A Preliminary Assessment of Landslide Detection in Leyte, Philippines Using an AI-Based U-Net Model on Sentinel-2 Imagery

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Abstract

The application of artificial intelligence (AI) based models offers a potential improvement over conventional approaches to landslide detection, which typically demand substantial resources and often require significant human expert involvement. Jadala (2019) describes the U-Net model as a convolutional neural network that is extensively used for accurate pixel-level semantic segmentation despite having only a limited dataset for training. This research explores the capability of the U-Net model for detecting the landslides triggered by Tropical Storm Agaton in Abuyog, Leyte in April 2022, using Sentinel-2 imagery and validated landslide inventories from Leyte, Davao de Oro, and Maguindanao del Norte. The model was trained using image patches that included Sentinel-2 Red, Green, and Blue bands, the Normalized Difference Vegetation Index (NDVI), as well as topographic features such as slope and elevation values acquired from an Interferometric Synthetic Aperture Radar (IFSAR) Digital Terrain Model (DTM). The observed results highlight the model's effectiveness in identifying landslide pixels, achieving a strong F1-score of 72.97. This performance was further supported by a precision of 79.54 and a recall of 67.46. Across all accuracy metrics, the U-Net model likewise achieved higher performance as opposed to other machine learning approaches such as the Support Vector Machine (SVM) and Random Forest (RF) classifiers, which were evaluated using the same dataset. Future studies should focus on incorporating additional training data across regions with varying geological characteristics to further enhance the model's accuracy.

1. Introduction

Landslides are destructive geological hazards that occur when materials such as soil, rock, or debris lose stability and move downward along a slope, primarily driven by gravitational forces (Bezerra et al., 2025; Nguyen, et al., 2025; Dias et al., 2023; Varnes, 1958). Such occurrences usually develop in mountainous or steep terrains and are often triggered by multiple factors, including intense rainfall, seismic activity, volcanic eruptions, deforestation, and land-use alterations. Each year, landslides cause widespread damage to communities across the globe, resulting in thousands of deaths, significant financial losses, and long-term impacts on safety and development (Dente et al., 2023; He et al., 2024; Li et al, 2024).

In the Philippines, the detection and monitoring of landslides have traditionally been conducted by human experts through visual inspection, remote sensing analysis, and field validation. This reliance on manual detection methods were seen as resource intensive, time-consuming and may have biased interpretations (Wang et al., 2020; Das et al., 2023). Several approaches are also used for landslide hazard mapping, including empirical and descriptive models employed by the Mines and Geosciences Bureau (MGB) through field-based assessments and checklists to produce maps (Manzano, 2014). Another approach is the utilization of statistical models, which rely on landslide inventories and environmental variables, but may be biased depending on data availability. Physically-based or deterministic models simulate slope stability using topographic, geologic, and hydrologic data, requiring high-resolution terrain and precise geotechnical inputs for accuracy (Alejandrino et al., 2015).

Artificial intelligence (AI) methods, specifically deep learning algorithms, present an auspicious alternative to traditional methods by analyzing satellite images over wide areas and identifying areas of interest more efficiently. Utilizing AI to automate landslide mapping processes can significantly minimize the manual effort involved in conventional detection practices. (Das et al., 2023; Liu et al. 2023). The use of AI is also an effective tool that can address issues on visual inspections that heavily rely on people's subjective judgement, which can be viewed as an "inconsistent criteria for detecting landslides" (He, et al., 2024). By training the model on labeled datasets, it learns to recognize complex patterns and characterized attributes associated with landslides, resulting in more accurate predictions and improved performance as additional data become available.

