Landslide Prediction using Deep-Learning Frameworks and WSN

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***Abstract*— Landslides are natural disasters that occur in nature due to factors such as climate change, heavy rainfalls, rising temperatures, soil erosion, earthquakes, hurricanes, volcanic activities particularly in hilly regions. landslides cause destruction of property, damage to environment and pose a threat to human life. Landslide prediction can help in warning people so that precautionary measures can be taken such as evacuation of villages, thereby ensuring safety. As landslides occur due to various measurable environmental factors such as soil erosion and rainfall wireless sensor networks can be used to monitor an area and measure these factors for detection and prediction of landslides. The use of satellite imagery and deep learning frameworks in predicting landslides takes this a step further by providing early detection of its occurrence. In this project we Investigate and compare landslide prediction using both wireless sensor networks and deep learning techniques. To solve the problem, we created a sensor network using multiple nodes. The nodes are embedded with sensors to sense the soil moisture and movement in the area. The data collected from these sensors are sent to the base station for further analyses. Two types of landslide prediction analyses are also mentioned in this report. We conducted a study on using deep learning-based image segmentation models for landside prediction. We also utilized satellite images from a landslide4sense dataset and used deep learning model U-Net to effectively map and detect landslides.**

***Keywords:* Landslide detection, WSN, Image Segmentation, U-Net**

I. Introduction

A natural disaster is an event that occurs in the nature, causing destruction to economy, property, leads to loss of life and damage to environment, examples of such events range from heavy rain falls, hurricanes to earthquakes and landslides which vary in the intensity of damage.

Landslides are one such prevalent disastrous event that pose a major hazard to people and property in populated areas. According to WHO statistics, from 1998 to 2017, landslides have affected 4.8 million people worldwide and have caused 18,000 deaths. On average 25 to 50 people are killed which causes 3.5 billion dollars in damage by landslides each year in the United States [1]. The most disastrous landslide happened in 1933 at Diexi, China which caused 2,500 deaths.

According to the United States Geological Survey, the largest landslide in terms of volume to occur on Earth was in connection with the 1980's mount St. Helens volcano eruption in Washington state, USA. The landslide had a volume of 2.8 cubic kilometers and travelled for about 22.5 kilometers down the north fork Toutle River [2].

There are several other landslides that happened due to various triggering events such as very heavy rainfalls, earthquakes, snow melts, river erosion, hurricanes, and another volcanic activity [3]. Which led to high fatalities, missing and injured people, displacement of people from their homes, destruction of villages and other consequences.

More landslides are projected to occur because of climate change, rising temperatures, soil erosion, and earthquakes, particularly in hilly regions. To visualize the global span of landslides we used NASA landslide catalogue [6]. As we can see from fig. 2 landslides are spread across the globe.

Fig 1: The landslide at Blackheath in New South Wales, Australia, triggered due to heavy rainfalls [4].

The information about occurrence of a landslide can help prevent extensive damage and alert people to take precautionary measures. As landslides occur due to various environmental factors, wireless sensor networks could be used to measure the occurrence of rainfall soil erosion and other physical factors and this information could be utilized in detection of the landslides.

The landslide detection in real time although it's very useful might not provide the quicker way to evacuate people and hence as the risk increases prediction of landslides well in advance becomes more important.

A geographic information system GIS consists of a database of geographic information that is obtained by using real world data. The data is collected from satellites or remote sensing. This data can be used to develop a deep learning model to predict landslide.

We aim to study and investigate the challenges associated with these two methods of landslide prediction.

Fig 2: NASA Global landslides Catalog

II. Literature Review

The use of sensors in the field of IoT have made many of the applications possible. Applications like remote monitoring or controlling something from a distance has been possible. Based on this principle, one of the most beneficial monitoring applications is the landslide detection.

Much research has already been done in this field, but the major issue arises in the prediction of a landslide. As mentioned above, landslide depends upon many factors and if all the factors are observed and analyzed correctly, till some extent a landslide could be predicted or at least landslide prone areas could be marked.

Kim et al [6], have made a wireless sensor network using gateways and nodes to detect any landslides. The sensory part of the node is equipped with gyroscopic and accelerometer sensor. It is used to detect the inclination angle and acceleration of the node whenever it dislocated along with the landslide. The communication part between the nodes and the gateway uses Bluetooth to transmit data. The technique used in this paper was feasible but using just one type of input from the sensors make the accuracy of the predication low.

Ramesh et al [7], proposed a method that is like the above paper as it uses wireless sensor network (WSN) of the detection of landslides. The major difference is that it uses two different sensors inputs to analyse the risk of landslides. The first sensor used here was a moisture sensor that uses water as a dielectric between the two electrodes to detect the percentage of moisture in the soil. The second sensor used here was a geophone sensor that was basically used to detect the movement of the ground. The working principle of this sensor is that its convers the movement to voltage. Apart from the sensory part, this network used in this paper was a bit different from the above-mentioned paper. It used Wi-Fi to make a connection between the nodes and with the help of satellite link, the data was sent to the Data Management Center.

