Analyzing the Role of Fusing Image and Time Series Data in Forecasting Rainfall-Induced Landslides

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Analyzing the Role of Fusing Image and Time Series Data in Forecasting Rainfall-Induced Landslides

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Abstract

Landslides are a widespread natural peril triggering remarkable destruction. The landslides induced by rainfall arise in all highland zones, triggering living beings and nature to be disarrayed. Global warming and ensuing changes in climate patterns have radically transformed the environment, resulting in a substantial increase in rainfall. Landslides and historical rainfall have a strong correlation. In today's world of information and Communication Technologies (ICT), natural catastrophes can be regulated effectively. The study proposes a multi-modal feature fusion, based on intermediate fusion approach wherein the features, respective to each modality are fused before classification. Two diverse data modalities and their respective models are fitted to build a multi-modal model. Deep learning sequential and computer vision models, Long Short-term Memory and Bidirectional Long Short-Term Memory based on the performance are selected to build a multi-modal fusion model to predict rainfall-induced landslides. The multi-modal is trained and validated using rainfall time-series data and landslide image dataset. The result obtained depicts the fusion approach is effective in predicting rainfall-induced landslides.

Keywords—Rainfall-Induced Landslides, Intermediate fusion, LSTM, Bi-directional LSTM, CNN-ResNet50v2

1 Introduction

Landslides, which are a potentially fatal event, can be destructive. A landslide is a type of mass movement that involves the removal of large amounts of rock, soil, and debris down a slope. Landslides can occur when the slope of a mountain or mountain becomes unstable due to factors such as erosion, weathering, or human activity. These factors can be caused by heavy rainfall, earthquakes, and volcanic eruptions. They can damage urban infrastructure, houses, block roads and water channels, resulting in contusions and fatal accidents. Landslides can cause environmental harm and monetary damage. It is essential to apprehend the landslide in advance and provide well-timed responses.

Throughout the world, landslides are caused by rain, although exactly how extensive rainfall is necessary to induce a landslide? For a long time, this ostensible question has remained unsolved. Recent studies indicate that landslide occurs in approximately 17.1% of the landforms, and that approximately 8.2% of the global population reside in landslide susceptible areas (Jia et al.; 2021). Rainfall is a major factor in increasing the gradient of landslides due to climate changes. (Gunasinghe et al.; 2023). The Intergovernmental

Panel on Climate Change (IPCC) predicts that global warming will lead to more recurring and severe precipitation and parched conditions, which can further increase the probability of landslides (Masson-Delmotte; 2021). As per the envisioned climate and environmental changes, landslide hazard to the population is anticipated to surge, and predominantly the hazard posed by the swift-moving, rainfall-induced shallow-landslides. The correlation between landslide attributes and climate transformation, particularly through rainfall data, was also examined Kirschbaum et al.; 2015a. Rainfall thresholds define the rainfall conditions that, when attained or surpassed, are likely to result in collapsing slopes (Guzzetti et al.; 2008).

1.1 Motivation

Several studies have been conducted to identify the landslide-prone areas using traditional machine learning techniques and deep learning techniques. Recent research implies that LSTM and CNN models have been employed independently to predict landslides (Xing et al.; 2020).

The research proposes a comparative study of multi-modal feature fusion model with deep learning models, like sequential model like Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM) and CNN-ResNet50V2. By combining sequential and CNN model, a strong and precise landslide prediction system is constructed. Sequential models can detect temporal variations in data such as rainfall and seismic activity, and thus alert before landslides occur. CNNs can accurately abstract spatial data from satellite imagery such as land cover and soil moistness, thus predicting landslides (Srivastava et al.; 2020a)(Bui et al.; 2020).

1.2 Research Question

The above research problem motivates the following research question: **To check landslides are induced by heavy rainfall how can employing feature fusion of deep learning models Long Short-Term Memory and Bidirectional Long Short-Term Memory (Bi-LSTM) network with a Convolutional Neural Network, CNN-ResNet50V2 advance landslide prediction accuracy by learning time-based trends from historical rainfall records and landslide events and spatial patterns from satellite Imagery that can act as an early alarming system to further accelerate the evacuation?**

1.3 Research Objective

- Apply and examine the deep learning model Long Short-Term Memory and Bidirectional Long Short-Term Memory (Bi-LSTM) network to study time-based trends from the historical rainfall records. Observing and deciding based on models' performance, selecting one to integrate with CNN-ResNet50V2.

- Apply and examine the deep learning Convolutional Neural Network models ResNet50V2 to learn the spatial patterns from satellite imagery.

- A study of multi-modal feature fusion model to predict rainfall induced landslides. Learning how the rainfall factor contributes to landslides.

- Employing multiple hyper-parameters namely Callbacks such as best model saving checkpoints, learning rate, early stopping, optimizers, define proper epochs , batch size and activation as per the requirement of the research objective to enhance the models accuracy and performance.
- Run the model on various epoch values and numerous hyper-parameter values to gauge the performance of the model.

1.4 Report Structure

The subsequent section in the proposed study will be separated into three sections with subsections in each section. The sections are as follows.

1. Literature Review

   The literature review will delve into existing research on landslide prediction. It will examine previous studies in terms of methodology, datasets employed, and the specific models utilized. This analysis will identify knowledge gaps and inform the proposed study's research questions and objectives.

2. Research Method and Specification

   This section will outline the research methodology employed to address the research question. It will detail the data collection process, data pre-processing techniques, model development, and evaluation strategies. The ethical implications of the research will also be discussed.

2 Related Work

The study focuses on the convergence of various data modalities to enhance their combined strengths. Two key domains are explored in the following: Section 2.1 explores the traditional model employed for detecting landslides. In Section 2,2, the focus is on reviewing recent research on predicting landslides using deep learning models to enhance the prediction.

2.1 Traditional methodologies for detecting Landslides

Landslides feign a substantial menace to both individual lives and foundation in various regions of the world. Instant and precise recognition of probable landslide areas is fundamental for disaster mitigation and preparedness. In latest years, the combination of machine learning procedures placed in landslide recognition has strengthened considerably due to its probable to improve the efficacy and accuracy of landslide estimation and plotting. It is difficult to detect landslide detection for large-scale regions, as conventional methods of landslide detection are long and relatively challenging to detect (Ray et al.; 2020). By detecting landslides after heavy rainfall, valuable insights into the factors that trigger these events can be gained. This expertise can be used to construct approaches for preventing future landslides and implementing effective early warning systems.

A discipline of Artificial Intelligence, Machine Learning, includes multiple methods and models that can be utilized to identify and foretell occurring of landslides. Supervised methods are widely employed and tested for their capability to predict landslides.

