Original Article

Chooralmala-Landslide Prediction Using Computer Vision and Its Verification Using Edge Impulse

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Abstract - In India, landslides are one of the common natural disasters happening across many regions, whose occurrence remains unpredictable. Though most of the landslides are natural, the root cause of such happenings may be linked with manmade disasters like deforestation, rise in population, urbanization over the hills, creating imbalance in the ecosystem, etc. Recently, such a landslide occurred in Chooralmala –Wayanadu on July 30th, 2024. This massive landslide resulted in a greater rate of fatalities and loss for the people living in that region. In this era of technology, using machine learning models and computer vision, natural disasters, especially landslides, could be predicted much earlier than their occurrence. This will pave the way for earlier warning or alarming messages to save lives in those particular red zone areas. In this article, the usage of software like EOSDA-Land viewer, which is an EOMS software, is considered to take the satellite image on a varied timescale over the Chooralmala-Wayanaud district. A machine learning model using Edge Impulse software has been developed to check the anomaly detection using k k-means algorithm, comparing the satellite images taken between the years 2014 and 2024. The satellite images taken through EOSDA-Landviwer are further processed via gray scale conversion, segmentation, and edge detection, followed by anomaly detection using a logic XOR operation, which is enhanced for validation and justification of the result using computer vision.

Keywords - EOMS, Edge impulse, Chooralmala-Wayanadu, Natural disaster, Landslide.

1. Introduction

Among the most destructive natural calamities, landslides are dangerous and unpredictable, particularly in hilly and mountainous areas like Chooralmala, which is in Kerala, India's Wayanad district. Chooralmala is notoriously vulnerable to landslides, especially during the rainy season, due to its steep slopes, intense monsoons, and delicate soil conditions. The environment, agriculture, infrastructure, and human life are all seriously threatened by these landslides. Geological surveys and sensor-based monitoring are two traditional landslide prediction techniques that frequently demand a large amount of resources and might not offer real-time information. The existing Landslide Early Warning System (LEWS) developed by NSRC, ISRO, uses rainfall thresholding and landslide susceptibility mapping with the data inputs from IMD rainfall, NSRC, DEM, soil, and land use, and is more efficient in hill areas like Uttarakhand. It is not yet fine-tuned for Wayanadu, Kerala. Even the Kerala State Disaster Management Authority Warning System (KSDMA), organized by the state government of Kerala, uses a threshold-only model and has not yet used AI fusion. The

IMD Landslide alerts(Pilot) prediction has limitations, such as limited spatial resolutions and generalized prediction at the district level. And to resolve these existing problems, as technology advances, real-time monitoring, early warning systems, and predictive analysis are made possible by Machine Learning (ML) and Computer Vision (CV), which have become effective methods to handle this difficulty. A novel approach is introduced by utilizing Edge Impulse software as one of the most accessible, creative, and user-friendly platforms for creating ML and CV models. It allows the deployment of ML models on low-power edge devices, making it ideal for remote and resource-constrained regions like Chooralmala. In this article, the potential of this software, Edge Impulse, is utilized to create a computer neural network-based prediction system employed to predict landslides. The satellite image data of this region is taken between the years 2014 and 2024 using EOMS software (EOSDA), as the varied time scale option in this software is allowed for 10 years from the year of occurrence of the landslide. (i.e., 2024) This approach provides an innovative, measurable, and affordable solution to landslide prediction, potentially preventing

fatalities and minimizing damage in areas like Chooralmala. In disaster management and pandemic management, new technologies like 5G, object sensing, cellular networks, smartphones, internet of things, and UAV-based systems, satellite-based systems are being used. Machine learning methods for pandemic and catastrophe management are reviewed in this article [1, 2] examines the most recent research and conclusions, data analysis, natural catastrophe prediction, and the use of technology to implement management strategies from a technological point of view. [3] discuss the core of this strategy, which is its capacity to learn from multiple sources and adjust to novel, unidentified event kinds. Furthermore, the framework improves forecast accuracy and adaptability by specifically integrating both qualitative and quantitative features. The findings show that OWML models can handle massive geographic datasets efficiently and react more precisely to impending dangers. [4] showcase the development and impact of machine learning in the field of geotechnical engineering for predicting disasters, highlighting the role of data analysis and modeling.