The most common way of detecting landslides is by using sensors to check the vibration in the soil, but this method is not scalable as landslides occur at a global scale and if we want to use the sensors to check the vibrations in soil we would only be able to apply this method where the landslide occur more frequently and also the cost and difficulties associated with the installation of such a sensor network is too great.

With the development in the field of satellites and space research we can capture images of different parts of the landscape. This development has been a boon to landslide prediction, we are able to detect the landslides with the images received from Sentinel-2 satellite. Sentinel-2 is an Earth observation mission from the Copernicus Programme [8,9] which is used for monitoring the landscape, it was launched to make to tackle the natural calamities and safeguard the life of millions of people. Sentinel-2 gives extraordinary views of Earth are provided by high resolution, innovative spectral capabilities, a sweep width of 290 km, and numerous return durations.

Once the image data has been obtained the next step would be to develop an image segmentation model. Image segmentation is a branch of computer vision that is used to extract the annotations of the features of interest in an image. Image segmentation as is off three types and instance mentation panoptic segmentation and semantic segmentation [10].

The recent advancement in the field of machine learning and artificial intelligence has paved the way for using deep learning methodologies in sensing natural calamities like landslides. The use of deep learning-based Image segmentation methodologies increased as it predicts the landslides effectively by analysing and interpreting the large amount of data provided.

There are many deep learning-based image segmentation models that have been proposed that use the satellite images pre and post landslide event to effectively train a neural network model to learn to distinguish between a landslide occurrence and non-occurrence. This trained model that is capable to classifying the landslide data, can then be used to predict the landslide on new data samples. Let us look at some of the models and their limitations.

Langenkamp et al [11] have used convolutional neural network (CNN), they have extracted the data from images received from Sentinel-2 and have also taken historical weather data for pre-processing. In the pre-processing stage, one image has been made into many images, they have used randomly sampled window of the original image for this process. After the pre-processing stage they are feeding the data into CNN which contains 8 learning layers. They have used the model to detect the landslide in Xinmo (China), despite the presence of clouds in the image they were successfully able to detect the landslides. The model was trained on 20 different landslides, using a 5-fold cross validation method [12]. They have used balanced accuracy, which gives 100% if there is a landslide and 0% if there are no landslides. The accuracies keep changing for them because they have not used enough data. For receiving better performance in their model, they could have used more images in their dataset.

Shiyu Luo et al [13] have predicted landslide using Synthetic Aperture Radar (SAR). They have used Safety factor (SF) in evaluating the soil slope stability. It uses soil moisture, slope angle, and soil features for the prediction. A SF value less than 1 denotes a high probability of a landslide incident [14]. When the SF value is larger than 1.5, a landslide is considered to be almost improbable to occur. Since standard SAR processors assume flat terrain, they have used Digital Elevation Mode (DEM), which represents the elevation of the ground. The Tropical Rainfall Measuring Mission (TRMM) has been used to note the soil moisture level. This model has been partially verified and there is a lot of scope to improve.

Shunping Ji et al [15] have used convolutional neural network (CNN), they have created their own dataset consisting of images of both with and without landslides; it also consists of the Digital Elevation Model (DEM) data. The study was conducted in the Bijie city, China. For preparing the dataset they collected data from the field survey, geologists from the State Key Laboratory and the position biases from the inventory data has been confirmed to be in the dataset. VGGNet, ResNet, Inception and DenseNet were evaluated in their landslide detection dataset. They have also compared the accuracy of all the models. They have also tested the model with other data and the model works in predicting landslides. This proves that their model which uses ResNet-50 boosted by their 3D attention module obtained the best result.

Ghorbanzadeh et al [16] have used Rapid Eye satellite images to analyse artificial neural network (ANN), support vector machines (SVM) and random forest (RF), and different deep-learning convolution neural networks (CNNs) for landslide detection. They have compared their work with mean intersection-over-union (mIOU) metric. They have also used normalized difference vegetation index (NDVI), a simple graphical representation that may be used to examine remote sensing data. In addition to these they have also used Digital Elevation Model (DEM) for measuring the elevation. In terms of semantic classifications and the recognition of intricate picture patterns, CNN may be the most effective. But it does not outperform the other Machine learning models (ANN, RF and SVM). The challenging part is to choose the correct the ideal CNN structure.