(Ayalew and Yamagishi; 2005) demonstrates the association among the parameters like predictor variable and criterion variables like slope, elevation using the logistic regression and combines with Bivariate Statistical Analysis to recognize the significant aspects influencing the occurrence of landslides. (Ado and Amitab; 2023) analyzed Support Vector Machine with four discrete kernel functions, namely multinomial degree, sigmoid, and linear, to predict landslides. The landslide susceptibility index was grouped into five classes using the natural break approach. Based on the research conducted by SVM, the result achieved was approximately 77% accuracy. (Wei et al.; 2019) utilized precipitation data in combination with groundwater altitude and its instability to construct a model to predict landslides. Using an SVM-based model, they attained an RMSE score of 0.144, signifying that data related to rainfall is vastly connected with landslides. (Palliyaguru et al.; 2020) effectively creates an integrated model that merges spatial technology and classifier random forest and achieved an accuracy of 80% indicating its robust prediction capability. (Srivastava et al.; 2020b) performs a comparative study employing machine learning methods such as Support Vector Regression (SVR), linear regression, back propagation neural network (BPNN) and Long Short-Term Memory network (LSTM) in predicting monthly rainfall and employing it as an prompt landslide warning system. The study shows that LSTM and BPNN perform well in handling the time series data like that of the rainfall data. The study also highlights that the deviation between the predictable intensity and the optimal rainfall limit can be used to expect the episodes of rainfall-induced landslides. (Meghanadh et al.; 2021) employed RF to detect landslides and the result showed that the Random Forest performed satisfactory in detecting landslides. Including feature engineering with machine learning can improve performance, which involves the process of choosing and extracting appropriate features. Furthermore, machine learning models tend to be difficult to understand with complex datasets, as there is a need for feature extraction done manually which is time consuming. Due to the same, machine learning can be detrimental to their ability to generalize various issues. To boost the performance of predicting landslides using traditional models, the need to integrate them with the advanced models that can extract the features is essential.

2.2 Deep learning models for detecting Landslides

In the age of Big Data, deep learning, a powerful subset of machine learning, has experienced significant advancements. It comprises a multi-layered architecture of organized neurons that are skilled on wide datasets to spontaneously learn progressively experienced representations of the input data. The progress in the deep learning field has led to significant advances in detecting landslides from satellite images. A combination of models employed to predict daily displacement by the rainfall-induced landslide. The integration of supervised model and neural network, such as AdaBoost BP neural network, is based on the idea of integration and it has many neural units which are responsible for integrating the data. Considering the daily cumulative rainfall and daily displacement recording is a significant factor in predicting the landslide (Tang et al.; 2022). Among the deep learning approaches a lightweight you-only-look-once (YOLO) with attention mechanism for landslides extraction has emerged as popular choice due to is speedy nature in object detection. However, traditional YOLO models face difficulties in accurately defining the irregular boundaries of landslides, as their outputs are typically bounding boxes that may encompass multiple landslides. This limitation underscores the need for improved models that can provide boundaries for landslides detection (Yang et al.;

2024). Applications of the fully convolutional network (FCN) and U-Net for landslide detection have been demonstrated by (Lei et al.; 2019) and built upon by many studies using different variants of these models. (Gao et al.; 2021) demonstrated a difference between U-net and ResUNet model using the Sentinel-2 images and Landstat-8 images. (Qi et al.; 2020) employed ResU-Net and UNet to identify landslides caused by heavy rainfall in Tianshui City, Gansu Province in July 2013.During training and testing on high-resolution (0.5m) GeoEye-1 images with near-infrared, red, and green bands, ResU-Net achieved an F1 score of 0.89, while UNet achieved an F1 score of 0.8. (Liu and Chen; 2021) compared DenseNet and CNN models for landslide inventory construction in Hubei Province, China. DenseNet achieved a Kappa coefficient of 0.965, outperforming CNN's 0.908. A contour-based semantic segmentation model is proposed for landslide detection in Nepal using annual Landsat images. For national-scale landslide detection an F1 score of 60% was achieved.

Previous studies have demonstrated that the prediction accuracy of Long Short-Term Memory (LSTM) is advanced to that of backpropagation neural network. (Nava et al.; 2023) provides a comprehensive comparison of seven different learning models for landslide displacement, including multi-layer Perception (MLP), LSTM, GRU, 2*LSTM, Bi-LSTM and Conv-LSTM. The study suggests that MLP is more suitable for forecasting the maximum displacement peaks, in contrast LSTM and GRU are more appropriate for estimating lower displacement crests. LSTM is a unidirectional model, as it depends exclusively on past state information. While the bidirectional LSTM (Bi-LSTM) is an expansion of the LSTM model It can increase its predictive accuracy by learning input time series data from both forward and backward directions (Zhang et al.; 2021). (Lin et al.; 2022) employs the local mean decomposition (LMD) algorithm is employed to decompose landslide displacement and obtain various posteriority of landslide displacement with different frequencies. The LMD -BILSTM model utilizes both short-term and long-term dependencies in the data, resulting in improved prediction accuracy.

In recent years, combining models to predict has become more prominent. They function as an effective way and as a resource allocation system by assigning different weights to the input feature to emphasize important information and predict based on the same concept. Fusion models help to leverage the diversity in the data and help to overcome the limitations of single-model approaches. On reviewing the previous work, multi-modal based prediction is not implemented much in predicting natural calamities, but in areas such as healthcare, autonomous vehicles and security systems. (Wang et al.; 2022) employs automatic features extraction and fusion from measured ultrasound signal and concatenation of three modules CEEMDAN (Complete Ensemble Empirical Mode Decomposition with Adaptive Noise) module, Attention-IMF and Convolutional Neural Network. The demonstrated experiment provides results that can effectively extract the discriminatory failing features of Unmanned Aerial Vehicle (UAV) and help the tail rotor to obey the balance and command the course. (Benzebouchi et al.; 2023) proposes a deep classification system that classifies chest X-Rays for Covid-19 detection using the feature extraction capabilities of ResNet, DenseNet, and VGG. The study utilizes aggregation techniques such as assembling and balloting, such as majority, average, and weighted to enhance prediction accuracy. The results demonstrate that the concatenation of model's ensembles yields accuracy of 97.95% accuracy and 98.2% F1 score.

