a landslide or a non-landslide by combining ResU-net, object-based image analysis, and ResU-net-object-based image analysis. The model estimates the possibility of landslide susceptibility in the research area, the Taiwan region after the Morakot typhoon in August 2013. This technology may enhance landslide detection and offer insightful information for disaster management and mitigation activities.

Advantages:

- This study uses the combined approach of OBIA and ResU-Net for accurate results.
- The integrated approach gave 73.14% accuracy compared to the ResU-Net alone, which gave an accuracy of 61.29%.

Disadvantages:

- The increase in recall value observed in the combined approach is not as remarkable as that of precision.
- This study is confined only to data collected through remote sensing methods.

2.2 Geoinformatic Analysis of Rainfall-Triggered Landslides in Crete (Greece) Based on Spatial Detection and Hazard Mapping

Athanasios V. Argyriou et al [7] proposed a project which focuses on detecting landslides induced by heavy rainfall in the Mediterranean Crete region. It intends to look into the relationship between other landslide-causing conditions and rainfall as the trigger component. Furthermore, the study aims to identify regions with a high probability of rainfall-triggered landslides during upcoming rainstorms in order to evaluate the geographical distribution of landslide hazards.

Advantages:

- Temporal satellite image's visual interpretation is used to overcome the topography-based shadow effects.
- The domino-effect is also considered while predicting climatic changes.

Disadvantages:

- There is a possibility of slight mismatches between the conditioning factors and threshold values used in the project and the actual location of the landslide.
- Geoinformatic analysis is confined only to data collected through remote sensing methods.

2.3 Landslide Detection Using Densely Connected Convolutional Networks and Environmental Conditions.

Haojie Cai et al [8] proposed a project which aims to leverage the benefits of DenseNets and their modified techniques to improve landslide detection. In order to develop novel landslide samples unique to the research region, the project takes into account a variety of environmental characteristics, including aspect, slope, elevation, terrain relief, profile curvature, plan curvature, lithology, bedding structure, NDVI, MNDWI, distance to fault, and rivers.

Advantages:

- The use of DenseNet can significantly enhance the accuracy of the landslide detection model. In comparison to optical imagery, the inclusion of DenseNet architecture resulted in a substantial increase of 9.7% in kappa and 9.1% in F1 scores.
- When compared to other networks, DenseNet exhibits the highest kappa and F1 scores.

Disadvantages:

- CNN is confined only to data collected through remote sensing methods.
- The model is unable to detect micro landslides.

2.4 Small Scale Landslide Detection Using Sentinel-1 InSAR Coherence

Marios Tzouvaras et al [9] proposed a system for detecting landslides in the Cyprus region has been proposed in a recent paper. The study showcases the utilization of Copernicus open-access datasets and The European Space Agency has made available an open-source processing software called SNAP (Sentinel's Application Platform) that can be utilized for detecting landslides caused by rainfall. The coherence maps generated using SNAP were imported into ArcGIS where the sea was removed, and coherence values were classified to develop the final coherence products.

Advantages:

- Coherent Change Detection (CCD) technique for landslide detection along with DInSAR technique.
- The true-positive rate, which is also known as sensitivity or probability of landslide detection, was 63.2% in the case of the coherence difference and increased to 73.7% for the normalized coherence difference.

Disadvantages:

- Probability of false detection of landslides was approximately 1%.
- The study is confined only to data collected through remote sensing methods.

2.5 Review of Satellite Interferometry for Landslide Detection in Italy

Lorenzo Solari et al [10] presented a comprehensive review of more than 250 papers analyzing various InSAR-related applications for landslide studies in Italy. The earliest application was recorded back in 1999, and on average, around 12 papers per year were published in this field. The highest number of papers, 37, was recorded in 2015. The primary focus of this review was to provide a complete analysis of landslide detection in Italy and to highlight the significant role played by satellite interferometry in monitoring and mapping landslides in the country.

Advantages:

- Approximately more than 250 papers were reviewed for analyzing.
- The review identified two main areas in which InSAR is commonly utilized as input for models in landslide studies: single landslide modeling and basin-scale susceptibility modeling.

Disadvantages:

- This review is neither focused on technical aspects, nor on a general presentation of the InSAR advantages and limitations.

2.6 Landslide Detection Using Remote Sensing A Review of Current Techniques.

Byrraju, S. V et al [11] proposed a system was designed to detect landslides in three distinct regions, including Etna, California Highway 1, and Anargyroi Greece, where unique factors contribute to landslides. The system used data obtained from the Sentinel-1 satellite, which features a C-band SAR sensor, and analyzed each of the three locations over a period of 36 days with acquisitions taken every 12 days. One critical step in the process was co-registration, which involved matching pixels from two acquisitions to accurately calculate phase differences, thus increasing coherence and reducing noise.

Advantages:

- The analysis employs DInSAR, with SRTM DEM being used as a reference to create phase maps of the regions.

- Thorough testing and evaluation of the effectiveness of DInSAR in analyzing landslides and recognizing their characteristics is done.

Disadvantages:

- The remote sensing methods are affected by a layover and shadowing principles.

2.7 Evaluation of Different Machine Learning Methods and Deep-Learning Convolutional Neural Networks for Landslide Detection.

Ghorbanzadeh et al [12] proposed a landslide detection system for the southern region of Nepal's Rasuwa district, which employed optical data from the Rapid Eye satellite and topographic factors. Machine learning techniques and various deep-learning convolutional neural networks were utilized in the system to analyze the potential for landslide detection. To assess its performance, the system used spectral data from Rapid Eye imagery with relevant topographic factors.

Advantages:

- The study results has impact on input window size and layer depth.
- The mIOU(Mean Intersection-over-Union) metric is used to measure the accuracy of the result.

Disadvantages:

- Topographical information reduced the accuracy of the results.
- The evaluation is unable to conclude whether the topographic information has an effect on the detection or not.

2.8 Landslide detection in mountainous forest areas using polarimetry and interferometric coherence

Ohki et al [13] proposed a system that uses a combination of PolSAR, InSAR, and DEM analysis to detect landslides in mountainous regions. The study was applied to detect landslides that occurred due to heavy rainfall in Northern Kyushu in July

2017 and the 2018 Hokkaido earthquake, employing L-band SAR data obtained from the ALOS-2 PALSAR-2 satellite. Fully polarimetric L-band SAR data from the same satellite was also utilized in this research.

Advantages:

- The study methodology also takes into account the LIA(Local Incidence angle) too in dealing with surface scattering.
- Obtained higher accuracy by combining many parameters from PolSAR, InSAR, and DEM.

Disadvantages:

- The model mistakenly detects the deforested area as a landslide.
- The results are affected by the layover effect.

2.9 Analysis of topographic and climatic control on rainfall-triggered shallow landsliding using a quasi-dynamic wetness index

M. Borga et al [29] proposed a model for the forecasting of topographic and climatic influences on the processes leading to shallow landslides in steep mountainous terrain. To estimate the geographical distribution of soil saturation in response to rainfall of a given length, the model employs a "quasi-dynamic" wetness index. There is no particular method for using the quasi-dynamic model in a digital terrain framework, despite the fact that it is specified by a straightforward algebraic formula. The quality of the database determines that this strategy is successful.

Advantages:

- The approach considers both temporal and spatial variability of soil moisture.
- The study findings can aid in land-use planning and hazard mitigation.

Disadvantages:

- The research may have limited applicability to other regions, and the accuracy of the results may be limited by data quality and availability.

2.10 Assessment of susceptibility to rainfall-induced landslides using improved self-organizing linear output map, support vector machine, and logistic regression

G.-F. Lin et al [30] proposed a system as a Quantitative landslide susceptibility assessment where it is important to reduce deaths, property damage, and financial loss caused by a landslide. An ideal model of landslide susceptibility is proposed to produce exact maps of landslide susceptibility and quantify landslide susceptibility. By evaluating the performance of Support Vector Machines (SVM), Improved Self-Organizing Linear Output map (ISOLO), Logistic Regression (LR), and four additional kernel functions, the optimal landslide susceptibility model was created.

Advantages:

- This research compares the accuracy of several models to determine landslide susceptibility.
- The research area is clearly defined, and similar places might benefit from the models.

Disadvantages:

- The model's efficiency is reliant on a high quality of input data, and the concentrates on a single research region.

2.11 Measuring landslide vulnerability status of Chukha, Bhutan using deep learning algorithms

S. Saha et al [31] presented research with the goal of supplying a better framework for assessing the Landslide Vulnerability Map (LVM) of Bhutan's Chukha Dzongkhags (district). Using images from Google Earth, government statistics, and field research, a total of 350 landslides—both recent and historical—were recorded. The 70:30 ratio was used to generate the training and validation sets. To evaluate the performance of the models, several statistical metrics such as the Relative landslide density index (R-index), the Area Under the Curve (AUC), and Receiver Operating Characteristics (ROC) were utilized.

Advantages:

- The study can aid in risk assessment and management.
- This study uses deep learning algorithms to measure landslide vulnerability in a remote and understudied region.

Disadvantages:

- Limited description of data collection and processing, and the focus on only one region limits generalizability to other areas.
- The accuracy of the results is dependent on the quality of the input data.