Zhiqiang Yang, Chong Xu and Lei Li [17] strongly suggest that the development in the field of machine learning has led the way to the use of different techniques in landslide detection which is very much time efficient. They have used the machine learning technique, convolutional neural networks (CNN). They have selected two different landslide datasets and the feasibility of the model has been validated. They have used Self-Attention and Multi-Head Attention modules. By encoding each entity in terms of the global contextual information, self-attention aims to capture the interaction between all ‘n’ entities. They have also used vision transformer which aims at introducing 3D pictures into the transformer structure [18]. By gradually increasing the receptive area, it enables the network to replicate the global environment and goes beyond CNN's capabilities of gathering global information. The ResU-Net has also been used which is set as the benchmark in the experiments. The model proposed and The ResU-Net has been trained with the same dataset and their accuracies has been compared. The performance of the model could be improved by combining CNN with a transformer. Since the goal of the landslide detection approach is to give supplementary scientific data for emergency rescue, it is crucial to pay attention to its complexity and length. Given that complex algorithms have a propensity to overload the hard-wires, performance and cost trade-offs must be considered for practical implementation.

Meylin Herrera Herrera [19] has presented an attempt to detect landslides that are happening around the world unlike the previous methods which use rule-based technique using feature threshold which are not used globally, resulting in them performing poorly in new regions. For dealing with the complex characteristics in the landslides the author uses OBIA. When the target objects are larger than the cell resolution, OBIA, an image processing technique, outperforms the pixel-based technique. The author has developed a two-stage segmentation algorithm for the picture in order to produce homogeneous segments and distinguish landslides from other kinds of slides. The Red/Green Difference (RGD) and k-means are used as input features in the first segmentation of the picture. Due to the first technique's extensive segmentation of non-landslide zones, the dataset is imbalanced. By integrating homogeneous non-landslide segments and using the Normalized Difference Vegetation Index (NDVI) as an input feature, the dataset is balanced in the second stage.

III. METHODOLOGY

A. Wireless Sensor Network (WSN)

The detection of landslides is inspired from the past research done in this field. The methodology used in this project is a combination of both [Landslide Detection using Wireless Sensor Networks] and [Real-time Wireless Sensor Network for Landslide Detection]. We are using a MPU6050 gyroscope plus accelerometer sensor along with a soil moisture sensor. Landslides depends upon many factors like earthquakes, looseness of soil that is directly dependent on how wet the soil is. There are many more factors, but these are the main and easily detectable characteristics which can be examined so that landslides can be predicted. The chances of landslides increase due to rain, so the system is synced with the weather to take extra care and be more robust. The moisture in the soil is detected using LM-28.

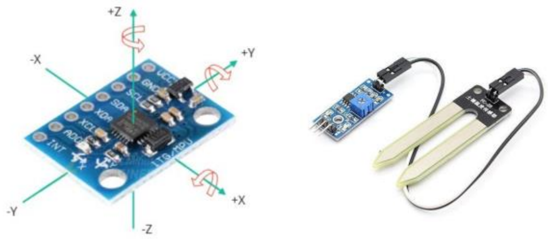


Fig 3: MPU6050 and FC-28

MPU6050 is a 6-axis motion tracking device that is a combination of 3-axis gyroscope and 3-axis accelerometer. It works on I2C communication that stands of Inter-Integrated Circuits. I2C is a very popular protocol that uses just two lines i.e., SDA (Serial Data) and SCA (Serial Clock) for communication. It operates on two modes either master or slave mode. The main advantage of this is that due to the use of sensor address, one master can connect many slaves by just using two lines until the addresses of the sensors are not same. LM-28 works on a very simple principle of variable resistance. The two exposed probes of the sensors work as variable resistors inside the soil. As the amount of water increases in the soil, the conductivity between the probes also increases. These reading are minute for a microcontroller to detect so, LM393 comparator is used along with it. The brain of each node is an ESP32. It is a MPU integrated with WI-FI that perfectly fulfills our requirements. It is a 32-bit microcontroller with I2C support. It has the capability to directly connect to the servers where all the data is sent to be analysed and even supports MQTT protocol.

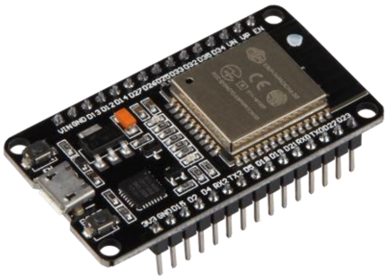


Fig 4: ESP32

The process of taking the data for each node is as follow, after all the initial setup that includes calibrating the sensors a connectivity is established. Calibration is really important for both the sensors used here because initial values can't be predicted. For MPU6050, the orientation when it is first placed places an important role to calculate the movement in the sensor after. The LM-28 also requires a pre-tested moisture value with minimum possible moisture in the soil. After the calibration and deployment of nodes, the connectivity is made with the server. The nodes use sensors to sense the data after an interval of time and send it to the server. The interval in which the sensor sends the data to the server is directly dependent on the weather. This is where the weather sync takes place. It is known that the risk of landslides increased in the presence of rain as it loosens the soil.