Considering the progressive nature of the fusion concept the paper presents implementation of multi-modal combination of sequential (Long Short-term Memory-LSTM, Bidirectional Long Short-term Model-Bi-LSTM) selected based on the accuracy and computer vision model (CNN-ResNet50V2) to predict rainfall induced landslides. The proposed approach utilizes intermediate fusion concepts where the features, which are relevant to individual modality, are concatenated before the last classification layer (Boulahia et al.; 2021). The intermediate fusion layer will focus on the spatial-temporal aspects from the time series and Image data respectively to provide the prediction on the rainfall-induced landslides.

3 Methodology

In this section, the research methodology will be outlined. Additionally, it will provide more information on every step necessary to execute the intended study, and the technical justification of the methodology's stages involved. The main objective of the study is to determine the role of fusing two diverse dataset in predicting landslides caused by rainfall. Additionally, verify that the proposed deep learning models are compatible to construct a multi-modal model. Figure 1. presents the steps to execute the same, including data collection, data preparation, model selection, model training, and evaluation.

3.1 Proposed Methodology

The methodology presented in this study works in six stages as presented in Figure 3. The initial phase data collection includes selecting datasets that complement the objective of the research, followed by data preparation. The base of the study is two datasets of diverse modalities time series dataset and image dataset. The GLC dataset is a foundation for generating time series dataset using CHIRPS for rainfall measurements. HR-GLDD is employed as an image dataset in the study. The Second phase includes data pre-processing wherein a time series sequence is created, and further data augmentation is accomplished.

The methodology, model selection phase is a crucial phase, wherein the model or algorithm best complementing the study is selected after the pre-processing phase. To have a successful selection of models, various parameters are considered like nature of the dataset, the goal of study is to determine whether the end goal is classifying, segmenting, or predicting probabilities. In accordance with the literature review, this study examines three deep learning models LSTM, Bi-directional LSTM and CNN-ResNet50V2 to create a multi-modal feature fusion model. Following the training of the deep learning models, they will be employed as a feature extractor in the multi-modal feature fusion model. Considering the nature of the datasets selected, as per the literature review, among the fusion techniques explored like early, intermediate and late, the intermediate fusion technique will be implemented in this study. Intermediate feature-level fusion is implemented, wherein the raw data is transformed into a higher-level representation by mapping them through a stack of layers, which act as multi-modal feature maps that allow to take advantage of both the modalities.

The last phase of the methodology includes assessing the performance of a trained model on a test dataset. This is the crucial phase of the AI building process, as the outcome of evaluation enables study to evaluate the model's performance, suggesting that any further hyper-parameter tuning is needed or not to improve the performance. The model performance of the sequential models is evaluated using accuracy, precision, recall, AUC, also by monitoring the loss during training and validation for the test data. Accuracy and loss are employed to evaluate the computer vision model and multi-modal

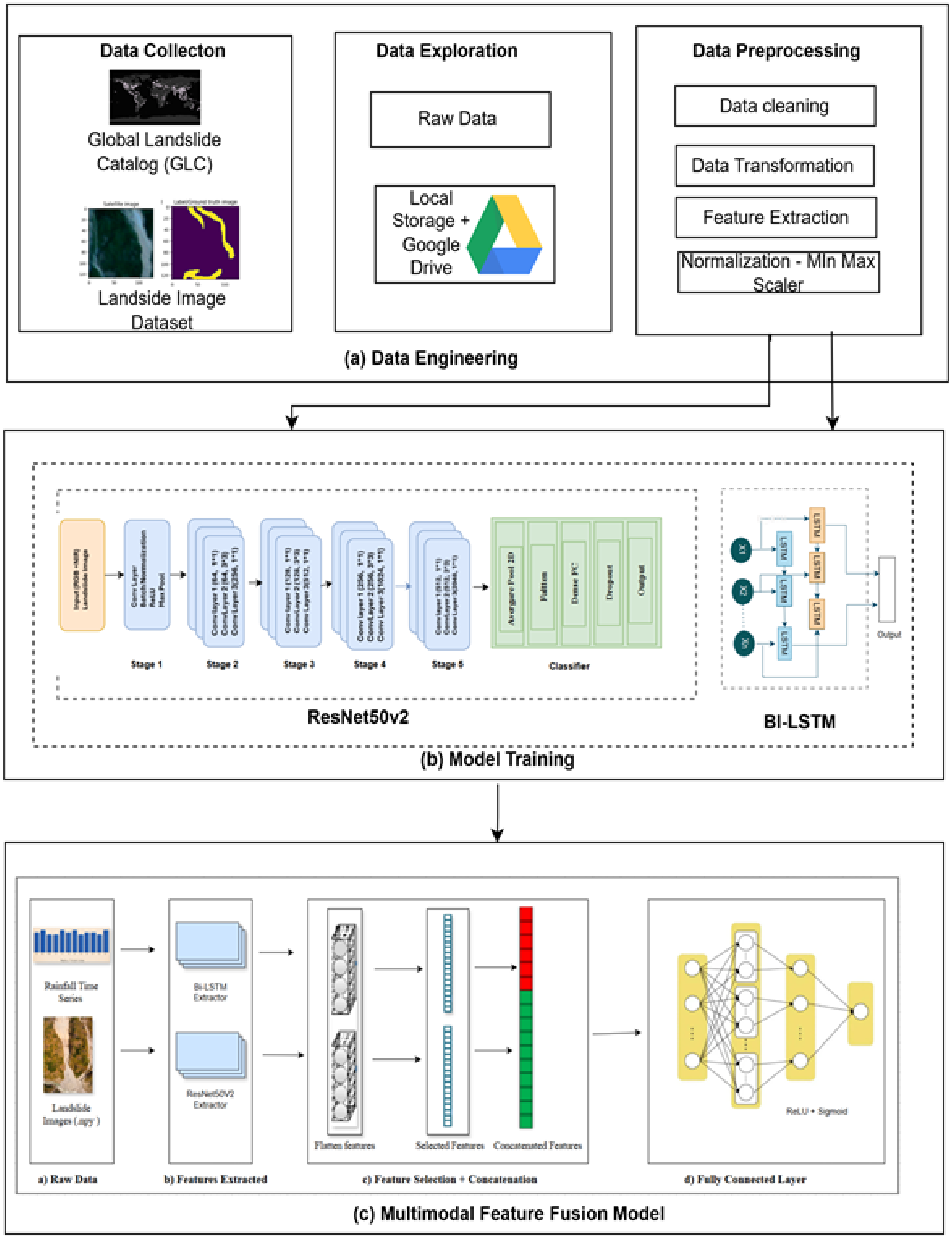

Figure 1: Proposed Methodology: (a) Data Engineering (b) Model Training (c) Multi-modal Feature Fusion Model

feature fusion model. The modelling and evaluation with an explanation will be further demonstrated in this study.