2.12 Rainfall threshold estimation and landslide forecasting for Kalimpong, India using sigma mode

M. T. Abraham et al [32] proposed a model that uses the statistical distribution of cumulative rainfall data as its input and standard deviation multiples to determine rainfall thresholds. The SIGMA model has been utilized at Kalimpong which is most susceptible to landslides. The study's dual objectives are to determine thresholds of regional rainfall for landslide activity in the Kalimpong area and to assess the SIGMA model's applicability in a physical setting that is distinct from previously studied locations.

Advantages:

- This research calculates rainfall thresholds and forecasts landslides with a Sigma model.
- The approach provides early warning systems for landslide risk management.

Disadvantages:

- The study focuses only on one region, and the accuracy of the results is dependent on the quality of input data.
- The accuracy of the results is dependent on the quality of the input data.

Chapter 3

ANALYSIS AND DESIGN

This chapter provides an analysis of the necessary requirements for the proposed project, including both functional and non-functional requirements.

3.1 Functional Requirements

Analyzing functional requirements involves conducting a comprehensive examination, analysis, and description of both software and hardware requirements to fulfill actual and essential criteria necessary for solving a problem. This process encompasses various stages or processes. The Functional Requirements include:

3.1.1 Software Requirements

Open-CV:
OpenCV (Open Source Computer Vision) is a programming library that contains a vast collection of functions designed primarily for real-time computer vision applications [14]. It is open-source software and can be used for a wide variety of tasks such as object detection, image processing, video analysis, and more. Open CV is written in C++ but has interfaces for various programming languages including Python and Java. It is widely used in both industry and academia for a variety of computer vision applications. Using Open-CV there were many real-world problems that were solved with better efficiency and accuracy. Open-CV gives a visual sense to the computer. OpenCV provides a deep learning module that supports popular deep learning frameworks like TensorFlow, Caffe, and PyTorch. This allows developers to build and train complex deep-learning models for tasks such as object detection, image segmentation, and facial recognition. OpenCV has a large and active community of developers and users who contribute to the library, provide support, and share their knowledge through forums, blogs, and tutorials. This makes it easy for developers to find help.

U-Net:
U-Net is a popular deep-learning architecture used for image segmentation tasks. It was introduced in 2015 and is widely used for biomedical image segmentation applications such as cell segmentation, tissue segmentation, and more. The

architecture of U-Net is based on an encoder-decoder design, which utilizes convolutional neural networks to extract features from the input image and produce a segmented output [15]. The unique feature of U-Net is that it uses skip connections, allowing it to combine low-level and high-level features to produce highly accurate segmentation results. U-Net has demonstrated impressive performance on various image segmentation benchmarks and is widely used in the research community and industry for various applications. U-Net has a symmetric architecture with a contracting path and an expanding path. The contracting path captures the context of the image, while the expanding path generates the segmentation map. U-Net has undergone several modifications and improvements to address its limitations. Some of the variants of U-Net include Attention U-Net, Residual U-Net, Dense U-Net, and Recurrent U-Net.

Snap Tool:
SNAP (Sentinel Application Platform) is a software tool developed by the European Space Agency (ESA) for working with Earth Observation data from the Copernicus Sentinel satellite missions. It provides a wide range of functionalities for processing and analyzing Sentinel data, including data import, pre-processing, visualization, and export. SNAP allows users to perform various tasks such as Calibrating and atmospherically correcting Sentinel-2 and Sentinel-3 data [16]. SNAP has a plugin architecture, which allows developers to extend its functionality by creating their own processing operators and workflows. This makes SNAP highly customizable and adaptable to different user needs. SNAP has an active community of users and developers, who contribute to its development, provide support, and share their workflows and plugins. This makes SNAP a vibrant and collaborative platform for processing Sentinel data.

ArcGIS Pro Tool:
ArcGIS is a software tool developed by ESRI (Environmental Systems Research Institute) for working with Geographic Information Systems (GIS) data [17]. It provides a wide range of functionalities for creating, editing, visualizing, and analyzing spatial data, including maps, imagery, and geographic information. ArcGIS can be used for various tasks such as creating and editing maps, including adding and editing layers, symbology, and labels, Analyzing and querying spatial data, finding patterns and relationships, and creating new information. ArcGIS is a powerful tool for spatial analysis, allowing users to analyze geographic data in various ways. It can perform advanced spatial analysis tasks such as proximity analysis, network analysis, and spatial statistics.

3.1.2 Hardware Requirements

- Recommended Intel Core i5 8400 or AMD Ryzen 5 3000 Series
- Recommended Windows 10 64-bit, Windows 11 64-bit
- Minimum of 8GB Ram
- 50 GB of available hard disk drive space
- Recommended: 2.6 GHz, 4 cores
- NVIDIA/AMD GPU for faster run-times for U-Net

3.2 Non-Functional Requirements

Non-functional requirements are constraints imposed on functional requirements.

- The area of interest should be of considerable area
- The Digital Elevation Model should be of 10m resolution
- The cloud cover should be less than 10 percent
- The Digital Elevation Model should be only from Sentinel-2 satellite
- The obtained sentinel-2 data should have a spatial resolution of 10m.
- Only sentinel-2 satellite data is to be considered.

3.3 Design Diagram

Design diagram is a diagram which is a visual representation of various modules of the whole project. Figure 3.1 represents the design diagram for the proposed methodology.

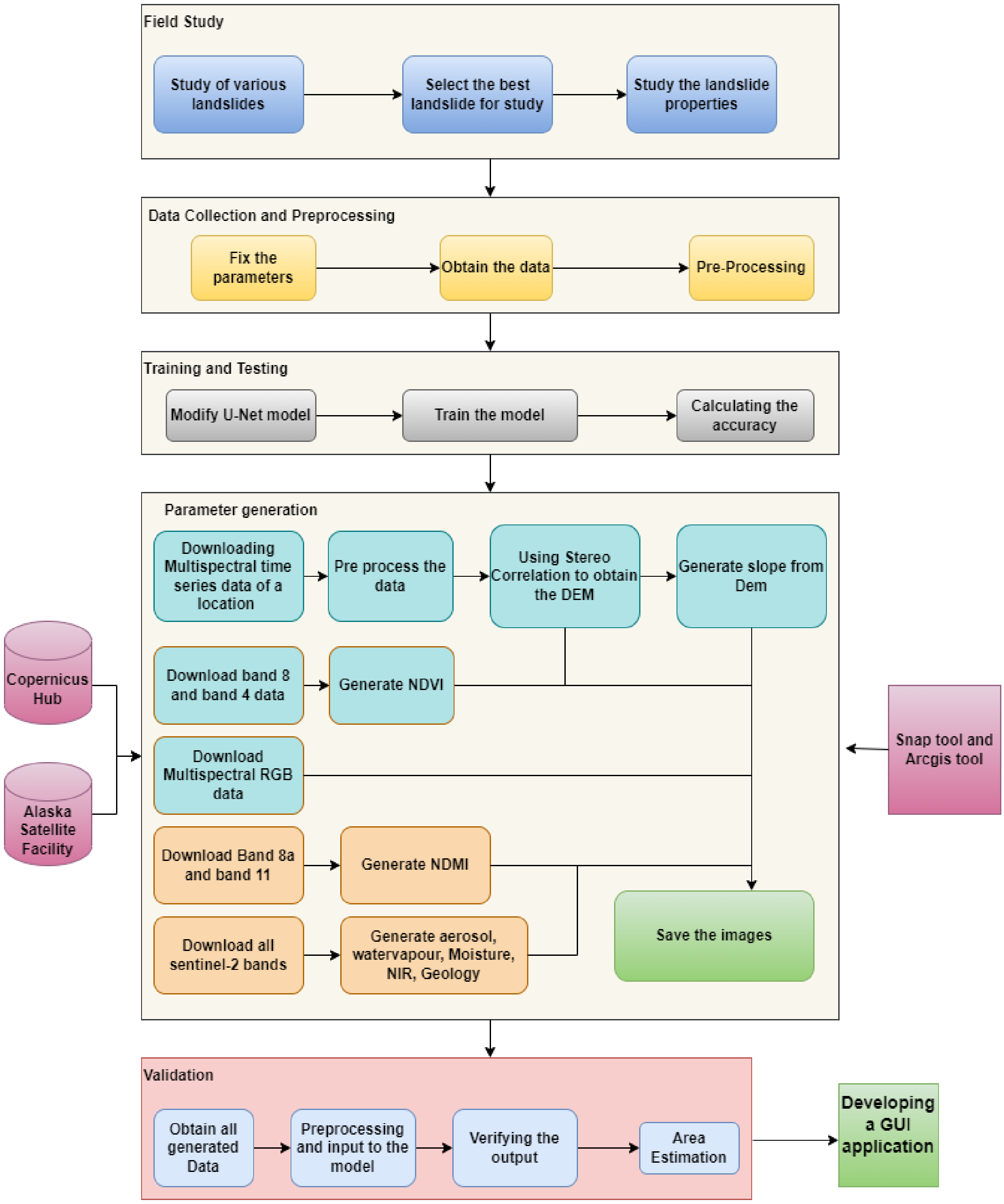

Figure 3.1: Design Diagram

In Figure 3.1, The first block denotes module 1 which is the field study. In the field study, we study the various types of landslides and various properties of landslides. Then we selected the best landslide for study which covers the properties of the majority of the landslides. This landslide is studied further to analyze its properties. In total, nine parameters were fixed for finding the susceptibility map of a region.

The second block is about module 2 which indicates the dataset collection and pre-processing. The dataset will be downloaded from the challenge. The data will be in form of .h5 files. These files are to be pre-processed as per requirement and made ready for training purposes.