2. Literature Review

[5] This research thoroughly examines the latest advancements in deep learning techniques used for segmenting remote sensing images related to natural disasters. Various well-known deep learning architectures, including FCNs, SegNet, PSP Net, U-Net, HRNet, FCDenseNet, and Deep Lab, have shown remarkable success in several applications, such as identifying forest fires, mapping floods, and assessing damage caused by earthquakes. [6] explains to support professionals in natural disaster management by creating a framework that can effectively categorize natural disasters and explain the outcomes through a combination of a deep learning model and an explainable AI (XAI) approach, ensuring dependability and straightforward interpretation for those without a technical background. In order to predict and lessen the impact of floods in Kasese District, this article [7] sought to create a prototype of a machine learning model. A participatory design science methodology was employed by the researchers. To gather historical climatic data, the team reviewed documents and brainstormed. The objective of [8] is to summarize research studies published since 2017 that concentrate on Deep Learning (DL) and Machine Learning (ML) techniques for managing disasters. Specifically, the emphasis has been placed on investigations related to disaster prediction and management, along with their risk factor and assessment of vulnerability, detection of disasters, monitoring of disasters, early warning systems, evaluation of damage, and responses following disasters, along with case studies. The findings of this research [9] underscore the potential of the Stacking model as an effective instrument for mapping landslide susceptibility, demonstrating superior performance compared to other techniques in accurately pinpointing areas at risk of landslides. The integration of various machine learning approaches within a hybrid framework significantly boosts the reliability and precision of these mappings.

Employing hybrid models deepens the comprehension of landslide dynamics and lays a scientific groundwork for developing effective risk mitigation strategies. This work [10] focuses on addressing this gap by providing a detailed overview of AI utilization in landslide susceptibility research. This study also utilized bibliometric techniques to examine a selection of 2892 articles published from 1991 to 2025, sourced from the Web of Science database. This study [11] identified fourteen factors that condition landslides, correlating them with 671 statistical landslides in the area. The research employed four multiple classifier systems, including the average, committee mean, median, and weighted mean of probabilities. The expected value of the random variable was demonstrated as the most effective system based on the mean of 800 independent MLTs, namely, receiver operating characteristics, curve coverage area, and real skill statistics associated with validation points. This model [12], preserved as a pickle file, acts as an important filter in creating a landslide initial alarming system. This research outlines the creation of models and performance evaluations, aiding in a practical, community-focused approach to landslide disaster resilience in Kerala. This study [13] confirms that spatial autocorrelation data can improve the algorithm's capacity to correctly distinguish between non-disaster-prone zones and disaster-prone zones, providing a route guide for spatial modelling in other disaster-prone areas.

[14] The main features for the multivariate forecasting of the Huangtupo landslide include available meteorological data like rainfall, air temperature, and the water level of the reservoir. Through feature engineering, extra features are generated from the monitoring data, and of these, only the pertinent variables are chosen using grey relational analysis. The machine learning methods are weighed with respect to their effectiveness and contrasted based on the root mean square error. Initial findings indicate that forecasts are very precise, particularly when the deformation pattern resembles the landslide activity observed previously. [15] 156 landslide areas in Malaysia's Cameron Highlands were chosen for this study using landslide inventory data from earlier studies that the authors worked on. Based on recommendations from earlier studies on the Cameron Highlands, this study takes into account a number of geoenvironmental factors, including all topographical regions like plane, inclination, curvature, curvature with plane total curvature, lithology, Sediment Transport Index (STI) and vegetation density etc. [16] In order to map and forecast disaster-prone regions in São Sebastião, Brazil—a location prone to disaster like landslides because of its steep topography and heavy fall of rain—this study uses machine learning approaches. Five algorithms were compared: Using a variety of environmental parameters as inputs, using methods to separate with the best hyperplane, an ensemble decision tree that votes on a result, a proximity-based classification method, a sequential ensemble technique to minimize errors, and a layered network that learn patterns. [17] With an emphasis on physically based causal models, this