3.2 Data Collection

Two datasets are employed in this study which are publicly available. One being rainfall triggered landslide dataset and the other being Landslide image dataset. The Global

Landslide Catalog (GLC) is an online database of rainfall triggered landslides recorded from 1988 to 2017 by NASA's open portal since 2007 and comprises of 11,033 landslide events.The GLC is developed with the goal of identifying rainfall induced landslides around the World regardless of size, impacts or location (Kirschbaum et al.; 2010)(Kirschbaum et al.; 2015b). The GLC dataset is considered as a base to develop the precipitation rainfall dataset based on important factors such as longitude, latitude, landslide date, and the landslide triggers. Figure 2. presents the distribution of the landslides and by what they are triggered. The chart indicates that there are approximately 72.11% landslides caused by rainfall in the GLC dataset. With the help of latitude, longitude and landslide date, the precipitation(mm) data is fetched from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) which is a 35+ year quasi-global rainfall dataset that spans 50°S-50°N and includes all longitudes (Funk et al.; 2015). It covers the period from 1981 to near-present. CHIRPS integrates our in-house climatology (CHPclim), 0.05° resolution satellite imagery, and in-situ station data to produce gridded rainfall time series. These time series are valuable for analyzing rainfall trends and monitoring seasonal droughts.

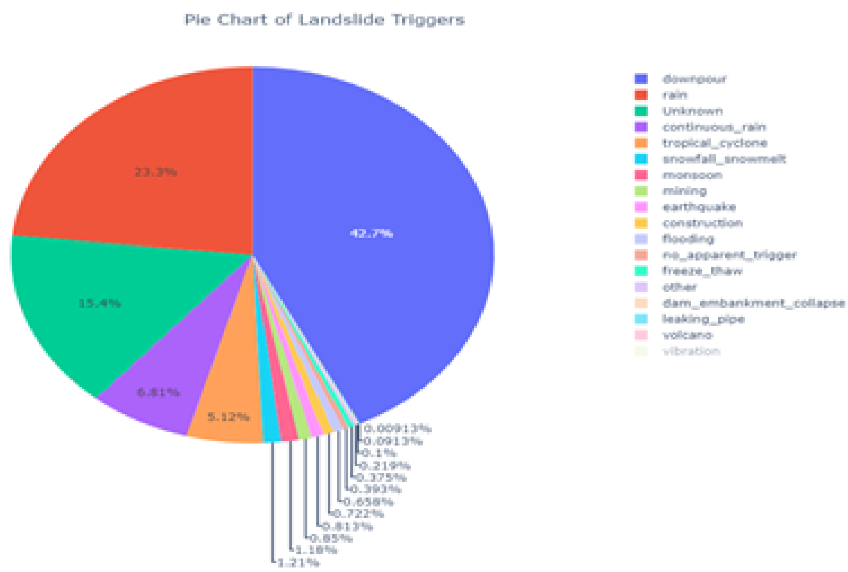

Figure 2: Distribution of events induced landslides

High-Resolution Global landslide Detector Database (HR-GLDD), a high-resolution (HR) satellite dataset (PlanetScope, 3m pixel resolution) for landslide mapping comprising of landslide occurrences from ten diverse physiographical regions globally in America, Southeast Asia, South Asia as presented in Figure 2 (Meena et al.; 2022)(Meena et al.; 2023). The dataset consists of ten multiple landslide events, each triggered by either rainfall or an earthquake. These events occurred in various geomorphological and topographical settings. The data is provided in the form of standardized image patches, each containing four spectral bands (red, green, blue, NIR) from PlanetScope imagery. Additionally, a binary mask is employed to identify landslide areas within each patch.

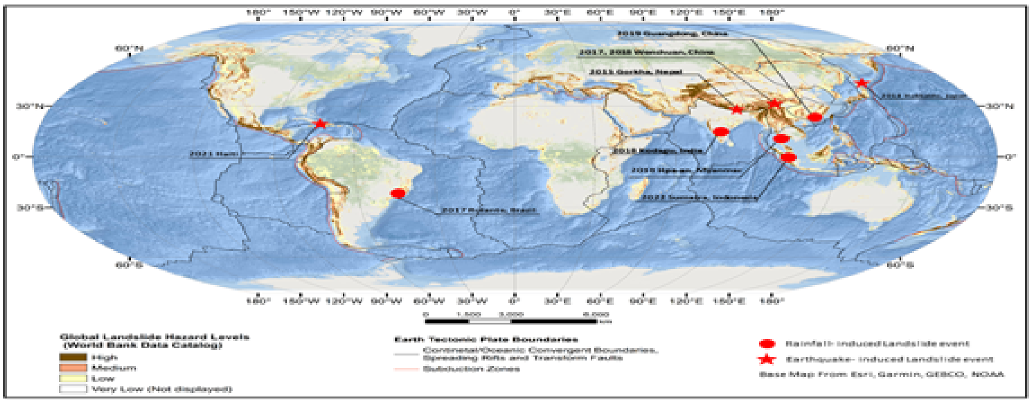

Figure 3: Comprehensive Dataset of Rainfall and Seismic-Induced Landslide Events from HR-GLDD

3.3 Data Preparation

In preparation stage, the Global Landslide Catalog (GLC) dataset is studied by exploring the fields and understand the distribution of the data, to address missing, duplicate values such as co-ordinates or missing dates, dropping unwanted data fields which do not have much significance as per the study. The Precipitation data 30-days and 60-days prior to landslide date is generated using UCSB-Climate Hazards Group (CHG) [1] [2] at a daily time scale. To assess the impact of the rainfall on the landslides, the cumulative rainfall before the landslides must be considered and cumulative rainfall for approximately 30 days and 60 days must be considered (Tang et al.; 2022). The precipitation data for 30-days and 60-days prior the landslide occurrence date is considered to create a time-series data that matches the landslide location images from the HR – GLDD data is downloaded in the form of netCDF (.nc) file from CHIRPS FTP server. Downloaded data is extracted using Python programming, using libraries such as xarray which is employed to open the netCDF (.nc) file [3]. Table 1. presents the important fields considered for the study.

3.4 Model Selection

The study uses a hybrid architecture that utilizes deep learning models for temporal and spatial features extraction using an intermediate fusion of features is proposed to predict rainfall induced landslide. This type of fusion utilizes the characteristics that distinguish each type of modalities to create a new representation, enabling the strength of both the methods. Through which a reliable prediction is achieved, compared to using a single modification prediction. To effectively capture the complex temporal and spatial constraints in rainfall data, multiple deep learning models can be employed. These models, when selected and integrated, can greatly enhance the accuracy of landslide predictions.