According to Xiang (2025), the U-Net model is a kind of convolutional neural network (CNN) structured to categorize every pixel in an image based on the object or region it represents and is particularly effective for tasks that require precise pixel-level classification, such as landslide detection in remote sensing data. It features a symmetric U-shaped structure composed of an encoder (contracting path) that captures contextual features through convolution and max pooling, and a decoder (expanding path) that reconstructs spatial details using upsampling and concatenation with corresponding encoder features via skip connections. U-Net is well-suited for small datasets because of its efficient use of feature information, offering high segmentation accuracy with relatively low computational complexity. Key advantages of the model include its simplicity and strong performance in boundary detection, and robustness in limited-data scenarios. However, it also has limitations, such as difficulty in capturing multi-scale features and challenges in distinguishing landslides from complex backgrounds when used in its basic form (Dong et al., 2022).

In 2019, Ghorbanzadeh et al. conducted a study comparing CNNs with traditional machine learning (ML) approaches, including Support Vector Machines (SVM), Artificial Neural Networks (ANN) and Random Forest (RF) for detecting landslides. Their research used data from RapidEye satellite imagery for two separate training dataset types (one is Normalized Difference Vegetation Index (NDVI) using Near-infrared (NIR), Blue, Green, and Red bands; the second one with added topographic layers such as slope, aspect, and curvature) and focused on a district in Nepal which was deemed highly vulnerable to landslides due to its inherent geological features and climate. It also highlighted the possible use of CNNs for landslide detection and emphasized that the ideal structure is not always straightforward. Nevertheless, the CNN model using only spectral information with a 16x16 pixel input window yielded the best results.

In a follow-up study, Ghorbanzadeh et al. (2021) assessed the "cross-regional applicability of U-Net and ResU-Net models for landslide detection" in sites across Taiwan, China, and Japan. In this context, transferability refers to how well a model trained in one region can be applied to another region without retraining and still maintain good performance. The results showed that although ResU-Net achieved higher overall accuracy, U-Net demonstrated stronger transferability. The impact of input sample size was also examined in this study, showing that the U-Net model achieved higher mean F1-scores when the input size was 128 × 128 pixels.

In 2022, Ghorbanzadeh et al. demonstrated the ability of U-Net in delineating landslides. In this research, the Landslide4Sense benchmark dataset, containing 3,799 image patches, was utilized to train and assess different deep learning methods. The dataset utilized the Near-Infrared (NIR), Red, Green, and Blue bands from Sentinel-2 imagery, along with elevation values and slope data acquired from a Digital Elevation Model (DEM). Quantitative results showed that U-Net was the second-best performing model, following ResU-Net, with a recall of 62.17, precision of 79.91, and an F1-score of 69.94.

This paper provides a preliminary assessment of U-Net's capability in detecting landslide affected areas, utilizing bands from Sentinel-2 imagery combined with elevation and slope data acquired from an IFSAR Digital Terrain Model (DTM). Specifically, the research aims to assess how effectively the model identifies landslides in Abuyog, Leyte, and to compare its performance with other ML techniques, such as SVM and RF, to demonstrate the capability of AI models for more efficient landslide detection in cases where validated data remains limited. Ultimately, the goal of the study is to aid agencies working on disaster risk reduction and management by developing methods requiring less human supervision in landslide detection.

2. Study Area

Leyte Island is highly susceptible to landslides because of its topography, climatic conditions, and underlying geological features such as the characteristics of its soil (Catane et al., 2007; Guthrie et al., 2009). Located in the Eastern Visayas region of the Philippines, the island is composed primarily of volcanic and sedimentary rocks (Aurelio and Peña 2010; Sajona et al., 1997) deformed by structures associated with the left-lateral strike-slip Philippine Fault Zone (e.g., Allen, 1962; Dusquesnoy et al., 1994; Lagmay et al., 2003). The island's eastern region generally receives heavy rainfall between October and March, whereas the western region experiences its rainy season from June to December and remains dry during the other months (Olaguera et al., 2025). From 2002 to 2014, a total of 280 landslides were identified across Leyte, with most incidents occurring in the elevated regions of the province (Eco et al., 2015). This includes the renowned Guisaugon rockfall-debris avalanche in 2006 (Catane et al., 2008). More recently, the National Disaster Risk Reduction and Management Council (NDRRMC, 2021; 2022) reported 10 landslide incidents in Leyte Island during the onslaught of Super Typhoon Odette (Rai) and 17 more were associated with Tropical Storm Agaton (Megi). Local field assessment of the regional office of the MGB (2022) noted 33 landslides and tension cracks in the Municipality of Abuyog while around 750 landslides and/or erosion sites were identified from satellite imagery after Tropical Storm Agaton (Minimo et al., 2023). The map shown in Figure 1 displays Abuyog, Leyte, detailing the area affected by the Tropical Storm Agaton landslides and where the U-Net model will be applied for detection.