study thoroughly examines this test on varied time scales for landslide prediction, emphasizing prediction of data, model identification, assessments, and optimizations. According to the analysis, the one that performs better than conventional techniques is deep learning, especially the Long-Short-Term Memory (LSTM) model. [18] emphasis on creating landslide susceptibility maps using cutting-edge learning techniques. Using the key machine learning classifiers, whether it is supervised, unsupervised, or reinforcement learning, data has been providing incredibly accurate maps for predicting future natural hazard events. Based on the [19] work's findings, Random Forest fared better than other models when using the dual information feature selection strategy. Having the dual information-based feature selection, it obtained an MSE of 0.0011; in the absence of feature selection, it obtained an MSE of 0.00157. Using feature selection in machine learning, the KNN regressor fared better than the other models, with an MSE of 0.00139. [20] Although patterns of spatial vulnerability have been clarified by this study, temporal forecasts have mostly remained empirical. The majority of machine learning methods have 75–95 percent overall success rates. Although this appears to be highly promising, there are still issues with the input data quality, the possibility of overfitting, and the correspondingly poor selection of prediction models, the unintentional inclusion of duplicate or noisy variables, and the technical limitations of only being able to predict specific landslide kinds and sizes. [21] develops LSM for the Chamoli district in India using three new positive-unlabelled learning-enhanced modelling: Elevation, Decision Tree. Random Forest, K-Nearest Neighbour, aspect, geology, slope, NDVI, range to lineament, lithology, range to river, geomorphology, range to road, and domestic land use are among the eleven factors that have been found to be responsible for landslides. By creating an ensemble framework that combines meta-learning and Recursive Feature Elimination (RFE), this study [22] improves the prediction of landslide susceptibility.

To identify important factors influencing neutralizing landslide and categorize landslide-prone zones, seven sophisticated machine learning algorithms using methods to separate with the best hyperplane, an ensemble decision tree that votes on a result, a proximity-based classification method, a sequential ensemble technique to minimize errors, and a layered network that learn patterns. were used with GIS tools and remote sensing. [23] Shift-invariant Convolutional Neural Networks (CNNs) and geospatial analytics are combined in the suggested framework to improve prediction accuracy. Previous landslide incidents are employed in assessing the model's performance, and quantitative indicators are used to validate it. [24] In order to examine the disaster-prone zone in Hanyin County, China, the primitive goal of this work is to create a unique deep learning model called Landslide Net (LSNet). Kernel Logreg (KL) and support vector classifier using soft margin are utilized as a reference model. The validation dataset and training dataset were constructed with

70% and 30% of the 259 disaster-prone zones, respectively, that were used to generate the inventory map. Each landslide predisposing factor was optimized using the Variance Inflation Factor (VIF). [25] employed the usage of the IOT network and system acquisition generation. Landslides were detected using vibration sensors, accelerometers, and humidity sensors. The Raspberry Pi (SOC) gathers and updates website statistics using the MQTT protocol. These telemetry flights can aid in better understanding the situation and alerting individuals to an imminent crisis. [26] performs an initial validation of the disaster's origins based on catastrophe theory and reviews the catastrophe event's evolution in depth using remote sensing imagery and multi-source data. The findings suggest that a pre-existing failure was reactivated in this massive landslide. It also aims to showcase scientific proof and useful advice for implementing critical disaster management and emergency resilience, coping capacity in China and other nations going through comparable hazards. It does this by summarizing the knowledge earned from India's reaction to the landslide induced by rainfall, and when combined with the context of China, it proposes specific remedies. [27] identified landslide-prone areas in Wayanad, Kerala, India.

High-rise altitude, inclination ups and downs, deep plateau, wetness index of stream, wetness index of topographic heavy rainfall history, geomorphology, and geology were among the many huge geospatial datasets used in the study. Then, in the process of identifying the disaster-prone zone specifically with respect to landslides, a variety of neural networks and pattern learning models are applied, including random forests, artificial neural networks, and deep neural network models. recurrent neural networks, gradient boosting machines, support vector regression, recurrent neural network, and logistic regression. The landslide inventory map, which includes 298 landslide sites, was used to train and validate the model. More than 60% of the land in Kerala's Idukki district, the study area, is vulnerable to landslides. Numerous catastrophic landslides occur in the zone due to the monsoon rainfall. The landslide is the most unpredictable disaster that may occur naturally, but the root cause analysis of most of these landslide occurrences is manmade. In this study [28], landslides frequently cause disruptions to the majority of the roads. An essential part of studies on the negative effects of landslides is landslide risk assessment, or LRA. The identification of disaster-prone locations is aided by the use of spatial multi-criteria analysis, integrated with many decision-making models that are employed to analyse spatial problems, location selection, route mapping, and for hazard risk assessment and susceptibility mapping. Understanding the scenario, by employing the root cause analysis, the present landslides as the Land Cover Change (LCC), which focuses on alteration in the physical properties of earth material types, was standardized since the LULC datasets lacked consistent classification, and their risk was studied in detail in this work [29].