Sequential models such as Long Short-term Memory (LSTM) are a type of Recurrent Neural Network (RNN) that employs a unique gate structure and internal memory unit to overcome the vanishing gradient problem (Hochreiter and Schmidhuber; 1997).

[1] `https://www.chc.ucsb.edu/data/chirps`
[2] `https://data.chc.ucsb.edu/products/CHIRPS-2.0/global_monthly/netcdf/byYear/`
[3] `https://docs.xarray.dev/en/stable/user-guide/io.html`

Data Field	Information
Landslide Date	Year, month, and day of the Landslide event
Latitude	Latitude of the location where the Landslide occurred
Longitude	Longitude of the location where the Landslide occurred
Precipitation_30 days	Precipitation in mm 30 days prior to landslide date
Precipitation_60 days	Precipitation in mm 60 days prior to landslide date
Landslide Trigger	Includes the most common triggers of landslide events. These include rain, downpour, continuous rain, tropical cyclone, monsoon, mining or digging, construction, earthquake, flooding, volcanic eruption, freeze/thaw, snowfall.

Table 1: GLC-CHIRPS data fields for research applications

This enables LSTMs to learn long-term dependencies in sequential data more effectively than traditional Recurrent Neural Network (RNNs). Due to which it is also called as a gated cell, as the LSTM possesses an ability to make decision to preserve or ignore the information in memory.

The deep-bidirectional LSTMs (Schuster and Paliwal; 1997) are a variation of traditional LSTMs, when given the sequence of data, a Bi-LTSM model feed input data to an LSTM model and then repeats the training via another LSTM model but on the reverse order of the sequence of the input data. Previous studies implemented by (Zhang et al.; 2021) Lin et al.; 2022 shows, the Bi-directional LSTM model significantly improves the traditional LSTM model by using both forward and reverse LSTM processes, it effectively integrates information from both prior and prospects contexts, allowing it to achieve accurate predictions. (Siami-Namini et al.; 2019) study presents that Bidirectional LSTM performs well compared to unidirectional LSTM in context of predicting financial time series data. To study the effectiveness of sequential models in comprehending and handling rainfall time-series data, a comparative study is conducted.

To complement the temporal analysis provided by sequential models, Convolutional Neural Networks (CNNs) can be employed. The study employs CNN-ResNet50V2 which is a deep residual neural network that utilizes residual blocks to facilitate the training of extremely deep neural networks proposed by Microsoft in 2015. This architecture effectively addresses the vanishing gradient problem, enabling the learning of highly complex representations. Leftover blocks are created as the skip connection method bypasses certain levels in between to link-layer activations to subsequent layers. The benefit of incorporating this type of skip link is that regularization will eliminate any layer that degrades architecture performance. As it is 50 layers it allows to capture complex spatial patterns like that of slopes, elevation and land cover, rainfall trends. This model effectively processes high-dimensional data by splitting convolution kernels and extracting features at multiple scales, making it robust to variations in lighting, object rigidity, and scale (Fitriasari and Rizkinia; 2021).

In the lights of the characteristics of the models outlined above, sequential models such as LSTM and BI-LSTM are employed to process rainfall time-series data to capture forward and backward dependencies. ResNet50V2 is utilized to extract spatial features from image data. Furthermore, employing feature fusion, merging the outputs from sequential model (LSTM or Bi-LSTM) and ResNet50V2 which allows the prediction models to leverage both temporal and spatial features. While constructing a multi-modal features fusion model, the sequential models among the LSTM and Bi-LSTM that perform best based on accuracy are selected to merge with the ResNet50V2.

4 Implementation

Several procedures must be followed while implementing multiple deep learning models. Suitable infrastructure must be chosen to train the model. While developing models as well as the configuration of hyper-parameter is essential to achieve efficient performance from the models.

4.1 Technical Infrastructure

This study conducted experiments using the Google Colab platform utilizing backend TPU with RAM: 4.23 GB /334.56 GB and Disk 15.15 GB /225.33 GB resources to ensure the model training and testing is conducted effectively. The implementation utilizes Pandas for data manipulation, NumPy for numerical computation, and TensorFlow as the machine learning framework. The blend of these hardware and software configuration enabled efficient implementation of the LSTM, Bi-LSTM, RestNet50V2 and multi-modal intermediate feature fusional integrated model to predict rainfall-induced landslides.

4.2 Data Pre-processing, Augmentation and Splitting

On loading the data successfully, pre-processing is the initial step performed. To enhance the performance of the model pre-processing, augmentation techniques are applied on the data.

On generating the precipitation data for 60-days and 30-days before landslide occurred date from the Global Landslide Catalog (GLC) dataset. An important parameter for the study, target is generated considering two scenarios first being, triggers such as rain and triggers closely related to rainfall like downpour, monsoon, tropical cyclone, continuous rain as landslides triggered by rain. If the precipitation for 30 days is greater than 150 mm, similarly for 60 days is greater than 200 mm and the landslide triggers are the one identified as rainfall triggers than the target rainfall induced landslide is considered as 1 else 0.

The data is normalized using *MinMaxScaler* [4] that scales the data linearly in the range of [0, 1]. A sequence is created for each record in the GLC dataset with features, target such as landslide location co-ordinates, landslide date, 60-days precipitation and 30-days precipitation and is landslide rainfall induced with a sequence length of 60 to generate a time series of length 60.

Data Augmentation technique such as oversampling employing the SMOTE technique is applied to time series data to analyze the performance of the sequential models with

[4] `https://scikit-learn.org/1.5/modules/generated/sklearn.preprocessing.MinMaxScaler.html`

sampling and without sampling to eliminate the class imbalance ratio 0.5 even though it is less than generally used threshold 0.8.

GLC time series data is split using the *TimesSeriesSplit*[5] function from the scikit-learn to split data into 5 folds for time series cross validation. The sequential models LSTM and Bi-LSTM are trained and tested using cross validation. The cross-validation mechanism randomly splits the data into training and testing data.

The Image dataset, HR-GLDD comprises of three steps namely, creation of binary mask, data sampling and tile patching. The dataset is divided into 60% for training, 20% for validation and 20% for testing the model capabilities. (Wei et al.; 2019)

To train, test and validate the multi-modal fusion model, the GLC dataset is divided into 70% training, 15% Test and 15% validation. Furthermore, as mentioned in (Wei et al.; 2019) HRGLDD dataset is 60% for training, 20% for validation and 20% for testing respectively.