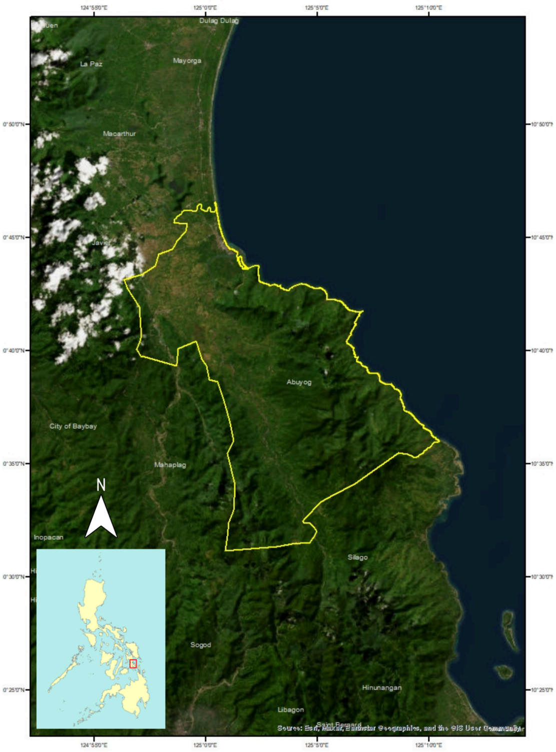

Figure 1. Location of Abuyog, Leyte
(Basemap adopted from ESRI)

3. Materials and Methods

3.1 Data Used

The training dataset consists of image patches with stacked spectral and topographic bands, along with their corresponding mask patches. Each image patch contains six bands: Red, Green, Blue, NIR, NDVI, Elevation, and Slope. Corresponding Sentinel-2 Level 2A data for each region were downloaded and the three primary visible bands, along with NIR, were extracted using Google Earth Engine (Jalan et al., 2025). Elevation values were derived from an IFSAR DTM grid with a 5-meter spatial resolution obtained from the National Mapping and Resource Information Authority (NAMRIA, 2013; in Rabonza, et al. 2015). The slope values in degrees were calculated in ArcGIS software. To ensure consistency, all bands were resampled to a spatial resolution of 10 meters (Qu et al., 2025).