The third block indicates the training part. The model is created as per the U-Net Architecture and a few enhancements was made to it to get better results. The model is trained on the dataset created.

The fourth module is about the validation of the model. The SR-530 landslide data is considered here. The data consists of DEM, Slope, NDVI, RGB, Aerosol content, water vapor, NDMI, NIR content, and geology data. The DEM is generated in the SNAP tool using the data gathered from the Copernicus hub and Alaskan satellite facility. Then DEM is then loaded into the ArcGIS and then Slope is generated. For NDVI, band-4 and band-8 are collected from the Copernicus hub and loaded into the ArcGIS tool. Using a raster calculator NDVI is generated. RGB image is directly downloaded from the Copernicus hub. The aerosol is obtained from band-1. The water vapor is obtained from band-9. The NDMI is obtained from band-8a and band-11. The geological data is obtained from the composite band 12-11-2. The trained model is validated with the data generated and test data. These are uploaded to Python and given as input to the model and the results are observed. After this, the geographical area where the landslide is likely to occur will be calculated.

The last module is about developing a GUI Application for this functionality. The GUI application is developed using the Tkinter framework. This application takes the input of the nine parameters and gives these images as input to the model and generates the output graph. This graph is converted into an image and stored in local space. This image is displayed on the application window. Additionally, for easy representation few other frames were also added which contain the output results of each module.

Chapter 4

SOFTWARE DESIGN

This chapter consists of the design of the software Life Cycle model diagrams and their detailed explanation. Software design is the process of creating a plan or blueprint for a software system that meets specified requirements.

4.1 Software Development Life cycle: Scrum Model

The project is divided into 5 sprints. The Product Backlog in Figure 4.1 includes Field Study, Obtaining the data and Applying U-Net, Parameter generation, and validation. Priorities are assigned to each backlog item and based on the priorities the backlogs are taken into the sprint backlog. During each backlog implementation, the daily scrum meeting is conducted that helps to know What worked from the last meeting? What work was done? Are there any roadblocks in your way? and after the backlog is complete, retrospection is done. This process is repeated until all the tasks are finished [18]. Figure 4.1 describes the life-cycle model used for the proposed model.

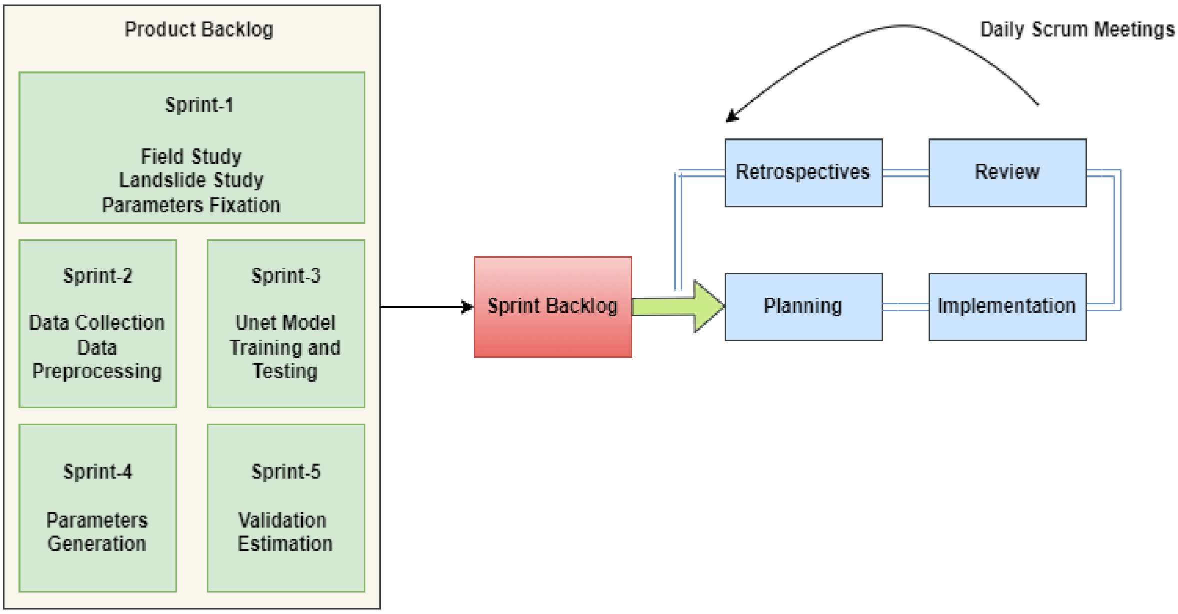

Figure 4.1: Scrum Model

4.2 UML Diagrams

4.2.1 Use-Case Diagram

A use case diagram is a type of UML (Unified Modeling Language) behavior or dynamic diagram that is used to model the functionality of a system. It employs actors and uses cases to illustrate how the system operates [35]. Figure 4.2 represents the Use case diagram of the system. In this system, the programmer applies U-Net Model to the dataset and saves the model. The user uploads the images through GUI and prompts for a landslide prediction label. The trained model takes the input, predicts it, and visualizes the result in form of a graph. The result in form of a graph is then shown to the user in the application [19].

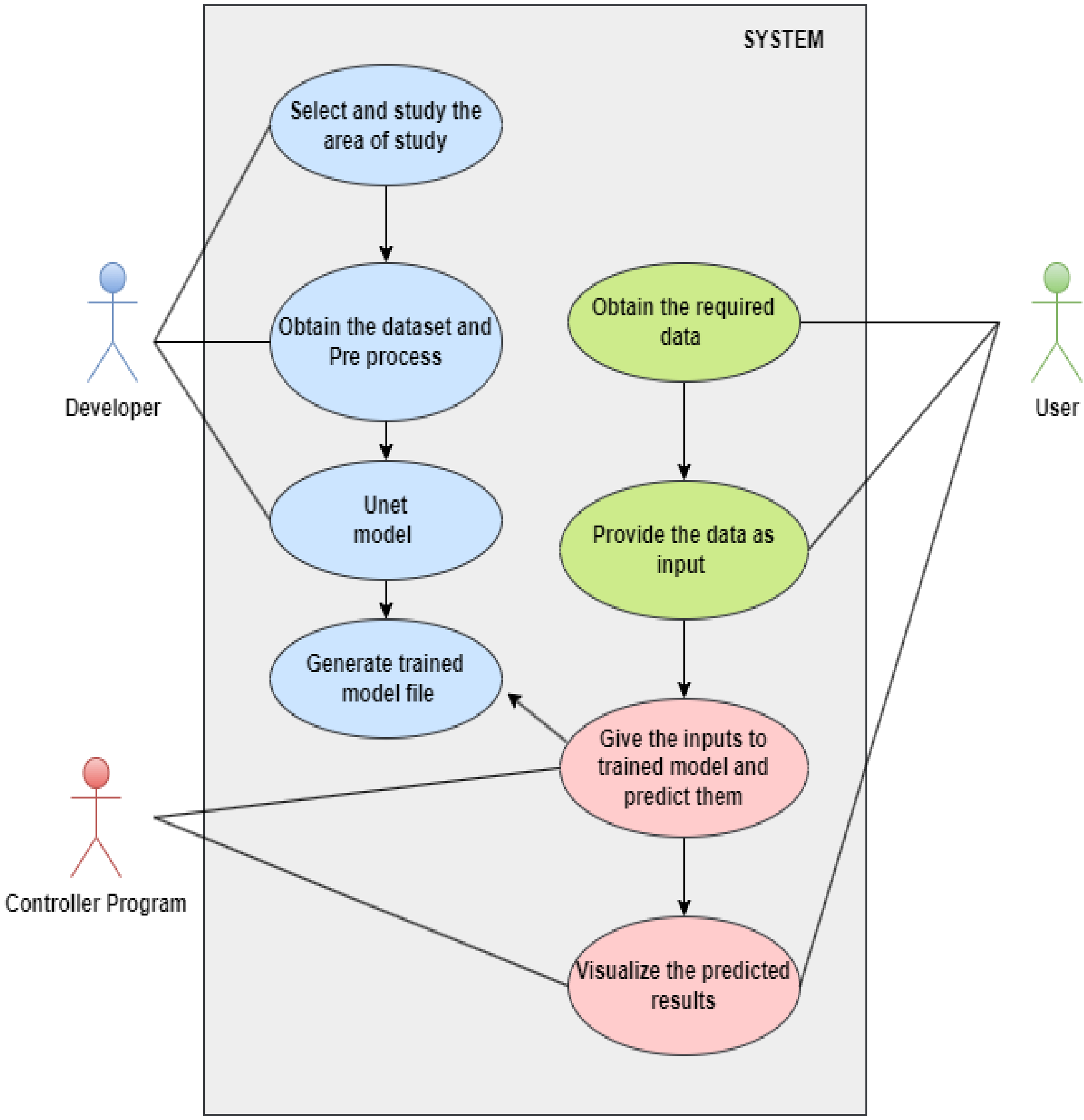

Figure 4.2: Use Case Diagram

4.2.2 Sequence Diagram

A sequence diagram is a type of UML (Unified Modeling Language) behavioral diagram that depicts the interactions and order of events between objects or components in a system. It illustrates how things interact in a sequential manner, showing the order in which these interactions occur [35]. Figure 4.3 represents the sequence diagram of the project work. In Figure 4.3, the actor or user initiates the interaction with the application. The user opens or runs the application. Then the application opens and an "upload" button will be displayed on the window. The user clicks on the "upload" button on the window. The interface will then open a file select dialog box. The user will then select the required images. The interface will get the paths of images selected and sends them to the controller program. The controller program loads the images and predicts the landslide susceptibility by giving them to the trained model and returning the NumPy array [20]. This array is converted into an image and sent to the interface. The image is displayed on the window for the user as a result.