Table 1. Comparison of Government reports and Articles who considered landslide prediction precisely in Wayanadu region alone

Article/Report	Study focus on	Method/Data used	Key findings	Limitations
ISRO / satellite analyses (news & ISRO briefings) — [31]	High-resolution optical & SAR before/after mapping to delineate runout and prior scars	Cartosat-3, RISAT, Sentinel, ISRO Lidar/optical products	Identified a large pre-existing landslide scar and quantified ~86,000 m² slipped area and long runout; supports remote sensing for rapid event mapping	Useful for rapid damage mapping but limited for *prediction* (retrospective) and cloud/vegetation may limit optical imagery.
Landslides journal — Mundakkai-Chooralmala analysis — [32]	Multi-disciplinary field + geomorphology + rainfall analysis of the July 30, 2024 event	Field mapping, IMD rainfall series, geology, photogrammetry/LiDAR	Detailed formation mechanisms, joint/fracture controls, and extreme rainfall role; demonstrates how geology + intense rainfall produced long-runout debris flows.	Field-intensive (high confidence for that event) — not a general predictive model; highlights need to integrate geology with remote sensing signals.
Machine learning / deep learning susceptibility mapping (multi-author) — [27]	RF/SVM/CNN/LSTM applied to geospatial & multi-temporal satellite data for susceptibility mapping	DEM, NDVI, land use, rainfall history, multi-temporal Sentinel/Landsat imagery	ML/DL models (RF, CNN, CNN-LSTM hybrids) achieved high accuracies (often 85–95%) for susceptibility mapping when trained with good landslide inventories. Studies show improved spatial prediction vs. simple statistical models.	Performance depends on quality/quantity of landslide inventory; many studies map *susceptibility* not exact timing. DL needs large labelled image sets and is less interpretable.
Copula / joint-probability rainfall hazard modelling (PIAHS) —[33]	Multi-site rainfall intensity-duration modelling using copulas to estimate landslide hazard probability	Multi-site IMD rainfall records, intensity–duration data	Produces joint spatial–temporal hazard maps that incorporate rainfall intensity and duration — improves linking rainfall thresholds to hazard probability	Relies on dense rainfall network and historical event attribution; does not include terrain/land cover directly — best combined with susceptibility maps.
ILDM / Kerala post-disaster technical report — [34]	Multi-agency investigation, response evaluation, and recommendations for monitoring/early warning	Field surveys, remote sensing, socio-economic assessment, IMD rainfall data	Confirms extreme rainfall as proximate trigger; recommends integrated early warning using rainfall thresholds + remote sensing indicators and stricter land management planning	Policy / operational focus — provides pragmatic recommendations but not an off-the-shelf ML model.
Case study: DInSAR / Sentinel-1 monitoring-[35]	Use of DInSAR to detect pre-event ground deformation	Sentinel-1 time-series SAR (DInSAR), interferometry	Demonstrated DInSAR can capture pre- and post-event deformation signals, supporting near-real-time monitoring potential in Wayanad.	DInSAR performance reduces in dense vegetation and very steep terrain; needs careful coherence handling and frequent acquisitions for timely warning.
Proposed machine learning model	Visual anomaly detection method using Edge impulse and justifying the same result with python code in computer vision (opencv)	NDVI of sentinel-2 data taken from EOSDA software in varied time scale for 10 years (2014-2024)	FOMO-AD visual anomaly detection algorithm method framed by Edge impulse ,XOR in computer vision	The resolution of NDVI satellite image taken EOSDA software plays vital role, the time scale limitation in the software decrease the number of test images

LULC-Land Use Land Cover datasets, which were derived from satellite image categorization and visual interpretation, were acquired from national organizations for the years 2000–2018 [30]. These comparisons say that over 50% of the landslides (ie, 58%) happened in highly greenish areas, and that forest plantations were the source of 50% of landslides that damaged roads and buildings, with built-up areas coming in second (25%). Table 1 shows the comparison of landslide reports prepared by government agencies and the article [27, 31-35], considering the Wayanadu region alone.