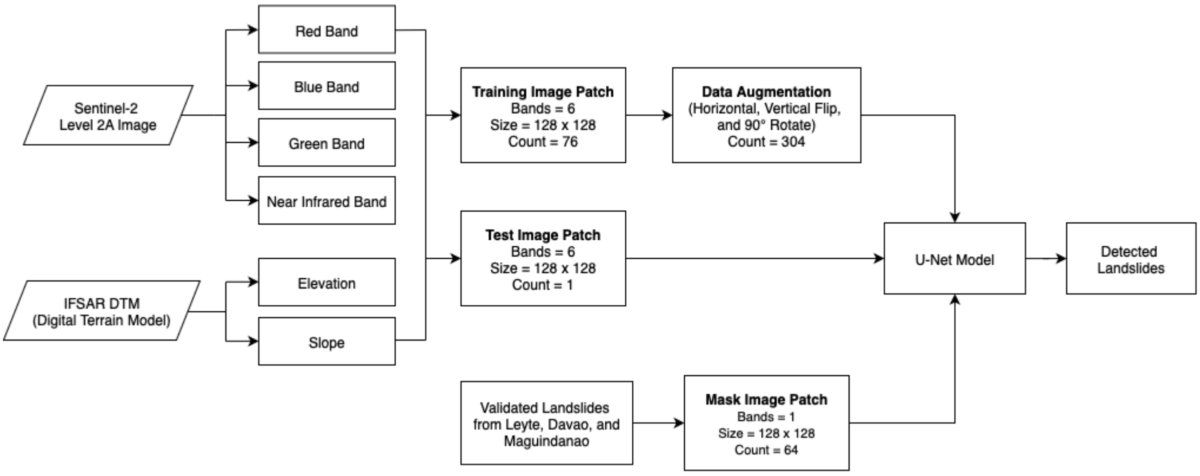

Figure 2. General workflow for landslide detection using U-Net.

Across the three regions with validated landslide data, the training dataset consisted of 76 image patches, each measuring 128x128 pixels and covering landslide-affected areas.

Mask data were then generated from shapefiles of rainfall induced landslides from different regions in the Philippines, including Leyte, Maguindanao, and Davao, as shown in Figures 3, 4, and 5. In 2022, the University of the Philippines Resilience Institute (UPRI) reported that the five-day rainfall caused by a low pressure area and followed by the landfall of Tropical Storm Agaton (Megi) caused multiple landslides between April 1–16 in the island of Leyte (Minimo et al., 2023). Later that same year, Severe Tropical Storm Paeng (Nalgae) triggered destructive debris flows in Datu Odin Sinsuat, Maguindanao del Norte, on October 27 (Ybañez, 2023). More recently, the UPRI reported that continuous rainfall in Davao de Oro led to the reactivation of the 2007 landslide area near a mining community in Zone 1, Barangay Masara, in the Municipality of Maco on February 6, 2024 (UPRI, 2024). All of these were validated through on-site assessments, reports and visual inspection of experts using Google Earth and Planet satellite images (Mendoza, 2024; MGB, 2022; Minimo et. al., 2023; NDRRMC, 2022; Ybanez, 2023). The corresponding Sentinel-2 Level-2A images closest to the event dates and with the least cloud cover were acquired on April 22, 2022 (for Abuyog, Leyte), November 7, 2022 (for Maguindanao del Norte), and February 10, 2024 (for Davao de Oro). The mask files were created by clipping the landslide shapefiles to each image patch and converting them into raster format, assigning a value of 1 to landslide pixels, and 0 to non-landslide areas (Zhu et al., 2025).

To address the shortage of validated landslide data, the training samples were increased through data augmentation methods. Volkova et al. (2024) emphasized that data augmentation is essential for improving model performance and stability, especially in situations with limited datasets. By generating additional and more diverse instances from existing data, augmentation helps expand the scope of the dataset, mitigate overfitting, and improve the robustness of models. Here, we augmented data by performing horizontal and vertical flips as well as 90° rotations to the image patches using Python. These transformations increased the dataset size by a factor of four, resulting in a total of 306 training samples.

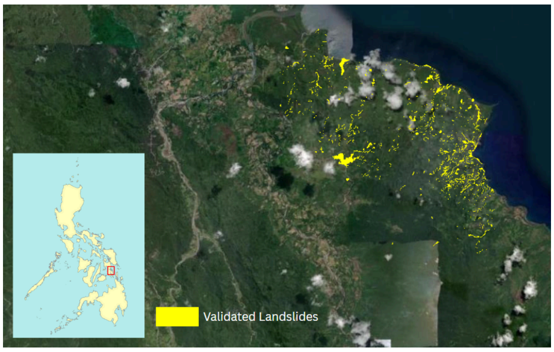

Figure 3. Validated Landslides in Abuyog, Leyte.

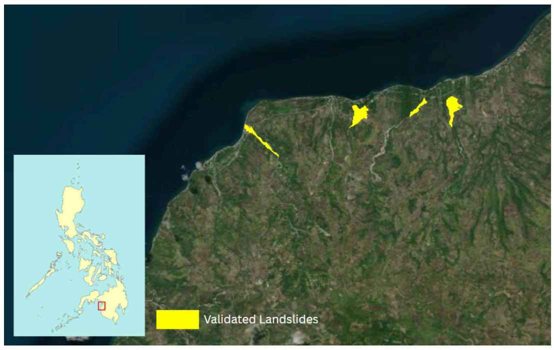

Figure 4. Validated Landslides in Datu Odin Sinsuat, Maguindanao del Norte.