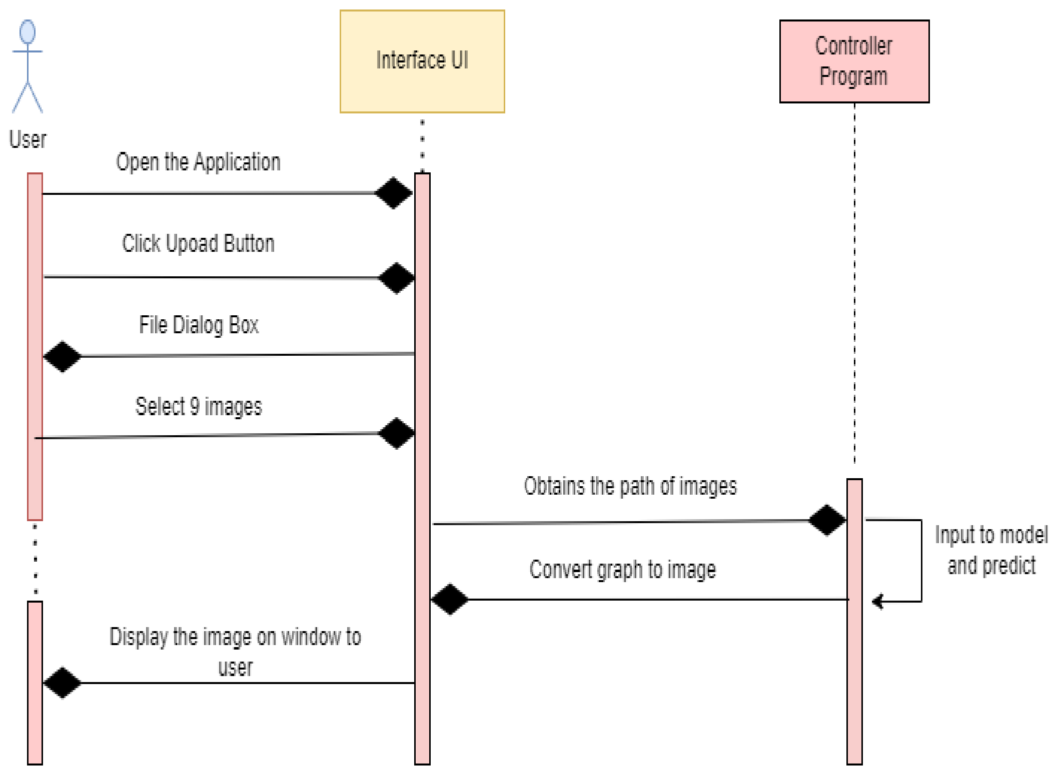

Figure 4.3: Sequence Diagram

Chapter 5

PROPOSED SYSTEM

This section includes the process flow diagram and methodology along with the algorithms of modules.

5.1 Proposed System

A flow diagram is a visual representation that displays the project's methodology graphically. Its purpose is to create a more logical order of the activities involved in the project. It allows for a clear understanding of the process and the steps involved in achieving the desired outcome.

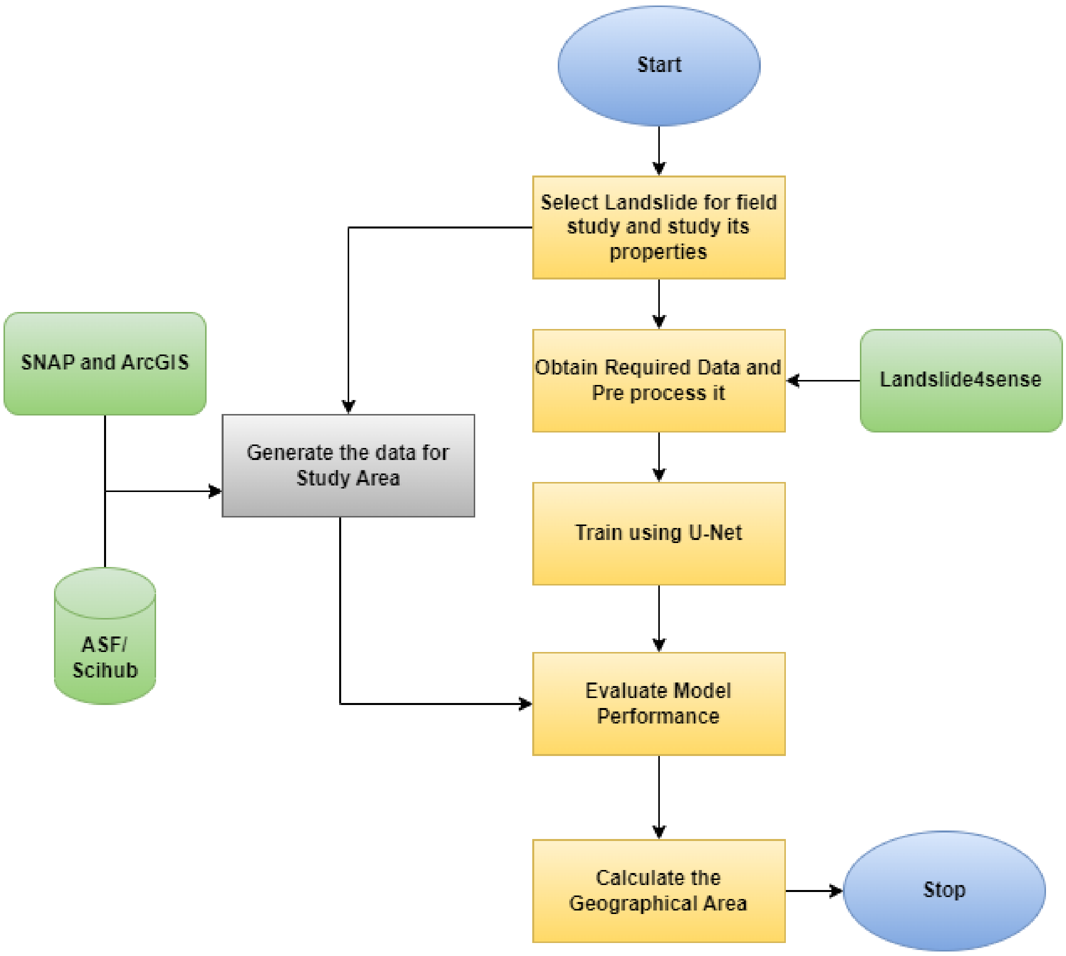

Figure 5.1: Flow Diagram

Figure 5.1 represents the flow chart of the project. The flow chart describes the process followed to achieve the desired results and also describes the methodology.

5.2 Dataset Description

The U-Net model is trained on the global landslide dataset in-order to detect the landslides globally. The dataset is obtained from the landslide4sense challenge.

Description:

1. The dataset is created by collecting 4844 samples of different landslides across the globe.
2. Sample link: *www.iarai.ac.at/landslide4sense/challenge/*
3. There are 3799 samples in the training data, 800 samples in the test data, and 245 samples in the validation data.

Details:

1. The Landslide4Sense dataset is comprised of three sets of image patches: the training set, the validation set, and the test set. The training set contains 3799 image patches, the validation set contains 245 image patches, and the test set contains 800 image patches.
2. Each data sample in dataset includes 14 bands.
3. The 14 bands in the Landslide4Sense dataset are derived from multi-spectral data captured by Sentinel-2, namely bands B1 through B12.
4. In addition to the multi-spectral data from Sentinel-2, the Landslide4Sense dataset also includes slope data from Sentinel-2, which is represented in band B13.
5. The band B14 represents the digital elevation model (DEM) obtained from Sentinel-2.

5.3 Methodology

The methodology of this project involves five modules in total. This study involves finding the landslide susceptibility of the given region by considering nine parameters

Field Study

To improve results, the initial step is gaining adequate information by analyzing landslide types and properties worldwide. The SR-530 landslide best represents the majority of landslides.

On March 22, 2014, a landslide occurred in Washington state, known as the Oso landslide or SR-530 landslide. This natural disaster caused lot of environmental and human loss. The adverse effects of SR-530 are mentioned in [21]. Table 5.1 shows the considered parameters and the reason for considering them.