4.3 Long Short-Term Memory

For data with temporal characteristics, recurrent neural network (RNN) is a frequently utilized Deep learning approach. As LSTM is sequential model, the Keras Sequential API[6] It is used to create a model and initiated as a first layer. A linear stack is created using one input tensor and one output tensor. 64 neurons are added with tanh as the activation to add non -linearity with return-sequence attribute set False as here with LSTM, obtaining a complete classification of entire sequence is conducted.

A dropout layer with a rate 0.3 is added to prevent over-fitting to data. Additionally, a dense layer is added with activation as sigmoid with one neuron to have a binary classification if the landslide event is triggered or not.

4.4 Bi-directional LSTM

In the event of rainfall-induced landslide studies, the current output related to the previous state should be examined, however, the future state also should be examined. In such situations, the contextual information of temporal rainfall is not considered by LSTM. To address such situations, Bi-LSTM is implemented in this study.

The Keras Sequential API is used to create the sequential model. Bidirectional LSTM layer is added from the Keras Layer API [7] , which processes the sequence in both forward and backward direction with 64 neurons to maintain its balance and avoid being under-fitted, as adding more neurons makes the model robust to learn more complex patterns in the data. The *return_sequence* attribute is set to False so that the next layer will return the entire output sequence for the next layer.

A dropout layer with rates 0.2 and 0.3 were experimented, after observing 0.3 is kept as the dropout rate so that the model drops 30% of the units during training, preventing it from being overly fit.

To improve the model's performance, one more layer of bidirectional LSTM is 32 units, for two reasons, allowing model to learn complex features from rainfall time series

[5] `https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.TimeSeriesSplit.html`

[6] `https://keras.io/guides/sequential_model/`

[7] `https://keras.io/api/layers/recurrent_layers/bidirectional/`

data. A binary classification activation sigmoid is added to the dense layer, which is the last layer with one neuron, to determine if the landslide event occurred.

4.5 ResNet50V2

ResNet50V2 model-formation stage initiates by establishing the input dimensions like the height and weight as per the input shape of the images. As the input shape of the images is (128,128,4), a 128*128-pixel area with 4 spectral bands (e.g. Red, Green, Blue and NIR). Employing *include_top = False* indicates the exclusion of the last fully connected layer, preparing the model to classify landslides and no landslides (Riyadi et al.; 2024). To enable the output layer of the residual model to detect landslide based on the dataset. By setting it to False ResNet50V2, it can be used as a feature extractor to learn spatial features and can be integrated easily with sequential models like LSTM and Bi-LSTM. To train the model from scratch, the weights are initialized to None and not *imagenet*. To accelerate the training and utilize the computational resources efficiently, the trainable parameter is set to False to freeze the model's weights. The freeze weights allow the model to learn more generic features of the dataset and store the learned feature for better comprehension.

ResNet is required to act as a feature extractor and combine with models like Bi-LSTM, is trained on different data modality. Hence Keras Sequential API is used to create models, which enables a linear stack of layers. Furthermore, GlobalAveragePooling2D is added to make the model compatible with input shape (128,128,4) and enables the combination with other models. It also enhances the model by reducing the parameters as the attribute keepdims = False (as default), it calculates the average value of every feature map around the spatial dimensions.

Activation functions [8] are an integral component of neural networks that enable them to learn complex patterns in data. They are responsible for transforming the input signal of a node in a neural network into an output signal that is then transmitted to the next layer. To avoid the neural network restricted to model only linear relationships between inputs and outputs activation functions are introduced to make neural network to handle non-linearities and learn complex mapping between inputs and outputs.

A dense layers is added with 256 neuron, where every neuron receives input for all the neurons of the previous layer, with activation as ReLU to add non-linearity in the data and considering the computational power compared to other functions like tanh and sigmoid in the early layers, To prevent model from over-fitting and improving generalization Dropout is added set to 0.5 indicating, 50% of the units in the previous layers will be randomly dropped during training.

To build the last layer as a binary classification layer which outputs between 0 and 1 namely no-landslide and landslide. A dense layer is added with one neuron and activation as sigmoid.

Thus, the steps create a sequential model that utilizes a ResNet model to extract features from input images, further features are processed through global average pooling layer, ReLU for adding non-linearity and learning complexity in the data, a dropout layer for regularization and finally an output layer with a sigmoid for binary classification.

[8] https://www.datacamp.com/tutorial/introduction-to-activation-functions-in-neural-networks

4.6 Multi-modal Fusion Model Design

The process of fusing these different modalities so that a model can learn from them is called multi-modal fusion. Multi-modal models are used to create multi-modal models. There are three types of fusion early, intermediate, late (Boulahia et al.; 2021)

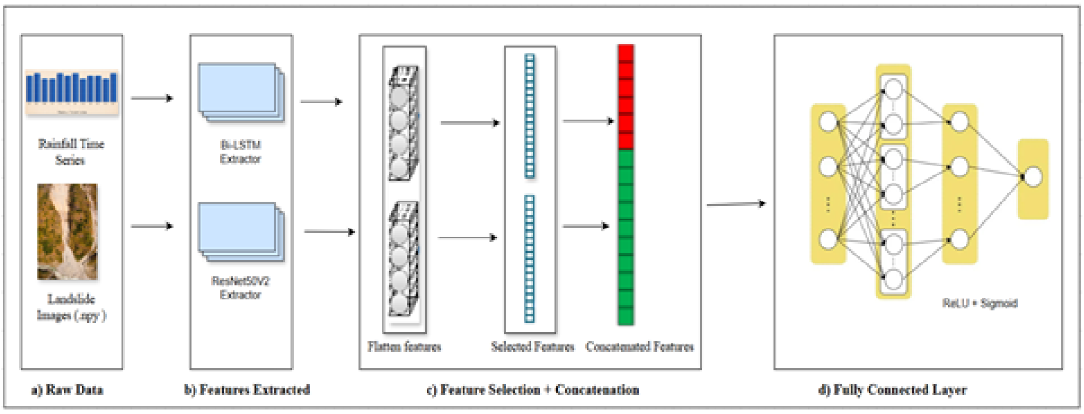

Figure 4: Multi-modal Feature Fusion Model architecture

Considering the two diverse modalities used in the study, the HRGLDD image dataset has improved spatiotemporal graininess, while the Global Landslide Catalog-rainfall induced landslides may have improved resolution but an extensive historical range. Employing Intermediate feature fusion ensures that the model leverages both datasets effectively and keeping target as is the landslide induced by rainfall.