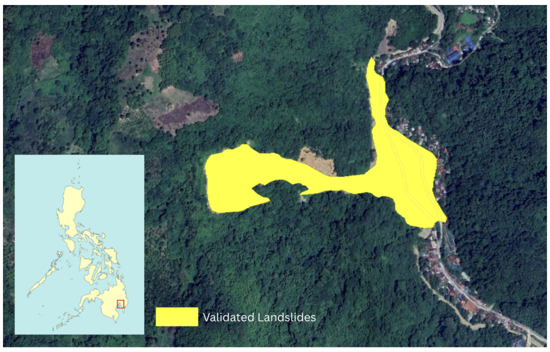

Figure 5. Validated Landslide area in Brgy. Masara, Maco, Davao de Oro.

3.2 Model Configuration and Training

Using TensorFlow/Keras, the U-Net was constructed with an encoder–decoder configuration that includes skip connections across equivalent layers. The encoder section contained four convolutional blocks with 16, 32, 64, and 128 filters, each formed by two 3×3 convolution layers with ReLU activation (Jalan et al., 2024) and He-normal initialization, followed by dropout layers and 2×2 max pooling for downsampling.

The bottleneck layer contained 256 filters and a higher dropout rate of 0.3 was applied to minimize overfitting. The decoder or expansive path mirrored the encoder using transposed convolutions for upsampling, concatenation with encoder feature maps, and subsequent convolutional layers with ReLU activation. A concluding "1×1 convolution layer with a sigmoid activation function" (Goswami, et al., 2025) produced the binary segmentation map distinguishing landslide from non-landslide areas. For model training, a binary cross-entropy loss function was used together with the Adam optimizer (Ogunpola et al., 2024). In assessing performance, the study used established indicators such as precision, recall, and F1-score (Eang and Lee, 2024). According to the definition of Hussain (2025), precision measures the proportion of all polygons identified as landslides by the model that were actually validated to be landslide polygons. It focuses on correctness of the landslide detections. Recall quantifies the completeness of the results, showing the percentage of all actual landslide occurrences that the model correctly identified. F1-score harmonizes recall and precision, providing a single indicator of the model's detection performance (Li et al., 2025).

Training was executed over 100 epochs, employing an iteration size of 4 samples. A model checkpoint callback was used to save the model weights from the epoch that achieved the highest validation F1-score, ensuring optimal performance.

3.3 Comparative Models

Aside from AI-based models, classifiers such as RF and SVM can also be applied to classify pixels from satellite imagery. Dias et al. (2021) and Wang et al. (2021) defined RF as a classification method that builds many decision trees by splitting data into homogeneous groups through binary rules. Each tree produces a class label, and the final decision is made through majority voting across all trees, while SVM trains on sample data to construct a model that classifies instances into their respective classes. In a two-class problem with linearly separable data, it chooses among the possible linear decision boundaries the one that minimizes generalization error, making the classification more reliable. Both classifiers are applied in several studies for the identification of landslides (Wang et al., 2021).

Dias et al. (2021) evaluated the RF, SVM, and Maximum Likelihood algorithms to determine their effectiveness in landslide detection within Itaóca, São Paulo, Brazil. The analysis utilized 5-meter RapidEye-5 multispectral data and elevation derived from the Shuttle Radar Topography Mission (SRTM) (Dias et al., 2021). Findings indicated that SVM outperformed the other classifiers, particularly when slope data were integrated, highlighting its suitability for identifying shallow landslides.