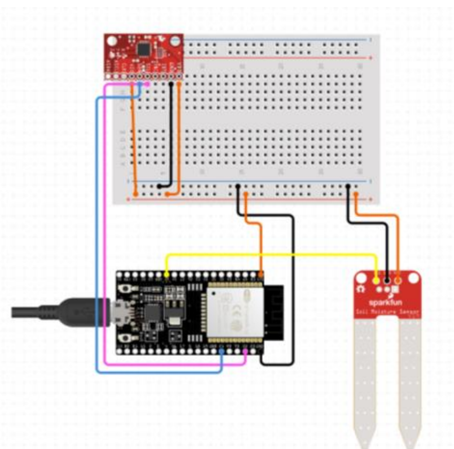


Fig 5: Circuit diagram of a single node

The sensors could be easily made to send data real-time and be robust, but the most important factor stopping is the power supply. Doing this will consume a very large amount of power and the battery used for each node won't last long. To prevent this, we have used sleep mode that uses extremely less amount of current and saves battery. The current consumption table has been shown below. In the sleep mode, only the RTC (Real-Time Clock) of the esp32 will be active and all the other units like the processor and the Wi-Fi will be turned off. After an interval of time that will be defined depending upon the weather and the conditions of the area, the device will wake-up, make a connectivity with the server, take readings from its sensors and then send it to the server for analyses.

Power Mode	Description	Power Consumption
Active	All the features work along with Wi-Fi	300mA
Deep-Sleep	RTC-Timer and RTC-Memory	10uA
Power-OFF	Main-Chipset is OFF	1uA

Table 1: Power consumption table

The above was the process of how the data from the sensors will be taken and how it will be sent to the server. The main part comes is how will we predict the landslides using the data. To do so, there can be two ways, that we thought off, one can be comparing the data region wise and other can be giving weightage to each sensor depending upon the region they are deployed. Both have its own benefits.

Region-wise data comparison

In this method the data from nodes from each of the region is taken and compared to the other region of the same area. For example, the data from the nodes from one side of the downhill is compared to the data of the other side of the downhill. This comparison can give out the idea on which region of the hill is prone to landslide. The reason behind this method is that as the area is same, the rainfall and earthquake will give out almost the same effect to sensors to all sides of the area but if there is a sufficient amount of difference between the readings of the sensors on different sides, then it can be concluded that there is a risk of landslides. There can be many reasons for different readings like water content on one side is more or maybe contaminated or even the soil has more moisture on either side which directly implies to risk of landslide. The accelerometer readings will be more accurate in such conditions as movement on one side of their hill is more as compared to the other will directly conclude to landslide detection.

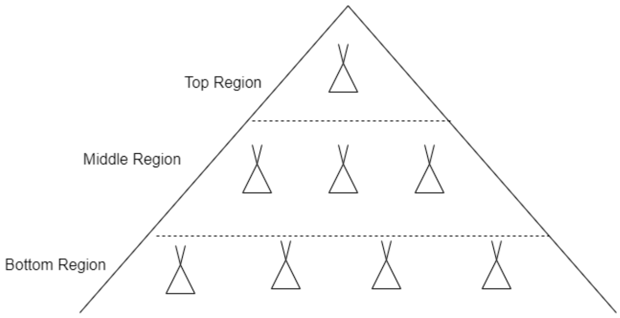


Fig 6: Regions on a hill

Weight-wise data analysis

In this analysis, nodes will be given weights depending upon their location on the hill and the risk of that regions having the landslide more. From the fig 5, it can be seen that the nodes on the top and middle will be given more weight than the bottom ones as they are more prone. The nodes at bottom are given less weight because it is known that water that lands on the hill walls down to the bottom, so in cases of rain soil having more moisture at the bottom is obvious and alternatively, if the moisture content is more in the middle or top, risk of landslide increases.

Implementation

To perform the experiment for the project, we had very limited option as it wasn't possible to test our sensors on actual hills but still, we tried to simulate the same situations and create a network of multiple nodes that send the data to the server. In the practical implementation we created two nodes and connected sensors with it. For the server, we used an already made free to use database known as thing speak, that is created to developers like us to test our IoT based projects. The code for each node is submitted along with this report.

For the purposes of testing our network we created two nodes. Each sensor recorded the readings and sent it to the server where the data was graphically represented dynamically. Although we have mentioned that the controller would be in sleep mode for most of the time but as the results were needed to be recorded and displayed real-time, we implemented the sleep mode separately who's code is also attached along with this report. To confirm our claim that sleep-mode will save battery, we have even tested the current consumed using a multi-meter and noted the readings that were almost like the values stated in the table [table number]. For the deep-sleep mode, the claim was written, but in case of active mode the readings varied a lot depending on the Wi-Fi range and time taken to connect to the server but as this happened once in a time interval, overall that current didn't affect and on an average the value stated in the same table is somewhat right.
After creating the nodes, we simultaneously sent the data taken from the sensors attached to the two nodes to the server and recorded the reading. The readings recorded were displayed on the database using graphs. The recorded data had to be studied based on the two analysis we mentioned before which can't be done with the data we get as the reading were simulated in artificial environment and even the number of nodes were less.