3. NDVI Satellite Images from EOSDA Land Viewer

The satellite images of the place Chooralmala in Wayanadu district of Kerala, India, were taken for the years 2014,2017, and 2020. These EOMS- Earth Observation and Monitoring Satellite images are considered from the EOSDA website, where there is an option for choosing the varied time scale (starting from the year 2014 to 2024, considered for this study). There is also an option to choose NDVI satellite images, where NDVI stands for Normalized Difference Vegetation Index. The NDVI data will be more appropriate for environmental monitoring, forestry, agriculture, and so on. Since in this study, the focus is on identifying the anomaly of chooralamala with respect to the difference in vegetation, deforestation, or any other man made environmental changes in the ten years between 2014 and 2024. Figure 1 is the NDVI satellite image of Chooralmala in the Wayanadu district, taken in the year 2014. Figure 2 is the NDVI satellite image of Chooralmala in the Wayanadu district, taken in the year 2017.

Fig. 1 NDVI satellite image of Chooralmala -2014

Fig. 2 NDVI satellite image of Chooralmala -2017

Fig. 3 NDVI satellite image of Chooralmala -2020

Fig. 4 NDVI satellite image of Chooralamala-2024 before landslide courtesy from thesouthfirst.com

Fig. 5 Google earth image of Chooralamala-2024 after landslide courtesy from thesouthfirst.com

Figure 3 is the NDVI satellite image of Chooralmala in Wayanadu district taken in the year 2020. Figure 4 is the NDVI satellite image taken in the year 2024 (February) before the occurrence of the landslide of Chooralmala in Wayanadu district. Figure 5 is the satellite image (Courtesy of Google Earth image – thesouthfirst.com) taken in the year 2024, showing the impact area where the landslide occurred in the region of Chooralmala in Wayanadu district.

3.1. Anomaly Detection using Edge Impulse Software

The Edge impulse software is employed to build a model using a machine learning algorithm that can find anomaly detection between the test data and train data. The NDVI satellite image taken in the years 2014, 2017, and 2020 is considered as train data (ie, Figures 1 to 3). The NDVI image for 2024 (taken in the month of February i.e., before the occurrence of the landslide) is considered as test data. The visual anomaly detection is added as a processing block with the k-means algorithm as the learning block while creating the impulse in the Edge Impulse software. The step-by-step procedure for finding the visual anomaly detection in Edge Impulse software is shown in Figure 6. The input images are uploaded to the Edge Impulse software. The uploaded images are categorized as test data and train data. Figure 7 shows the raw data uploaded and its features created in the Edge Impulse software platform. In comparison, retraining the model with a threshold value of 2.9 is considered after feature generation. Figure 8 shows the feature generated for the train data in Edge Impulse software. This highlighted red zone in Figure 9 is compared now with Figure 5, taken in the year 2017. It shows that the highlighted areas in both pictures, Figure 9 (anomaly area highlighted from Edge Impulse) and Figure 5 (satellite image showing the actual landslide region that happened in Chooralmala Wayanadu), are more or less the same, and hence the model is working well.