For comparison with the U-Net model in this study, RF and SVM classifiers were also implemented using the Python scikit-learn library (Nibedita et al., 2025). The RF model was established with 300 estimators and to enhance stability and fairness, class weights were balanced, and a constant random seed was employed to ensure all trials were repeatable. The prepared dataset served as input for model training and testing. The model's performance was assessed using F1-score, precision, and recall (Beg et al., 2024), supplemented by a confusion matrix to identify and examine specific misclassifications. To generate spatial predictions, the six input bands were extracted from each Sentinel-2 tile on a per-pixel basis, reshaped into a two-dimensional feature matrix, and classified using the trained RF model. The SVM model was trained on a balanced sample with up to 15,000 landslide pixels and twice as many non-landslide pixels, due to higher computational requirements. The classifier was implemented as a pipeline that first standardized the features and then applied an SVM with a radial basis function, which enables nonlinear separation of classes, and balanced class weights to address data imbalance. To produce probabilistic outputs, the trained model was further calibrated using a CalibratedClassifierCV with sigmoid scaling on half of the test set.

4. Results and Discussion

Training the U-Net model on both the prepared and data-augmented images resulted in robust performance metrics, including an F1-score reaching 72.97, a recall rate of 67.46, and a precision value of 79.54. Figure 6 presents the prediction of the model for a single training image patch with its corresponding RGB composite and landslide mask file. The predicted landslide features demonstrate strong correspondence with the actual pixels presented in the mask image. Minor discrepancies are primarily confined to the boundaries or edges of the features.

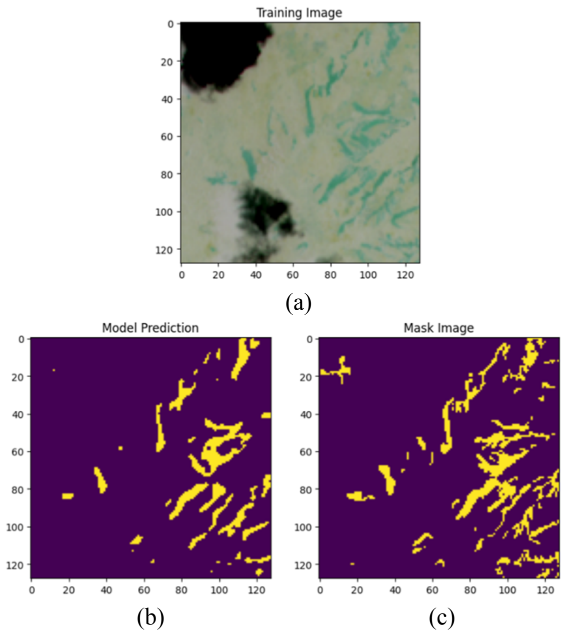

Figure 6. Output of the U-Net Model:
(a) RGB composite of the training image, (b) landslide prediction of the model, and (c) the actual landslides in a portion of Abuyog, Leyte.

Figure 7 shows the detected landslide (shaded in red) in the test image patch that is not part of the training dataset. For cross-validation purposes, the accuracy metrics in this leave-one-out scene was noted. Against the training data, the generated model resulted in an F1-Score of 73.64, recall of

62.85, and precision of 89.90, showing that the model was able to generalize effectively to unseen areas and maintain consistent detection performance even when applied outside the training samples.

The model appears to successfully detect both the massive and small soil-rich landslide deposits in Barangays Bahay and Pilar (Figure 7). However, it fails to recognize the veneer deposits of one of the two debris flows in Pilar (Figure 8). In the field, these deposits were thin layers of sediments left on the ridges where a debris flow ran over. These were recognized to have more of the gray (tuffaceous) components compared to the brown and clay-rich second debris flow deposit which was concentrated in the valley. This may indicate that the model needs to have more training data from volcanic ash or lithic-rich landslide deposits (e.g., lahar flows and debris flows).