Parameters	**Reason**
DEM	Elevation at each pixel [22]
Slope	Slope at each pixel [23]
NDVI	Vegetation at each pixel [24]
RGB	Identification of landslide [26]
Aerosol	Faster cloud formation, after landslide effect [27]
NDMI	Soil moisture and soil rigidity [26]
Water vapour	Faster cloud formation, after landslide effect [27]
NIR	Energy reflected, soil roughness and global warming [27]
Geological band	Lithology, cracks, previous landslides [26]

Table 5.1: Parameters

Dataset Collection and Pre-Processing

Further developing the data set for training will be done. For this, Landslide4sense challenge is chosen as the data source. In the challenge, the sentinel-2 satellite data for 4844 locations across the globe are provided. This helps in training on global data set. The downloaded data will be containing the three folders for training, testing, and validation purpose. The data is stored in form of .h5 files in these folders. Each .h5 file will be denoting a separate geographical location. The .h5 file will contain the data of all band information of the sentinel-2 satellite. The following steps are followed to obtain the required data:

- **Download:** Download the data from the website
- **Extract:** extract the required binary data from .h5 file
- **Pre-Process:** After the data extraction, pre-processing is done. Pre-processing is done to get efficient and required results.
  - Resampling to 10m resolution in ArcGIS using 'Resample' tool [39]

– Resize the obtained image to 128*128 size using 'resize' method in OpenCV Library. [34]

– Normalize the obtained Numpy array using Min Max Scalar with a range of -1 to +1. [34]

– Replace 0 with 0.01 to avoid zero division error using 'where' method in numpy library. [34]

Model Training

The total data set contains 4844 samples. U-Net model is trained with the data created for training and validated with testing data. Figure 5.2 represents the model architecture followed. This architecture differs from the existing standard U-Net architecture in the usage of the number of units in Conv2D layers and Conv2DTranspose layers, Adding Dropout layers to avoid over-fitting and changing the activation function to "sigmoid" from "softmax" for the output Conv2D layer. The concatenate layer helps in skipping connections. The conv2D with Max pooling and Conv2DTranspose with Conv2D are used in encoding and decoding. The model is trained with metrics as accuracy, recall, precision, f1score, custom loss and dice gain. Equation 5.1, 5.2, 5.3, 5.4 are mentioned in [36]. The equation 5.5 is mentioned in [37]. The equation 5.6 is mentioned in [38].

$$Accracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{5.1}$$

$$Precision = \frac{TP}{TP+FP} \tag{5.2}$$

$$Recall = \frac{TP}{TP+FN} \tag{5.3}$$

$$F1Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{5.4}$$

$$Customloss = \frac{1}{n}\sum_{i=1}^{n}(y_{true} - y_{pred})^2 \tag{5.5}$$

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{5.6}$$

$$DiceGain = 1 - \frac{2 * \sum_{i=1}^{n} y_{true} \cdot \sigma(y_{pred})}{\sum_{i=1}^{n} y_{true} + \sum_{i=1}^{n} \sigma(y_{pred})} \tag{5.7}$$

In the above equations TN, TP, FN, FP atands for True Negative, True Positive, False Positive and False Negative terms in confusion matrix [36]. Ypred and Ytrue stands for predicted and actual values. n is 32, which represents the batch size. Equation 5.6, which is sigmoid function, is used in Equation 5.7

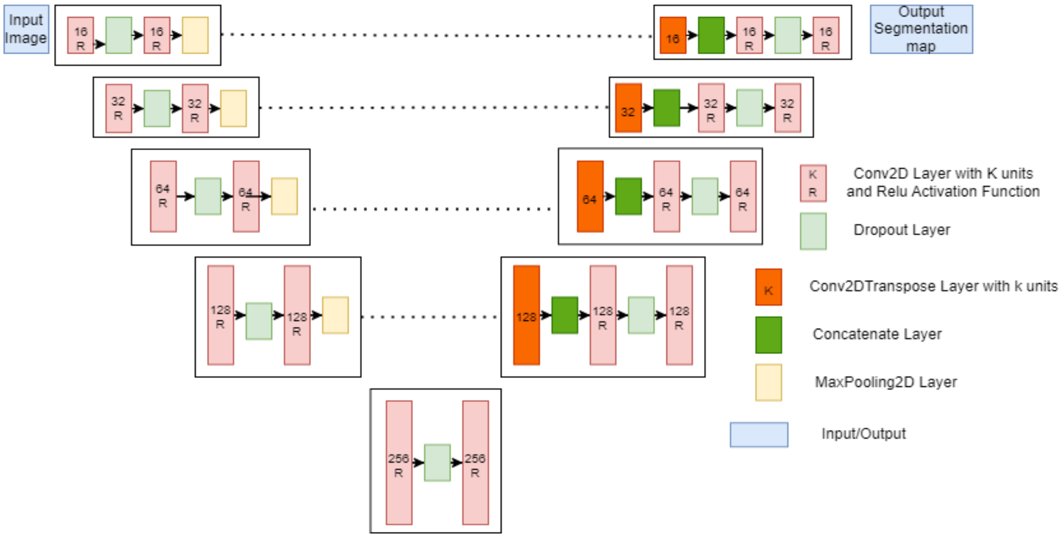

Figure 5.2: Model Architecture

Model Validation

Validation of the trained model is done to check the behavior of the model upon providing various kinds of data. To validate the trained model, input from both the validation dataset and manually generated data for the field study region will be provided to the model. The model can be validated with the testing data provided in the dataset by following similar steps which were followed for providing the train data as input to the model. To validate the model with manually generated data of SR-530, the first step will be generating the DEM, then Slope from DEM and then generating all the other required parameters from the sentinel-2 data. Figure 5.3 shows the source and details of each parameter.

Parameter	Source	Formula/technique	Resolution	wavelength	Methodology
DEM	Sentinel-2 data	Stereo correlation	10m-60m	442-2202nm	Stereo Correlation , Extract [22]
Slope	DEM	$\frac{Y_2-Y_1}{X_2-X_1}$	10m-60m	442-2202nm	From DEM, Extract [23]
NDVI	Band8, band4	$\frac{B8-B4}{B8+B4}$	10m	753.5nm	Raster Calculator, Extract[24]
Natural Color	Band2-3-4	Composite	10m	571.6nm	Combine, Extract [26]
Aerosol	band1	Extract	60m	443nm	Download from Sentinel-2, Extract [27]
Water vapor	band9	Extract	60m	940nm	Download from Sentinel-2, Extract [27]
Moisture index	Band 8a-11	$\frac{B8A-B11}{B8A+B11}$	20m	1237.5nm	Raster Calculator, Extract [26]
NIR	band8	Extract	20m	865nm	Download from Sentinel-2, Extract [27]
Geological band	Band 11-12-2	Composite	20m	1430nm	Combine, Extract [26]

Figure 5.3: Parameters Description

For generating DEM, the following sequence of steps were applied [22].

- Load the sentinel-2 data
- Pre-process (atmospheric correction and noise removal)
- Co-registration
- Stereo correlation (obtain X,Y,Z)
- Extract elevation
- Post-processing (Deburst and smoothing)
- Export

After obtaining the DEM, the rest are to be generated in ArcGIS.

- **Slope**: Use the "Slope" tool in ArcGIS to identify the steepness of each raster cell in DEM [23]. Open the DEM in the ArcGIS platform and generate a slope using the "slope" tool in "spatial analyst tools".

- **NDVI**: The Normalized Difference Vegetation Index (NDVI) is a universal vegetation index that assesses the intensity of vegetation and can be used to compare differences in vegetation over time. Open band8 and band4 data in the ArcGIS tool and generate NDVI using a raster calculator. The equation 5.1 represents the formula to generate NDVI. [24]

$$NDVI = INDEX(B8, B4) = \frac{(B8-B4)}{(B8+B4)} \tag{5.8}$$

- **RGB Image**: The RGB multi-spectral image will be readily available in the Copernicus open-access hub. Download it for the required location [26].

- **Aerosol**: The band 1 of the sentinel-2 satellite contains the aerosol content. The Copernicus open access hub provides the sentinel data which consists of all 12 bands. Band 1 can be opened and clipped according to the shape file of the SR-530 region. [27]

- **Water Vapour:** The band 9 of the sentinel-2 satellite contains the water vapour content. Band 9 can be opened and clipped according to the shape file of the SR-530 region. [27]

- **NDMI:** Normalized Difference Moisture Index (NDMI) gives the moisture content in the soil. It is generated by considering bands 8a and 11. The equation 5.2 represents the formula to generate NDMI. [26]

$$NDMI = INDEX(B8A, B11) = \frac{(B8A-B11)}{(B8A+B11)} \tag{5.9}$$

- **Near Infrared Band:** The band 8 of the sentinel-2 satellite contains the NIR content. Band 8 can be opened and clipped according to the shape file of the SR-530 region. [27]

- **Geology:** The band 11-12-2 of the sentinel-2 satellite contains the Geological content. The bands 11,12,2 can be opened in the ArcGIS tool and geological content can be developed using the composite band tool and clipped according to the shape file. [26]

- **Pre process and Predict:** After all the data is kept ready, Pre process these images. Resample to 10m [39], Resize to 128*128, Normalize and replace 0 with 0.01 [34]. Give these images as input to the model and predict the landslide susceptibility heat map for the Oso region. From it, Estimate the geographical area where the landslide is likely to cover by identifying the spatial resolution of the result.

Graphical User Interface

After the model validation, the development of the GUI is done. When the user uploads the nine required parameters to the model, the application loads the images and gives the images to the model to predict [25]. The model returns the NumPy array representing the prediction results. This NumPy array is plotted as a graph and saved as an image to the local disc. After saving, the saved image will be displayed in the Tkinter window using the "PhotoImage" widget available in the Tkinter module.

5.4 Algorithms

This project consists of a total of five modules. The first module is about analyzing the landslide types and properties. The second module is about dataset obtaining and pre-processing. The third module is training using the U-Net model. The fourth module is about validating the trained module and the last module is developing the GUI application for it using the Tkinter framework.

5.4.1 Module-2 : Data Collection and Pre-processing

Input : Dataset
Output: Training and Validation data.