4. Anomaly Detection Using Computer Vision

Figure 11 shows the train data (2014) NDVI satellite image of Chooralmala, Wayanadu, which has been converted to a gray scale using Python code in computer vision, as shown in Figure 12. This gray-scale image is further segmented and Edge detected as shown in Figure 13. Similarly, Figure 14 shows the test data (2024) NDVI satellite image of Chooralmala, Wayanadu, which is further converted to a gray scale as shown in Figure 15. This gray-scale test data is further segmented and Edge detected as shown in Figure 16. Now, the edge-detected and segmented images in Figures 13 and 15 are taken to perform the XOR operation using the Python code in computer vision. Before this, both images are ensured for their similarity in size. In the XOR operation, the output image pixel is 0 for black color and 1 for white color. Generally, the output pixel value turns 1 when there is an image difference while comparing the two different inputs, and hence, all white color in the output image represents the difference. In the vice versa, if the two input images are identical, then their XOR operation value is 0, which means the pixel value is 0, and thus the black color in the output image of the XOR operation indicates the similarity among the two input images (ie, 2014 and 2024). This bitwise comparison of pixels between the two images gives clarity in identifying the anomaly.
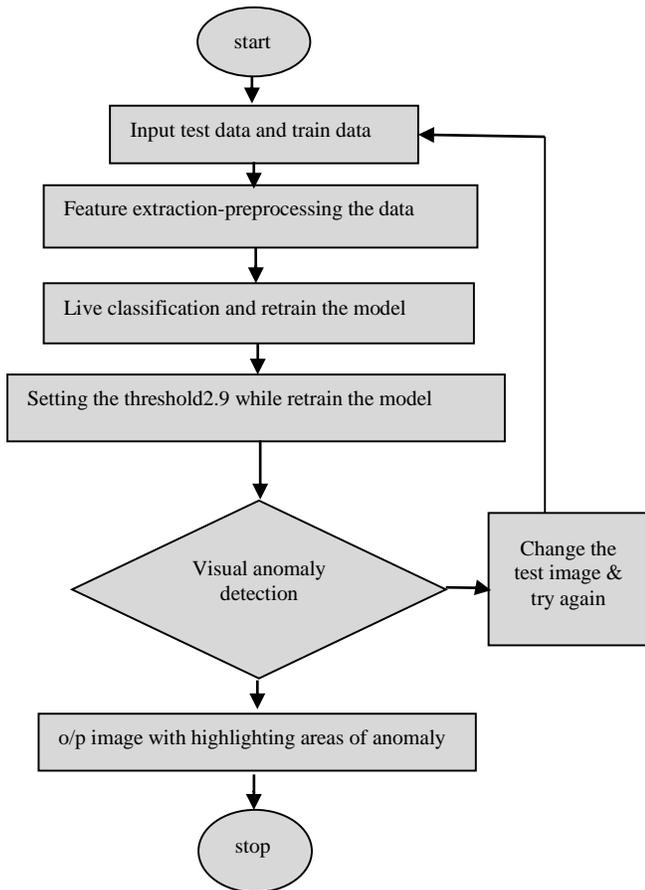
Fig. 6 Raw data in Edge impulse software
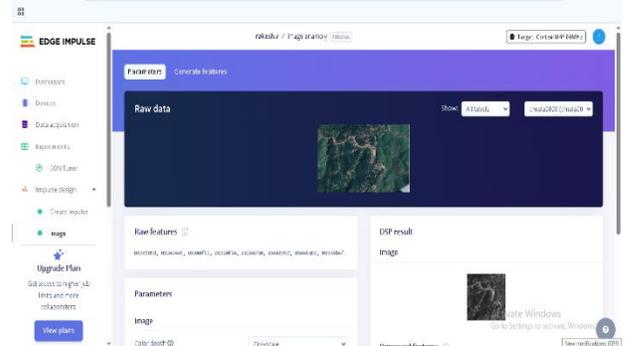
Fig. 7 Raw data in Edge impulse software
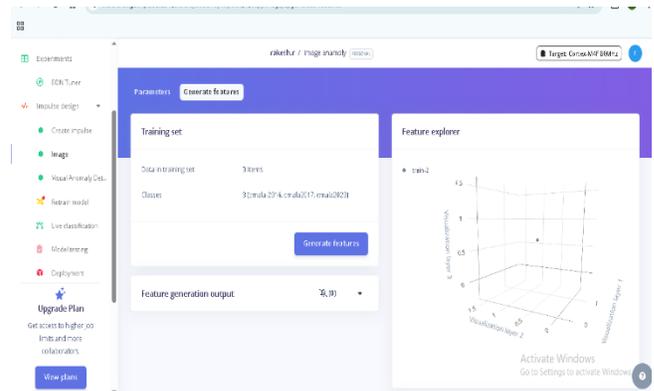
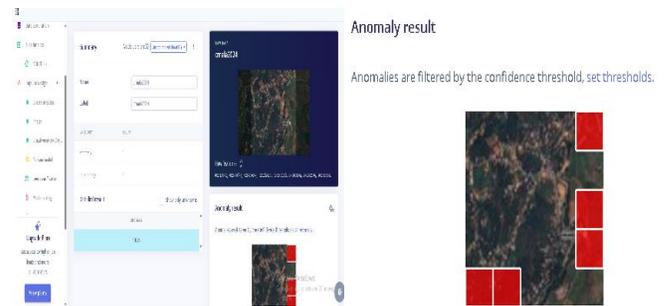**Fig. 8 Features generated for train data in Edge impulse software**