B. Deep-Learning Method

The As seen in the above literature, we can use the NASA global landslide catalogue that has the information about the landslide with coordinates and extract the images from the sentinel-2 satellite using the coordinates to create a database of pre and post landslide images and train our deep learning model on it.

Sentinel-2:

Sentinel-2 is a Copernicus Program Earth observation project that routinely collects optical images of the land and coastal waterways with high spatial resolution. The Copernicus Sentinel-2 constellation consists of two polar orbiting satellites that are phased at 180 degrees from one another and put in the same sun-synchronous orbit. Due to its vast sweep width (290 km) and extended return time, it would be able to monitor changes in the state of the land surface (10 days at the equator with one satellite and 5 days with two satellites under cloud-free conditions, resulting in 2-3 days in mid-latitudes). This Sentinel-2 Mission Guide provides an overview of the satellite, ground segment, and mission objectives. In addition to orbital characteristics, coverage, sensor payload, and data outputs, the list also includes Copernicus services and associated legacy missions [20].

Sentinel 2 Bands:

There is a Multispectral Imager on the Sentinel-2 (MSI). This sensor has 13 spectral bands and pixels with a size range of 10 to 60 metres. It has 10-meter resolution in its near-infrared (B8), green (B3), red (B4), and blue (B2) channels. The ground sampling distance for its red edge (B5), near-infrared NIR (B6, B7, and B8A), and short-wave infrared SWIR (B11 and B12) is all 20 metres. Its cirrus band (B10) and coastal aerosol (B1) have pixels that are 60 metres wide.

Spectral bands for the Sentinel-2 sensors					
Sentinel-2 bands	Sentinel-2A		Sentinel-2B		
	Central wavelength (nm)	Bandwidth (nm)	Central wavelength (nm)	Bandwidth (nm)	Spatial resolution (m)
Band 1 – Coastal aerosol	442.7	21	442.2	21	60
Band 2 – Blue	492.4	66	492.1	66	10
Band 3 – Green	559.8	36	559.0	36	10
Band 4 – Red	664.6	31	664.9	31	10
Band 5 – Vegetation red edge	704.1	15	703.8	16	20
Band 6 – Vegetation red edge	740.5	15	739.1	15	20
Band 7 – Vegetation red edge	782.8	20	779.7	20	20
Band 8 – NIR	832.8	106	832.9	106	10
Band 8A – Narrow NIR	864.7	21	864.0	22	20
Band 9 – Water vapour	945.1	20	943.2	21	60
Band 10 – SWIR – Cirrus	1373.5	31	1376.9	30	60
Band 11 – SWIR	1613.7	91	1610.4	94	20
Band 12 – SWIR	2202.4	175	2185.7	185	20

Table 2: Sentinel-2 spectral and QA bands obtained from [21]

Sentinel-2 provides access to the image data that is freely available to use at Sentinel Open Access Hub [23]. However, it is expensive in terms of storage requirements to extract the image data based on the location coordinates (longitude and latitude) obtained from the NASA landslide catalog database as each image is off about 1 to 2GB in size and if we want to create a substantially large database with landslide pre and post images of allocation we would require a lot of computational resources. this was evident in the literature [19], a limitation of which was not being able to capture enough data to train the model.

Ghorbanzadeh et al [23] have introduced Landslide4Sense as the benchmark for landslide detection. They have used 3,799 image from the Sentinel-2 satellite and ALOS PALSAR. The dataset has been collected from four different times and geographical locations: Iburi (September 2018), Kodagu (August 2018), Gorkha (April 2015), and Taiwan (August 2009). They have used 11 models of deep learning techniques which include U-Net, ResU-Net, PSPNet, ContextNet, DeepLab-v2, DeepLab-v3+, FCN-8s, LinkNet, FRRN-A, FRRN-B, and SQNet. They have done the experiment to prove that ResU-Net outperforms the other models. The main problem is that the deep learning models lack the publicly available data and landslide images. They have created a unique benchmark dataset from Sentinel-2 satellite and ALOS PALSAR which supplies promising data sources. The landslide benchmark dataset is suitable for providing an explicit norm for comparisons of the generalisation capabilities of new DL models proposed for remote sensing image segmentation and classification, including unsupervised, self-supervised, and semi-supervised methods for landslide detection.

We plan to use this data set and perform our analysis to study how landslides can be predicted using deep learning methodology.

Dataset Description:

The Landslide4Sense data's training, validation, and test sets includes 3,799, 245, and 800 photo patches. There are a total of 14 bands in each image patch, including:

- B1, B2, B3, B4, B5, B6, B7, B8, B9, B10, B11, and B12 from Sentinel-2 multispectral data.
- The slope data for ALOS PALSAR is B13.
- ALOS PALSAR produced the digital elevation model (DEM) known as B14.