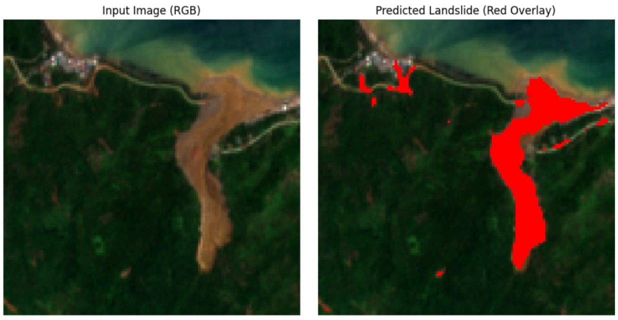

Figure 7. Detected landslide in a test image patch covering Barangays Bahay and Pilar (Base Image from Sentinel-2).

Figure 8. A frame from the April 14, 2022 drone footage of the landslide area in Barangay Pilar, Abuyog (label modified from Minimo, et al., 2023; footage from GPM TV Philippines via Youtube).

Accuracy Metrics	U-Net	RF	SVM
F1-Score	72.98	62.97	60.97
Precision	79.54	60.43	67.86
Recall	67.47	65.73	55.36

Table 1. Comparative performance of U-Net, RF, and SVM in detecting landslides.

Table 1 shows the evaluation of the performance between the U-Net model with image classifiers such as RF and SVM, using standard classification performance metrics. The RF classifier yielded an F1-Score of 62.97, with corresponding precision of 60.43 and recall of 65.73. Conversely, SVM produced an F1-Score of 60.97, achieving 67.86 precision but only 55.36 recall. Clearly, the U-Net model achieved higher values across all metrics. This difference can be attributed to the nature of U-Net as a deep learning semantic segmentation model (Hussaine et al., 2025) capable of capturing both fine-scale texture details and broader spatial context directly from an image, unlike RF and SVM which classify each pixel independently based on spectral features. Landslides often exhibit irregular shapes and heterogeneous spectral signatures, which makes pixel-based classifiers prone to misclassification, especially along boundaries or in areas with similar land cover types. Since U-Net utilizes both the spectral and spatial structure of the terrain, it reduces noise, produces more consistent results, and delineates the extent of landslides more accurately.

5. Conclusion

This research demonstrated the applicability of U-Net for identifying landslides in Abuyog, Leyte using Sentinel-2 imagery, specifically utilizing the Red, Green, and Blue bands, NIR, NDVI, and elevation and slope values from the DEM as training data, despite the limited availability of validated landslide datasets. The model showed strong performance, obtaining an F1-score of 72.97 and a precision rate of 79.54, and recall of 67.46 during training, and comparable results when applied to an unseen test image patch where it resulted in an F1-score of 73.64, 62.85 and 89.90 for recall and precision, respectively. The relatively high precision indicates that the U-Net model was effective at minimizing the incorrect classification of non-landslide areas as landslides (false positives), such that most of the pixels it classified as landslides were indeed correct. However, the lower recall suggests that the model missed a number of actual landslide pixels out of all landslide pixels in the validation data, particularly in areas with subtle or less distinct spectral and spatial characteristics. Accordingly, the model successfully delineated both the massive and small soil-rich landslide deposits but showed limitations in detecting thin veneer or lithic-rich deposits, such as those from volcanic and debris flow events.

In comparison with conventional classifiers such as RF and SVM, the U-Net model performed better than both methods across all accuracy metrics. This advantage is a result of U-Net's ability to simultaneously learn spectral information and spatial context, enabling it to reduce classification noise, delineate irregular boundaries, and capture the heterogeneous characteristics of landslide deposits more accurately than pixel-based classifiers.

Overall, the results showed that U-Net is a reliable and effective approach for landslide detection using remotely sensed data. Future research should aim to incorporate additional landslide data from diverse Philippine regions to expand the training data. This expansion is crucial for enhancing the ability of the model to detect various landslide types and compositions, supporting its effective application across areas with varying geological characteristics.

This study can be valuable in formulating programs for more effective disaster risk reduction strategies. Through the use of AI-based landslide detection models, local government units, agencies and organizations relevant to DRRM can efficiently extract landslide data from satellite imagery to support community planning activities including land use management and infrastructure development. It can also contribute to rapid assessments, including areas that may not be readily accessible to emergency responders after large scale hazard events.

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