1. Traverse the Train and Test directories within the dataset.

   1.1 initialize k with the number of files in the directory

   1.2 Assign val with k,128,128,13 zeroes array

   1.3 Assign label with k,128,128,1 zeroes array

   1.4 Loop from i equals 1 to k

      1.4.1 Assign RGB data to three dimensions out of thirteen in val array
      1.4.2 Assign NDVI data to fourth dimension
      1.4.3 Assign Slope data to fifth dimension
      1.4.4 Assign Elevation data sixth dimension
      1.4.5 Assign aerosol data to seventh dimension
      1.4.6 Assign water vapour data to eighth dimension
      1.4.7 Assign moisture index data to ninth dimension
      1.4.8 Assign NIR data to tenth dimension
      1.4.9 Assign geology data to last three dimensions in val array
      1.4.10 Assign Label data label array
      1.4.11 Resize to 128*128 and Normalize to -1 to +1 range
      1.4.12 Replace 0 with 0.01

5.4.2 Module-3a : Model Generation

Input : Accuracy Requirements, Keras Layers details [40]
Output : Trained model

1. Take 3799,128,128,13 sized array as input using Input Layer.

2. Loop for four times to create a deep Contractive path.

2.1 Apply a 3x3 convolution with ReLU activation, same padding and appropriate units using Conv2D Layer.

2.2 Apply Dropout layer with 0.5 drop ratio using Dropout Layer.

2.3 Apply a 3x3 convolution with ReLU activation, same padding and appropriate units using Conv2D Layer.

2.4 Apply a 2x2 max pooling operation with stride of 2 to reduce the spatial dimensions using MaxPooling2D Layer.

3. Create Bottle Neck Unit.

3.1 Apply a 3x3 convolution with ReLU activation, same padding and appropriate units using Conv2D Layer.

3.2 Apply Dropout layer with 0.5 drop ratio using Dropout Layer

3.3 Apply a 3x3 convolution with ReLU activation, same padding and appropriate units using Conv2D Layer.

4. Loop for four times to create a deep expansive path.

4.1 Apply a 3x3 Transpose convolution with ReLU activation, same padding and appropriate units using Conv2DTranspose Layer.

4.2 Concatenate the feature maps from the corresponding contracting path layer.

4.3 Apply a 3x3 convolution with ReLU activation, same padding and appropriate units using Conv2D Layer.

4.4 Apply Dropout layer with 0.5 drop ratio using Dropout Layer.

4.5 Apply a 3x3 convolution with ReLU activation, same padding and appropriate units using Conv2D Layer.

5. Apply a 1x1 convolution with Sigmoid Activation to map each feature vector to the desired 'one' class.

6. Compile the model with metrics as Accuracy, Recall, Precision, F1Score, Dice Gain, Custom loss and Callbacks as Model Checkpoint and Early Stopping.

5.4.3 Module-3b : Model Training

Input : Data for Training, Validation and compiled model
Output: Trained Model

1. Provide definitions for recall, precision, custom loss, dice gain, and F1 score used in evaluating classification and segmentation models.

2. Define input shape as 128,128,13.

3. Load the data for training.

4. Begin training the model by fitting the compiled model with the train data.

5. Evaluate the model on the test data.

6. Get the Accuracy, loss, precision, recall, F1-score values for the test data.

5.4.4 Module-4 : Model Validation

Input : Oso landslide data
Output: Oso landslide susceptibility map

1. Assign val with 1,128,128,13 sized zeroes array.

2. Read the parameter images and store them in seperate arrays

3. Resize into 128*128 size, Normalize and replace 0 with 0.01.

4. Assign RGB data to three dimensions out of thirteen in val array.

5. Assign NDVI data to fourth dimension.

6. Assign Slope data to fifth dimension.

7. Assign Elevation data sixth dimension.

8. Assign aerosol data to seventh dimension.

9. Assign water vapour data to eighth dimension.

10. Assign moisture index data to ninth dimension.

11. Assign NIR data to tenth dimension.

12. Assign geology data to last three dimensions in val array.

13. Predict val and store in predresult.

14. plot the predresult.

15. Calculate the Geographical area.

5.4.5 Module-5 : Developing GUI

Input : Model, Data for Prediction
Output: Landslide susceptibility map

1. Import cv2, matplotlib, Tkinter modules.
2. Create a main window for the GUI app.
3. Give the window perfect geometry and a title.
4. Create a label and give the project title.
5. Create a button and associate it with 'upload' function.
6. Import the prediction method from module 4.
7. Save the plotted graph as an image, obtained after prediction and return to the main event.
8. Display the saved image on the screen using a 'PhotoImage' widget.
9. Add additional frames for additional information to be displayed.

Chapter 6

IMPLEMENTATION

This section represents the implementation part for all the modules involved in our project.

6.1 Output Screen Shots

Module-1 output

Module-1 involves the selection of best landslide. It involves analyzing different types of landslides and different properties of landslides. Figure 6.1 represents the Oso area before the landslide occurrence and after the landslide occurrence.

Figure 6.1: Oso Before and After Landslide

Module-2 output

Module-2 involves dataset collection and pre-processing. The dataset is downloaded and pre-processed to make it acceptable to the model. All data samples are combined and stored as a NumPy array. Figure 6.2 represents a sample tuple of the dataset containing all the considered parameters

Module-3 output

Third module involves training the U-Net model with the dataset created. The training involves the usage of metrics like accuracy, precision, f1score, custom loss, dice gain, and recall. The concatenate layer helps skip connections. The Max pooling and Conv2DTranspose are used in downsampling and upsampling. Table 6.1 represents the results of validation with 800 samples.

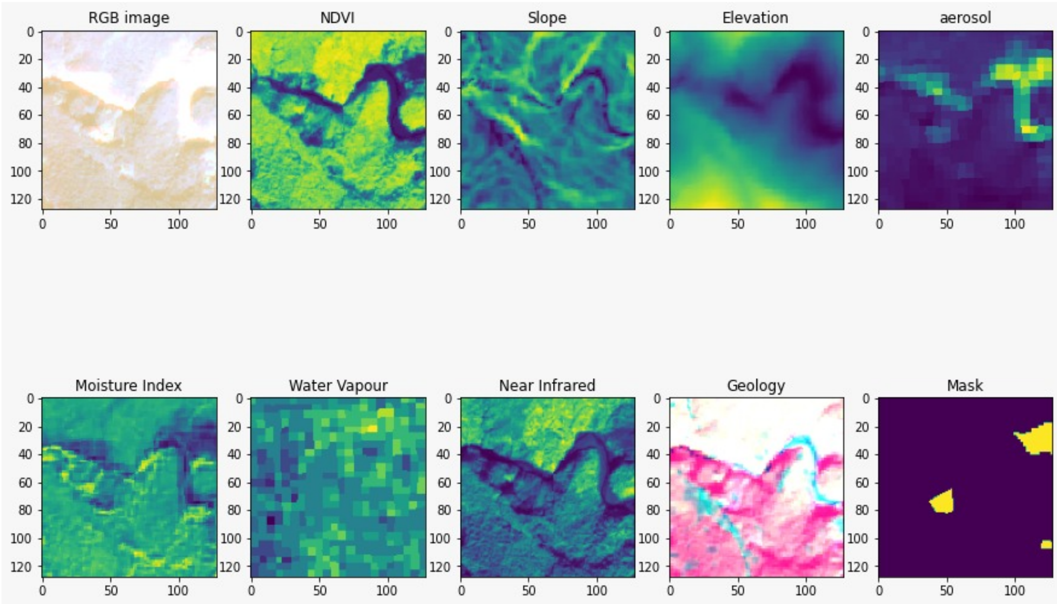

Figure 6.2: Sample Data

Metric	Value
Accuracy	0.98
Loss	0.04
Recall	0.59
Precision	0.78
F1-Score	0.67
Dice Gain	0.94
Custom loss	0.01

Table 6.1: Model Validation Results

Module-4

Module-4 involves generation of required parameters for the SR-530 landslide. Figure 6.3 represents the generated SR-530 data. Given these as input to the model, a susceptibility map will be obtained. From it, the geographical area of the landslide cover will be determined. The area obtained is 0.0648 km^2. The actual landslide coverage area from the internet results [28] is 0.0607 km^2. Our model predicted it with 93% accuracy. Figure 6.4 shows the calculation of area and calculating its accuracy.

Module-5 output

In module-5, an interface will be created keeping in view an easy representation of the system and portability. Figure 6.5 shows the sample layout of the developed GUI using Tkinter in Python.