All bands in the competition dataset were scaled to a resolution of around 10 metres per pixel. The image patches are 128 by 128 pixels in size and have pixel-by-pixel labels [24].

This was a competition where we were given dataset and were asked to implement different deep learning methodologies to predict landslides.

On January 24, 2006, the Advanced Land Observing Satellite (ALOS) was launched by the Japan Aerospace and Exploration Agency (JAXA) [25]. It was still in use on May 12, 2011. ALOS, also known as DAICHI, captured 6.5 million scenes during its five-year operating life.

The image data from Sentinel-2 is coupled and processed with DEM and slope information which has been obtained from ALOS PALSAR.

Data Preprocessing:

Our training data consists of 3799 images of size 128 by 128 pixels and of channel width 14 bands and the mask labels associated with the images are of the size 128 by 128 pixels. All the images are in the format of .h5 files which had to be extracted.

For our analysis we have divided the training data set into three parts for testing, training, and validation, where the testing set is stored separately to later evaluate the model performance.

we have also calculated the normalized difference vegetation index (NDVI), which is a standard index that is used to specify the relative biomass of an area. This can be calculated from the red band and the near infrared NIR band.

$$NDVI = \frac{\mathrm{NIR} - \mathrm{R}}{\mathrm{NIR} + \mathrm{R}}$$

Out of all the 14 bands we have chosen RGB red, green and blue colour bands, slope and elevation from ALOS PALSAR, the newly calculated NDVI index for our analysis.

So, the data now consists of RGB image the end NDVI index, slope and elevation, and the corresponding label i.e., mask associated with it for training the supervised model. we can see from the below images that if there is a landslide occurrence it will be marked in the corresponding mask label and if there is no landslide in the image the corresponding mask label will be empty.

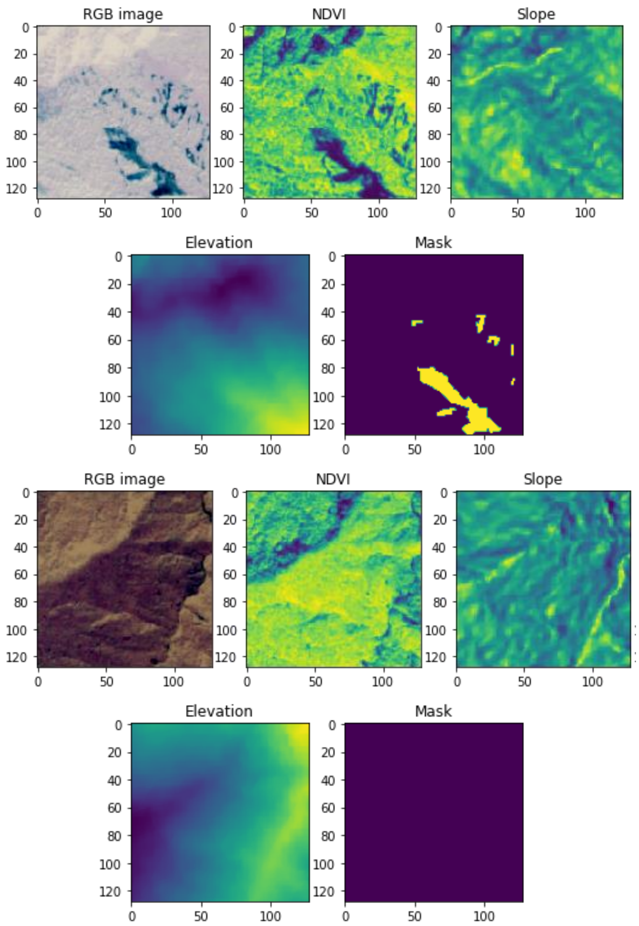


Fig 7: data with label example after preprocessing (a) with presence of landslide (b) no presence of landslide

Model Selection:

Image segmentation, a domain of computer vision and digital Image processing is used to classify images into categories by breaking them down into segments and performing classification task. The image segmentation models consist of an encoder-decoder network That provides a segmentation map of the original image.

The deep learning image segmentation models consists of neural networks that perform segmentation tasks using encoder-decoder structures. And the last step after successful image segmentation process would be the classification of the obtained semantic labels that signifies the presence or absence of an event and in our case a landslide.

Convolutional encoder decoder architecture is one of the famous ones used for this task. For our analysis we selected a basic image segmentation deep learning model called Unet.

U-Net:

U-net was modelled as a fully convolutional network for using in the field of biomedical image [26]. It was then modified to work with lesser number of images and give more accurate segmentation. An encoder network followed by a decoder network can be used to summarise its architecture. In contrast to classification, where the deep network's final output is the sole aspect that matters, semantic segmentation requires a mechanism for projecting the discriminative features that were learnt at various stages of the encoder onto the pixel space. Skip connections between the encoder and decoder routes, which allow the transfer of fine-grained aggregate information from the encoder path to the equivalent layers in the decoder path, reinforce the U-Net design, similar to other FCNs.