In particular, the multi-modal model starts with extraction of the feature vectors from each modality separately. In Figure 4. block(a), the multi-modal architecture is presented for two modalities. For each modality, a deep feature extractor is used for rainfall time series and Landslide Images. Among the two sequential models (LSTM and Bi-LSTM) trained on same GLC with time-series dataset, is selected depending on the performance of the model based on evaluation metrics applied. Bi-LSTM extractor and ResNet50V2 extractor is employed loading .h5 files using the Keras function *load_model.* respectively. A Feature extractor is built by considering the last layers of the deep neural networks Bi-LSTM and ResNet50V2. Early layers in deep neural network learns low level features in data like that of edges and texture when we consider CNN models, while the later layers (deep layers) learn complex features in data using the Keras new functional API Model [9], that uses intermediate tensors enabling to drastically extract sub-components of the model. Similar with Bi-LSTM as well as shown in Figure 4. block(b).

The Feature extractors are further used to predict on the train, validation and test over each modality to comprehend each model learning and extract the features. To ensure that both features set have same number of records min function is used, further concatenation of the selected features is created, from both modalities time series and images as presented in Figure 4. block(c).

The intermediate multi-modal feature fusion model takes the fused features as input. Further two dense layers with RELU activation with 256 and 128 is created for further processing of the combined features with dropout layer with 0.3 and lastly a dense layer

[9] `https://keras.io/api/models/model/#model-class`

with single neuron with activation as sigmoid for binary classification to build a fully connected fusion model as presented in Figure 4. block (d).

On observing the model's performance, regularization with a penalty was added in each dense layer to prevent over-fitting.

4.7 Modelling Callbacks

To maximize the model performance, the callback plays an important role as they also help to prevent model over-fitting and improve its performance. Models like LSTM, Bi-LSTM, ResNet50V2 and Multi-modal feature fusion are employed in this study. To optimize the performance of the model specific callbacks from Keras[10] are applied to the model while fitting the model. ModelCheckpoint is used to save the model when the validation loss shows improvements.

By observing the validation loss, the point during training when the model achieves the lowest error on unseen data can be known. To prevent over-fitting in neural networks by monitoring specific metric during training and stops the training process when the metric stops improving for certain number of epochs a callback EarlyStopping is applied to the models. ReduceLROnPlateau is applied while fitting to reduce the learning rate when the monitoring metric has stopped improving.

The summary of the configured callbacks for models employed in the study is presented in Table 2. below.

Model	**Callbacks**	**Configuration**
LSTM and Bi-LSTM	EarlyStopping	monitor='val_loss', patience=5, restore_best_weights=True
	ReduceLROnPlateau	monitor='val_loss', factor=0.5, patience=3, min_lr=0.000001
ResNet50V2	EarlyStopping	monitor='val_loss', patience=5, restore_best_weights=True
	ReduceLROnPlateau	monitor='val_loss', factor=0.5, patience=5, min_lr=0.000001
	ModelCheckpoint	monitor='val_loss', save_best_only=True, verbose=1
Multimodal Fusion Model	EarlyStopping	monitor='val_loss', patience=10, restore_best_weights=True
	ReduceLROnPlateau	monitor='val_loss', factor=0.5, patience=5, min_lr=0.000001
	ModelCheckpoint	monitor='val_loss', save_best_only=True, verbose=1

Table 2: Model Configurations and Callbacks

[10] `https://keras.io/api/callbacks/`

5 Evaluation

This section encompasses all the significant assumptions and evaluations that are part of the implementation process. The study comprises of three sections. In the first part sequential models LSTM and Bi-LSTM are analyzed on rainfall times series data. The second part includes training and evaluation of ResNet50V2 on landslide image data and the third part includes training and evaluation of multi-modal feature fusion model.

5.1 Experiment 1: Sequential Model Evaluation

LSTM and Bi-LSTM models are evaluated using *TimeSeriesSplit* cross validation for the temporal nature of the data ensuring that the model learns from the historic data to anticipate future outcomes. Both the models are compiled employing Adam optimizer and loss set to binary cross entropy function.

The performance of models with and without sampling is assessed using metrics such as accuracy, precision, recall, and AUC. Accuracy is the primary evaluation metrics encompassing both training and validation accuracy in the study, even though sequential models are assessed on precision, recall, and AUC while experimenting, accuracy is considered as a performance driver. The sequential models training is executed with 50 epochs and batch size 32.

A comparative summary of accuracy for LSTM and Bi-LSTM is presented in Table 3 below. After analysis the training and validation accuracy Bi-LSTM is selected to build a multi-modal feature fusion model along with ResNet50V2.

Accuracy	**LSTM**	**Bi-LSTM**
Training Accuracy with Sampling	0.8653	0.8969
Validation Accuracy with Sampling	0.8653	0.8968
Training Accuracy without Sampling	0.8602	0.8978
Validation Accuracy without Sampling	0.8601	0.8978

Table 3: Model Performance

5.2 Experiment 2: ResNet50V2 Model Evaluation

Implementation is conducted by employing Adam optimizer, loss set to binary cross entropy and evaluated using metrics accuracy. The ResNet50V2 training executed with 50 epochs and batch size 32. The model achieved a training accuracy of 71.31% with a loss of 0.57, validation accuracy of 68.31% with a loss of 0.60 and testing accuracy of 67.88% with loss of 0.59. The accuracy of the training data augments steadily through the epochs, demonstrating that the model is learning from the data. The validation accuracy varies with validation loss declining, implying that the model is simplifying on the unidentified data. ResNet50v2 model training loss along the epoch is presented in Figure 5. and model accuracy along the epoch is presented in Figure 5.

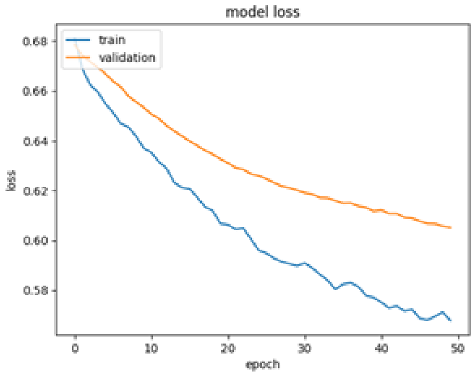

Figure 5: ResNet50V2 model loss along the epoch

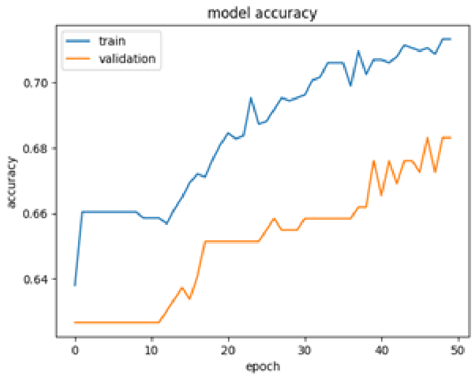

Figure 6: ResNet50V2 mode accuracy along epoch

5.3 Experiment 3: Multi-modal Feature Fusion Model Evaluation

The multi-modal is assessed based on accuracy and loss of model during training, validation and testing data. The Multi-modal is complied using Adam optimizer and binary cross entropy and metrics accuracy for 50 epochs and batch size 32. The multi-modal is trained twice in this study after observing the first run, the regularization is introduced. Without regularization, the training loss indicates that the model is learning and improving over the epochs, but the augment in the end in the graph as shown in Figure 7. indicates that the model is commencing to over-fit the training data. The validation loss shows constant rise than the training loss, indicates the over-fit.