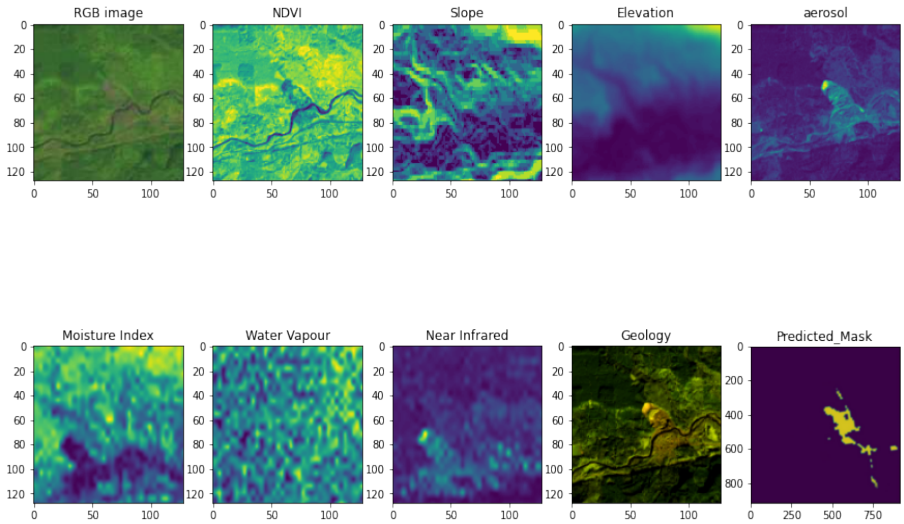

Figure 6.3: Model Validation

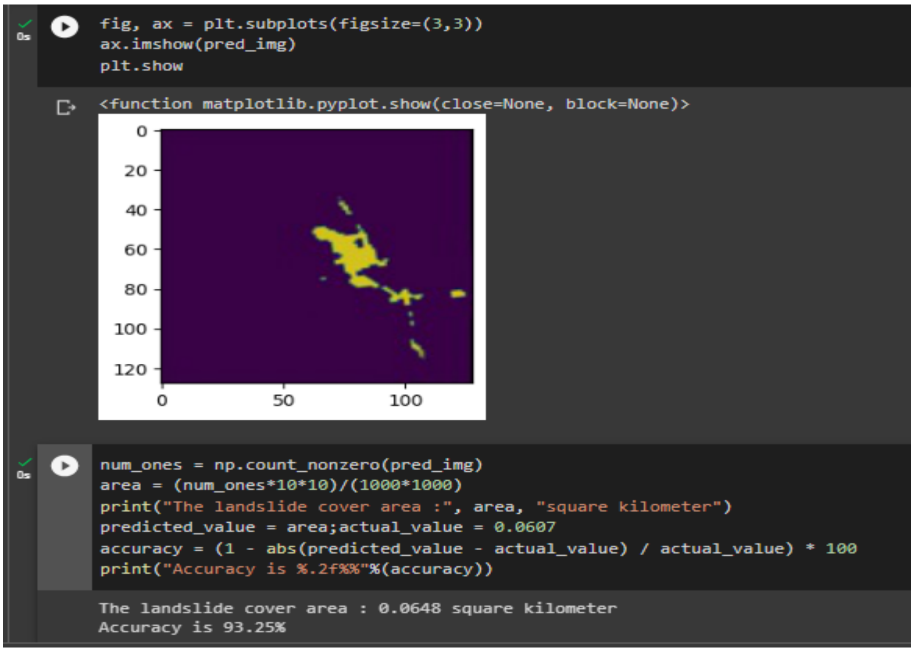

Figure 6.4: Landslide Area Estimation

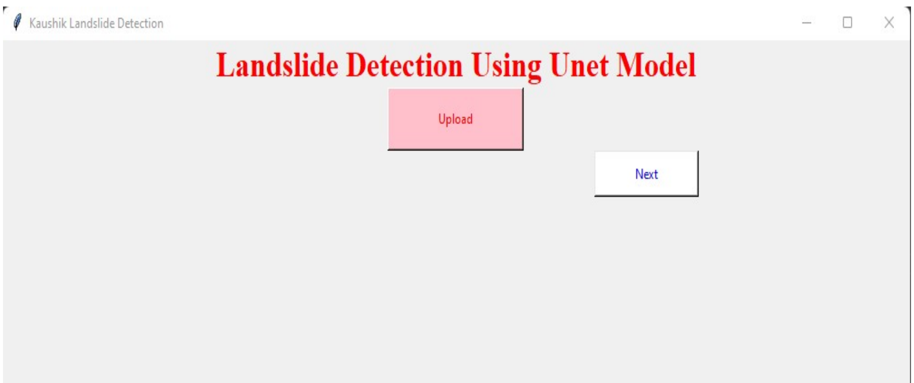

Figure 6.5: GUI Application

6.2 Result And Analysis

This section involves the presentation of results and the analysis made on the obtained results.

6.2.1 Methodology Comparison

Table 6.2 represents the evaluation against the papers cited in the literature review section, with the goal of achieving superior results in comparison to those previously reported.

The methodology proposed in this study utilized the Global Landslide dataset to enable the detection of landslide occurrences on a global scale. To achieve this, the U-Net model was chosen as it has proven to be effective for segmentation tasks and provides efficient results. The study also considered various parameters to identify landslides caused by different factors. All these additional properties contribute to the novelty of our study.

6.2.2 Model Prediction

A Python GUI was created with Tkinter to show results from a landslide prediction model. The GUI prompts the user to upload nine images corresponding to nine parameters that are considered in the model. These images are then pre-processed and used to make predictions, and the resulting graphs are displayed to the user in the application window. An example output from the model is shown in Figure 6.6, which demonstrates the successful prediction of the SR-530 landslide. The predicted result is 93% accurate compared to the actual data.

Landslide susceptibility is a complex phenomenon that can be influenced by a wide range of factors. These results suggest that all nine parameters considered in the model play an active role in determining the susceptibility mask, with each parameter having either a positive or negative correlation with landslide occurrence. The nine parameters considered in the model likely represent a variety of geological, topographical, atmospherical, and environmental factors that can contribute to landslide occurrence.

From these results, the complex interactions between the parameters and landslide occurrence can be analyzed. By identifying the correlations between each parameter and landslide occurrence, the most important factors that contribute to landslide susceptibility can be highlighted.

Reference	Dataset	Parameters	Technique
In [6]	Sentinel-2 data for Taiwan	All sentinel-2 bands	Res-UNet and OBIA
In [7]	Sentinel-2 data for Greece	Rainfall	CNN model
In [8]	Sentinel-1 data for China and Hubei	Terrain, Topographic and lithological parameters	Dense-Nets
In [9]	Sentinel-1 data for Cyprus	DEM using DInSAR	CCD technique and DInSAR
In [10]	Sentinel-1 data for Italy	Elevation and Slope	Analysis on 250+ landslides
In [11]	Sentinel-1 data for Etna, California, Anargyroi	DEM, Slope	Review on current technologies
In [12]	Rapid Eye Satellite data for Rasuwa, Nepal	Topographic information	ANN, SVM, Random Forest, CNN.
In [13]	ALOS-PALSAR data for Kyushu	DEM and Rainfall	PolSAR, InSAR, Dual PoLSAR
In [29]	Sentinel-1 data for Cordan, Italy	DTM, DEM, Rainfall	Qausi Dynamic index, SVM, Random Forest
In [30]	Sentinel-2 data for Taiwan	Sentinel-2 all bands	LN-SVM, PL-SVM, RBF-SVM, LR and SIG-SVM
In [31]	Sentinel-2 data for Chukka	All Sentinel-2 bands	Relative landslide density index, Sequential Model
In [32]	Sentinel-1 data for Kalimpong	Elevation, Slope, Rainfall	SIGMA model.
Proposed Methodology	Global Sentinel-2 data	Atmospherical, Geological and Topographical	Stereo Correlation and U-net

Table 6.2: Comparision of Proposed and Existing Approaches

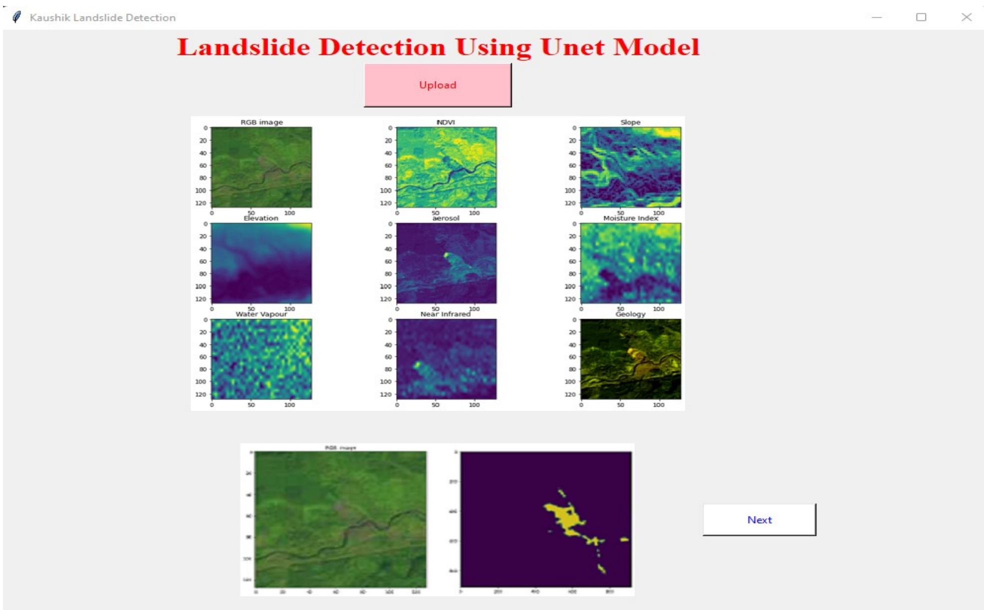

Figure 6.6: Application output

6.2.3 Correlation Analysis

Correlation is a technique used in statistical analysis that helps to identify which input parameters are most strongly correlated, which can be useful in feature selection and model development. The Correlation can be found using 'corrcoef' method in NumPy package. Figure 6.7 represents the Correlation between input parameters and the output landslide susceptibility label.