The network is modelled according to the original U-Net architecture specifications, with the difference that kernel initializer [27] (the method using which weights are updated) has been specified to be he_normal i.e., it draws the weight samples from a truncated normal distribution centered at zero. The performance of the model greatly improved after using the kernel initializer.

Metrics for evaluation of model performance:

The confusion matrix for a binary classification problem with a positive and negative class is given below in the table.

Actual Class	**Predicted Class**	
	Negative	Positive
Negative	True Negative	False Positive
Positive	False Negative	True Positive

Table 2.2: Confusion matrix for binary classification.

Precision: It is the ratio of correctly predicted positive observations to the total predicted positive observations. The equation for precision is given below:

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

Recall: It is the ratio of correctly predicted positive observations to all observations in actual class.
The equation for recall is given below:

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

F1 Score: It can be calculated by averaging precision and recall. As a result, this score considers both false positives and false negatives. F1 frequently surpasses accuracy, especially when the distribution of the classes is unbalanced. Accuracy operates most effectively when false positive and false negative costs are about equal. In situations when the costs of false positives and false negatives differ greatly, it is advantageous to employ both Precision and Recall.

$$\text{F1 score} = 2\ X\ \frac{\text{Recall x Precision}}{\text{Recall} + \text{precision}}$$

IoU: Intersection of Union or Jaccard index is an important measure when it comes to object detection applications using images. it is a measure of how well the predicted images area match (overlap) as compared to the actual ground truth. Having a higher IoU value is a good indicator of a model performance.

$$J(a,b) = \frac{|a \cap b|}{|a \cup b|}$$

IV. RESULTS

A. Wireless Sensor Network Method

The experiment we performed for this part of the paper was a success as we were able to make the nodes, take data from the sensors and send it to the database. We were also able to graphically represent the data we got from the sensors for better analysis. The comparison part that we have to do, to predict any landslide risks was done by making graphs of different nodes data using python. Though we had to use random data but still we were able to do that by recording the data and using it to plot the graphs.

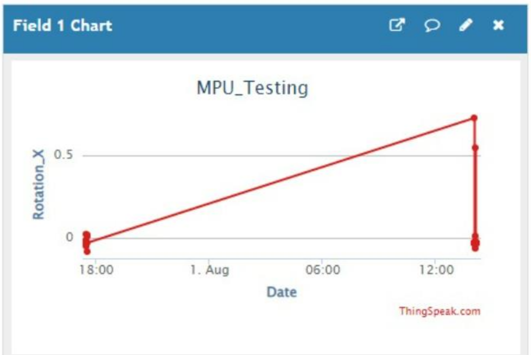


Fig. 8: MPU6050 data graph

B. Deep-Learning Method

The model has been trained for 20 epochs, where the training and validation loss and accuracy plots are obtained as shown in the below image. NIR band.

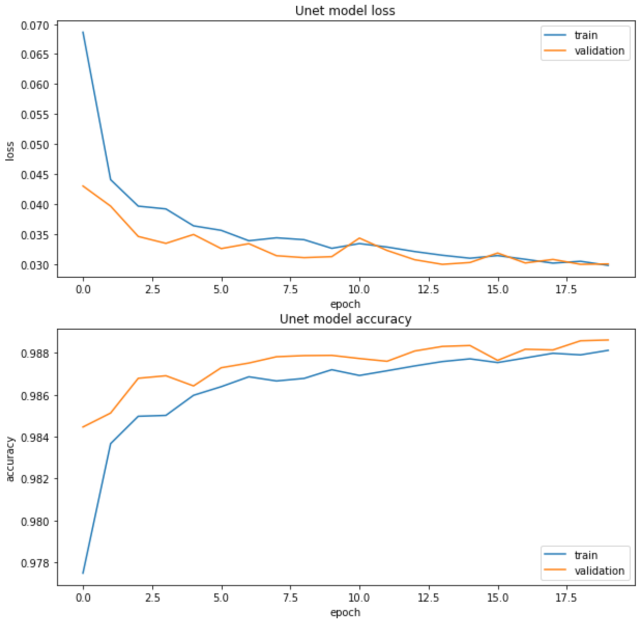
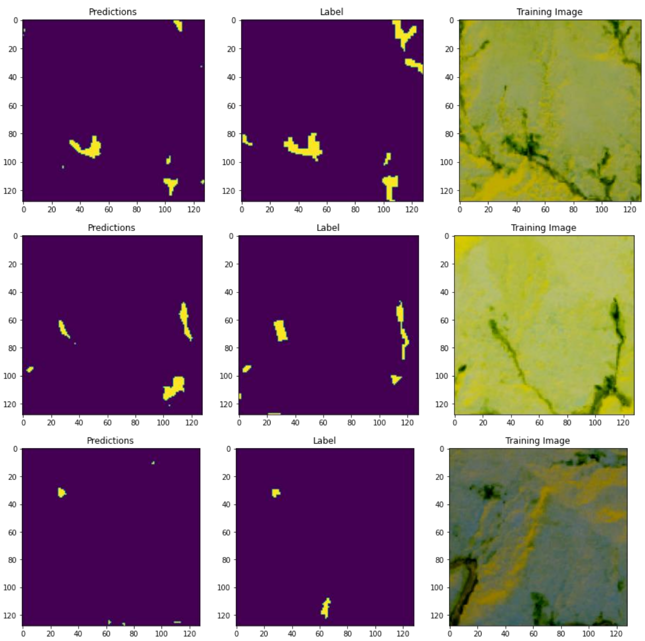