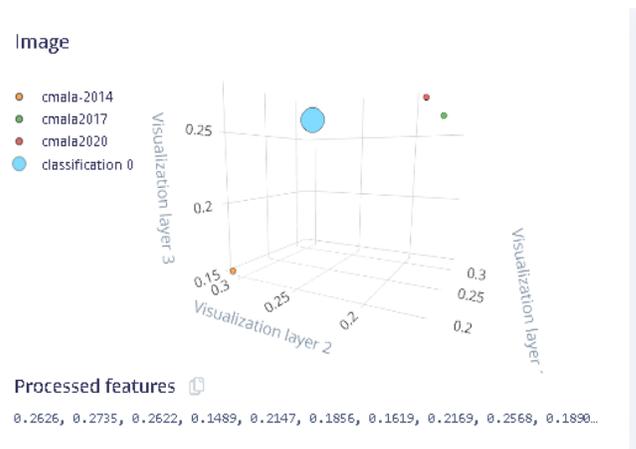**Fig. 9 Live classification highlighting the anomaly detected region in Chooralmala**

Processed features
0.2626, 0.2735, 0.2622, 0.1489, 0.2147, 0.1856, 0.1619, 0.2169, 0.2568, 0.1890...

Fig. 10 Classified features showing anomaly between train data (2014,2017,2020) and test data (2024)

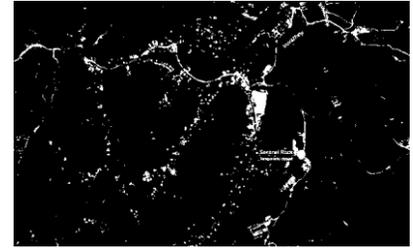**Fig. 11 NDVI –Chooralmala 2014**

Fig. 12 NDVI –Chooralmala 2014-gray scale

Fig. 13 NDVI –Chooralmala 2014-Edge detected and segmented

Fig. 14 NDVI –Chooralmala 2024
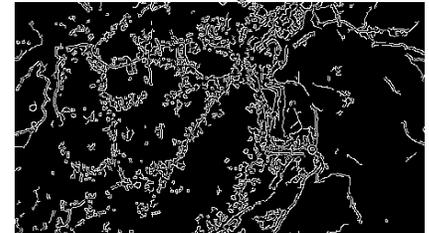

Fig. 15 NDVI –Chooralmala 2024-gray scale

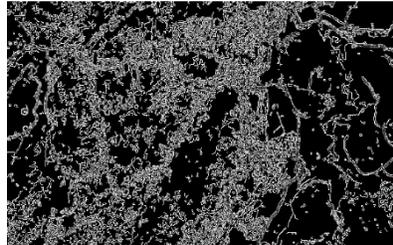**Fig. 16 NDVI –Chooralmala 2024-Edge detected and segmented**