To reduce the over-fit, study experimented to add regularization L1/L2. The penalty of L1=0.01 and L2 =0.02 is added to each dense layer in the design discussed in the implementation section. After adding regularization, the training and validation loss and accuracy, that model progressed training-wise, with training accuracy of 88% with loss of 0.57, validation accuracy of 89% with loss of 0.52. and testing accuracy of 87.60% with loss 0.51. After regularization, the model training loss along the epoch is presented in Figure 8. and model accuracy along the epoch is presented in Figure 9.

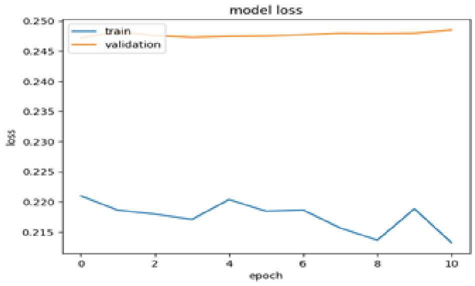

Figure 7: Multi-modal loss along the epoch without Regularization

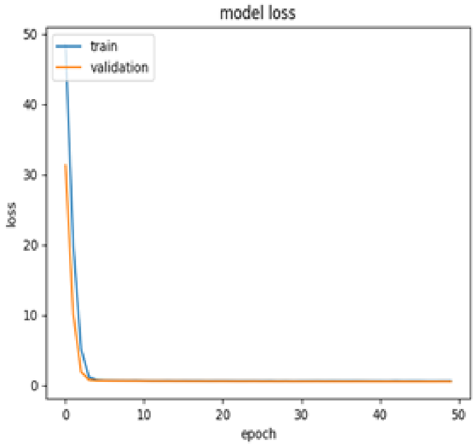

Figure 8: Multi-modal loss along the epoch

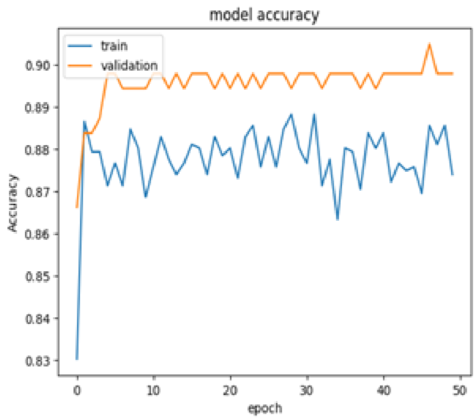

Figure 9: Multi-modal accuracy along the epoch

5.4 Discussion

In this research, three deep learning models are employed to predict rainfall induced landslide. In the first experiment, creating a separate sequence for 30-days and 60-days precipitation to construct time series was a difficult task while maintaining the input shape. To address the difficulty, time series sequence with 60 days of precipitation before the landslide occurred is implemented, considering its beneficial as both short-term and long-term dependencies will be assessed. As literature review highlights, with temporal dependencies of the time series data, proper splitting data, and ensuring that the model is trained on past data and tested on future data, selecting a suitable evaluation method becomes crucial. Consequently, *timeseriessplit* cross-validation is applied to split data, train, avoid over-fitting, and evaluate the sequential models LSTM and Bi-LSTM.

In the second experiment, as ResNet50V2 the input shape accepted is (224,224,3) and image input shape in the dataset is (128, 128, 4) with 4 channels (RGB +NIR), which restricted to enable pre-trained weights 'imagenet '. To address this, the input shape of the ResNet50v2 is set to (128,128,4). Additionally, ResNet50v2 is not to be updated during the training process, the weight at the base layer is freeze, as suggested in the previous literature review. This makes the model trained on the dataset, which is intended for a specific task.

In the third experiment, considering the correct fusion approach to construct a multi-modal was a crucial task, as the approach should be well suited to dataset nature and the combined model should be able to generalize as expected. With considering the literature review for other concepts like action recognition assisted to choose a correct approach (Boulahia et al.; 2021). To create extractor, selecting layers from the pre-trained model Bi-LSTM and ResNet50v2 in experiment one and two respectively was difficult. Considering the structure of neural network helped to locate solution, the deep layers were selected to create extractor. The concept of deep learning models that early layers learn only features like edges, texture if image is considered for instance and deep layers will learn complex features in image.

The above outlined are the difficulties and improvements, addressing the same model achieved training accuracy of 88% with loss of 0.57, validation accuracy of 89% with loss of 0.52. and testing accuracy of 87.60% with loss 0.51 in this study.

6 Conclusion and Future Work

The study assesses a multi-modal features fusion (intermediate fusion) model, with a fusion of feature extracted from sequential model, Bidirectional LSTM and Convolutional Neural Network (ResNet50V2) to learn spatial-temporal features to predict rainfall induced landslides. Employed on Global Landslide CataLog (GLC) dataset with landslide triggered by rainfall with CHIRPS to fetch precipitation data for the GLC landslide occurred date to generate time-series data and High-Resolution Global landslide Detector Database (HR-GLDD) landslide Image dataset. Multi-modal feature Fusion, a deep learning approach that employs a qualitative feature approach to recognize the varied features among diverse modalities, aiding efficient fusion. The main goal of using intermediate fusion is to employ the strength of both different types of datasets and model and creating a combined model that yields results that can be used in real world to predict landslide considering the rainfall received. The multi-modal with intermediate approach of Fusion yields an training accuracy of 88% and testing accuracy of 87.60% as per study conducted.

The Future work can be directed towards, analyzing the performance of the sequential and computer vision models that are found well suited using the intermediate feature fusion approach, to build a comparative study implementing the other fusion approach as well namely, early and late fusion with more diverse dataset. The current study considers, studying effects of rainfall as a factor for landslide occurrence using precipitation threshold, the study can be progressed to consider soil saturation, seismic threshold, changes in ground water to make landslide prediction more diverse and stronger.

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