Fig 9: (a) loss vs epoch curve for training and validation sets (b) accuracy vs epoch curve for training and validation sets.

After evaluating the model on the test set, we can see that the predictions made by the deep learning model are very close to the actual prediction maps. This can be evaluated by numerous metrics.



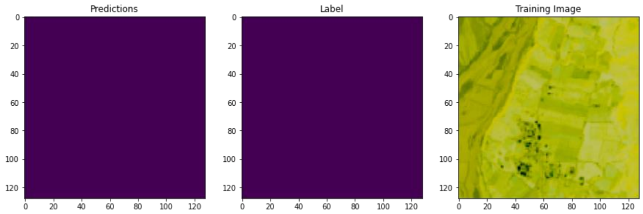


Fig 10: predictions made by U-net model compared to actual labels of image

Recall: 59.9%
Precision: 78.3%
F1: 67.9%
IoU: 51.4%

Now evaluating the model on test data which does not have mask labels associated with the image data, we can see that our model maps the landslide in the area well. This can be used to predict the occurrence of landslides by using the image data that extracted in a future time.

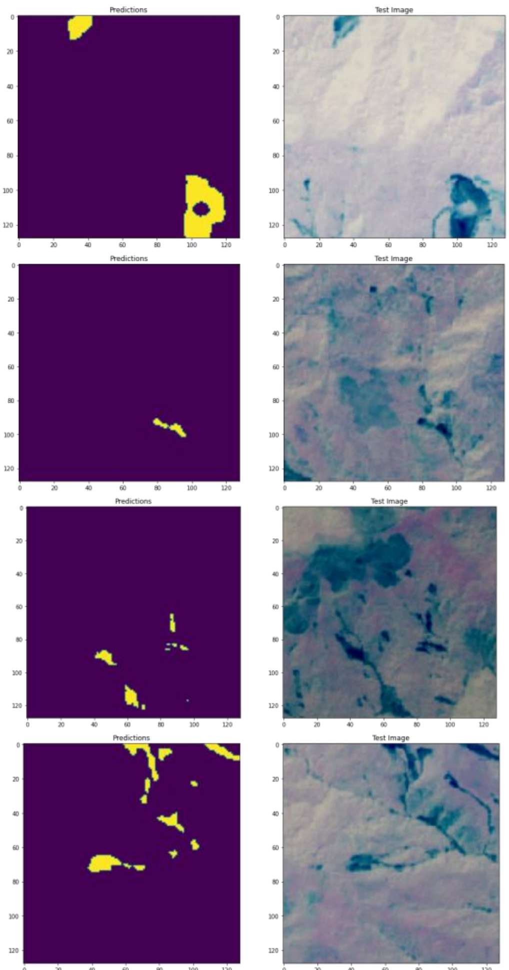


Fig 11: predicted mask of test images without labels

V. CONCLUSION

In this project we tried to implement two types of solutions to a single problem. The main aim was to predict landslides by analysing data of different types to give out a prediction. Hence after seeing the results from both the methods we can conclude that both methods are useful and have their own pros and cons. The advantage of using deep-learning method was that the whole area can be covered as the satellite images efficiently covers everything. This same comment can't be made regarding the WSN because the area it covers directly depends upon the number of nodes that are going to be deployed. On the other hand, WSN is more robust and the frequency of getting the data can be manually set depending on the weather or any manually predicted risk. In the end, we can see that both methods are equally important and using it together as discussed in future work maybe a great benefit and might incredibly increase the accuracy of landslide prediction.

VI. FUTURE WORK

While doing the study on both the methods, we realised that both consist of some disadvantages that was covered by the other method. Ignoring the cost of the system for now, combining them together can-do wonders. One of the methods of doing so can be by using the Kalman-Filter to combine both the data and then predicting and danger of landslides. Apart from this, the methods implemented in this project should be verified by actually implementing it on real regions so as to make improvements in predictions strategies and also improving the threshold values if required.

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