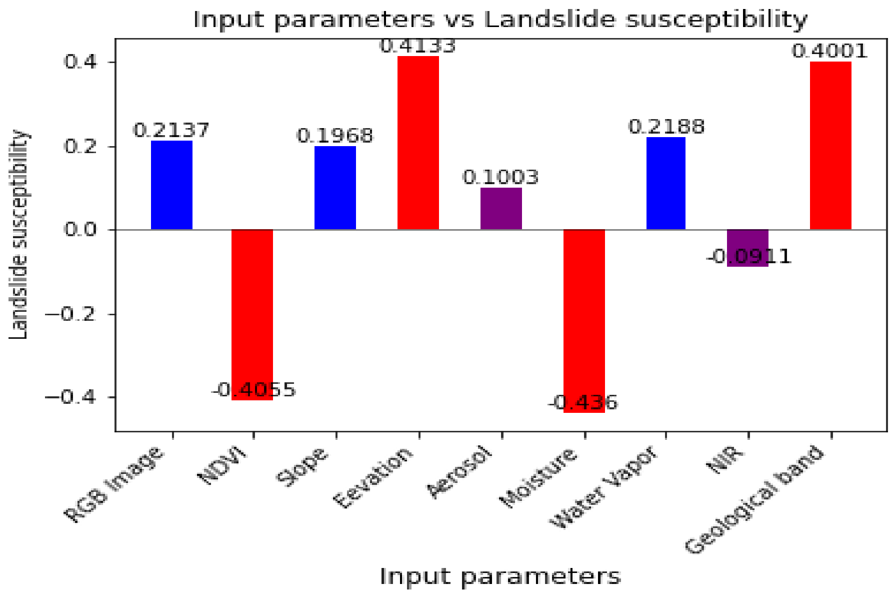

Figure 6.7: Parameter's Correlation with Landslide

From Figure 6.7 the impact of parameters on the landslide susceptibility can be divided into three groups.

The first group of parameters considered in the analysis includes NDVI, Elevation, Moisture Index, and Geological band. The correlation values for these parameters are close to ± 0.4. Among them, NDMI has a higher correlation because soil strength is indirectly proportional to landslide occurrence and higher NDMI values indicate greater soil strength. Elevation (DEM) has the next highest correlation as higher elevation can lead to steeper slopes, which can contribute to landslide occurrence. The Geological band helps in identifying unstable rock structures, previous landslides, and dry soils, which are all directly related to landslide occurrence. NDVI helps identify vegetation levels, with higher levels indicating greater soil strength and lower landslide susceptibility. By considering these different parameters, a more comprehensive assessment of landslide susceptibility can be provided.

The second group of parameters includes RGB images, slope, and water vapor. RGB images can help identify landslides visually, but may not always accurately represent the depth and texture information necessary for accurate identification. The slope parameter measures the steepness of the elevation and is positively related to landslide occurrence. Since the main objective is not landslide intensity, the slope has less impact compared to elevation in this context. Water vapor values can vary according to wind speed, temperature, etc., but higher values suggest a higher likelihood of rainfall and a higher release of water vapor trapped in the soil. As this value can alter with atmospheric and topographical conditions, this may not be the most reliable parameter.

To complete the analysis, a third group of parameters includes Aerosol and NIR. These are atmospheric and climatic parameters and are very unstable and uncertain. Landslide prediction based on these parameters may vary due to these unstable conditions but they do not show any negative impact on the model.

Chapter 7
TESTING

This chapter includes the testing of the proposed system. As we followed the test-case-driven development , these test cases are developed first and based on these test cases, the work is done..

7.1 Test Case I: Validating the model with validation data

Project Name: ESTIMATION AND ANALYSIS OF LANDSLIDE OCCURRENCE BY COMBINING GEOGRAPHICAL AND ATMOSPHERICAL STUDY USING UNET MODEL						
Test case Id: 1			Test Designed By: Vishnu			
Test Priority: High			Test Designed Date: 15-03-2023			
Module Name: Remote Sensing and DL				Test Executed By: Vishnu		
Test Title: Model behaviour with Valid data				Test Executed Date: 15-03-2023		
Description: Verifying the model behaviour upon providing the validation data.						
Pre-Conditions: User should contain all nine required parameters						
Stage	Test Steps	Test Data	Expected Result	Actual Result	Status	Remarks
1	Providing the images to model	Data from validation folder	Landslide susceptibility of that region	Landslide susceptibility of that region	Pass	Nil
2	Verifying model output and area	Vlidation data and area	Match actual results with predicted results.	Actual results matched with predicted results.	Pass	Nil
Post-Conditions: Model behaviour with validation data should be good						

(7.1)

7.2 Test Case II: Validating the model with study area data.

Project Name: ESTIMATION AND ANALYSIS OF LANDSLIDE OCCURRENCE BY COMBINING GEOGRAPHICAL AND ATMOSPHERICAL STUDY USING UNET MODEL	
Test case Id: 2	Test Designed By: Kaushik
Test Priority: High	Test Designed Date: 23-03-2023
Module Name: Remote Sensing	Test Executed By: Kaushik
Test Title: Verifying model behaviour for study area	Test Executed Date: 23-03-2023
Description: Verifying the model behaviour upon proving the manually generated study area's data	
Pre-Conditions: User should have all nine required parameters	

Stage	Test Steps	Test Data	Expected Result	Actual Result	Status	Remarks
1	Provides images as input	Data from sentinel satellite	Landslide susceptibility of study area	Landslide susceptibility of study area	Pass	Nil
2	Verifying the model output and SR-530 area	Model Output, SR530 area and shape	Matching of Model output with actual results	Landslide area and shape were matched with actual results	Pass	Nil
3	Verifying the Prediction Accuracy	Prediction and required Accuracy	Prediction Accuracy greater than 90%	Prediction Accuracy is 93.25%	Pass	Nil

Post-Conditions: Model behaviour verification with manually generated data should be successful

(7.2)

7.3 Test Case III: Testing the Tkinter Application

Project Name: ESTIMATION AND ANALYSIS OF LANDSLIDE OCCURRENCE BY COMBINING GEOGRAPHICAL AND ATMOSPHERICAL STUDY USING UNET MODEL	
Test case Id: 3	Test Designed By: Kaushik
Test Priority: High	Test Designed Date: 28-03-2023
Module Name: Remote Sensing and DL	Test Executed By: Kaushik
Test Title: Testing the Tkinter Application	Test Executed Date: 28-03-2023
Description: Testing the behaviour of the application in various cases.	
Pre-Conditions: User should contain all four required parameters in proper format	

Stage	Test Steps	Test Data	Expected Result	Actual Result	Status	Remarks
1	Providing the images to application	Data with user	Landslide susceptibility of that region	Landslide susceptibility of that region	Pass	Nil
2	Less than nine images uploaded	Data with user	Displays error message	Displays error message	Pass	Nil
3	Wrong image format uploaded	Data with user	Displays warning message	Displays warning message	Pass	Nil
4	Different sized images uploaded	Data with user	Displays warning message	Displays warning message	Pass	Nil

Post-Conditions: The behaviour of the application should be satisfactory

(7.3)

Chapter 8

CONCLUSION AND FUTURE WORK

Landslides are natural disasters that can occur at any time and for various reasons, such as rainfall, deforestation, and human interventions. Detecting landslides before they occur is a challenge, as there are usually no clear signs of an impending landslide. With the help of remote sensing and deep learning, we can detect potential landslides by analyzing the deformation patterns of various landslides. To predict landslides, continuous monitoring of the location is required. This involves observing the slope, elevation, vegetation index, rainfall, and geological content of the location. By analyzing the results, we can determine the susceptibility of the location to landslides. Upon training with the U-Net model, the obtained accuracy is 98%, the loss is 0.04 and F1 Score is 67%. If a landslide susceptibility map of the region is obtained, the geographical area of landslide cover can be determined. For SR-530, the landslide cover area is predicted with 93% accuracy. Once a landslide pattern and an effective area are identified, the local government can immediately issue an alert to the commuters and take necessary measures to prevent any damage.

Remote sensing and optical image analysis with the help of drones can improve the accuracy of the landslide detection model. The model can be further enhanced by using more advanced architectures and adding additional parameters for more accurate results. Various Deep Learning and Machine learning algorithms can also be used to process the data collected from remote sensing and optical image analysis.

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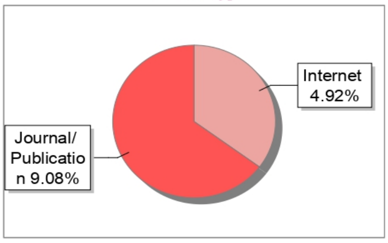

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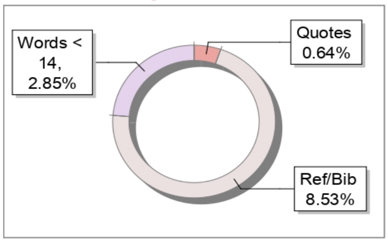

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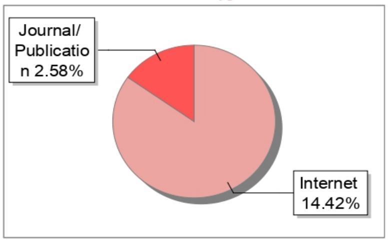

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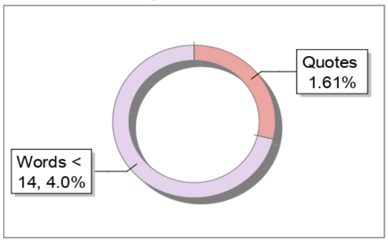

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