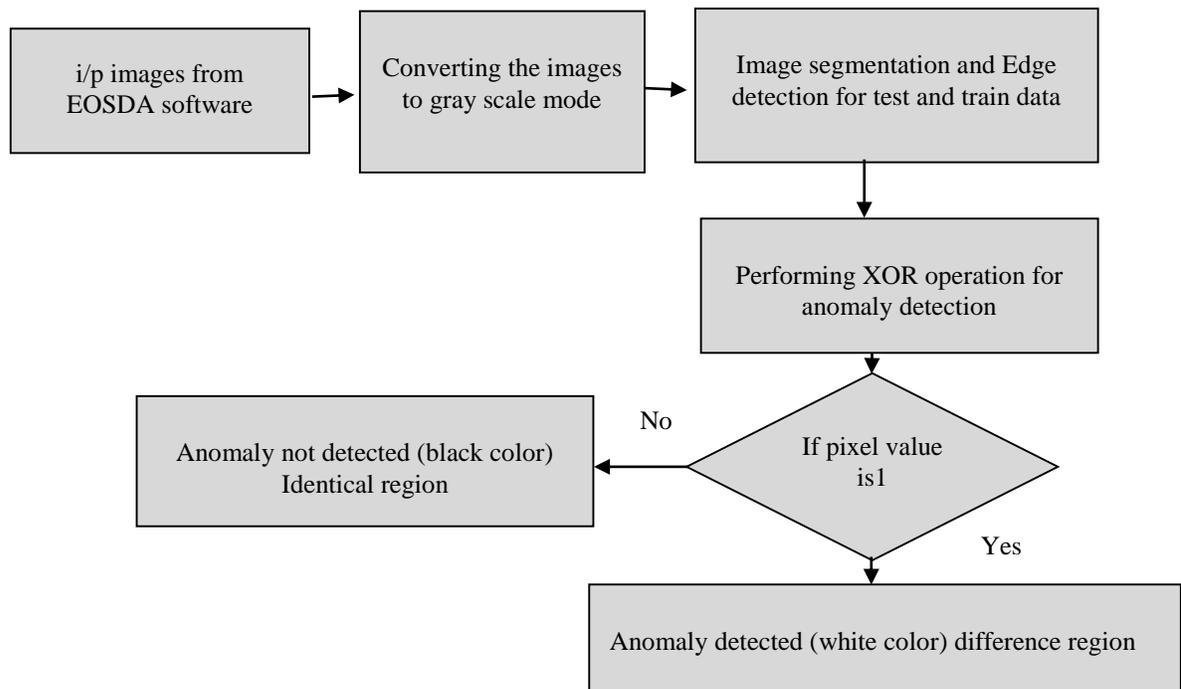**Fig. 17 Output of the XOR operation (showing anomaly) comparing Figure 13 and 16**

Fig. 18 Block diagram showing the anomaly detection using computer vision

Thus, in Figure 17, it indicates more white color lines showing the drastic urbanization and manmade deforestation in this particular zone has resulted in creating the anomaly, and hence that falls as the reason for the landslide that happened in the same year 2024, latest in the month of July 2024. Though there are many factors influencing this landslide, one of the root causes of the landslide may be deforestation and rapid urbanization, spoiling the ecosystem. And this deforestation and rapid urbanization are purely man made disasters against Mother Nature. Figure 18 indicates the diagrammatic flow of the procedure in anomaly detection using computer vision, starting from image input taken from the EOSDA software to the final anomaly output (by comparing the train data and test data) as shown in Figure 17.

5. Results and Discussion

A machine learning model using Edge Impulse software has been developed to check the anomaly detection using the k-means algorithm, comparing the satellite images taken between the years 2014-2020, which were considered as the train data (ie 2014,2017, and 2020 image data), and the NDVI satellite image of 2024 was considered as the test data. Comparing the feature extraction of this train data with test data has evolved in forming Figure 9 with highlights proving the anomaly area, which is more similar to the landslide occurred area, as shown in the Google Earth image shown in Figure 5.

Thus, our anomaly detection prediction machine learning model works efficiently, highlighting or identifying the landslide prediction zone exactly. The efficiency of this prediction machine learning model could be further increased by adding more training data. Though there are many papers related to the prediction of land sliding, the most appropriate work considering the Wayanadu Landslide detection as a case study [27] is considered for comparison as given below in Table 2. The algorithms like LR, SVM, ANN, GBM, CNN, LSTM were used to identify the satellite image anomaly for

landslide prediction detection, where the accuracy level achieved was 85%, but the predictive model is static. In this article, a novel algorithm named FOMO_AD (Faster Object More Objects) developed by Edge Impulse is used for visual anomaly detection.

A method is applied for the prediction of landslides with the comparison of NDVI satellite images, and is able to achieve an accuracy level of 80%, where the predictive model is dynamic. FOMO_AD is based on selective feature extraction and scoring functions like GMM anomaly detection. The detailed comparison of these existing machine learning models and their algorithms used for prediction is discussed in Table 2 and also in Figure 19, comparing the accuracy level achieved between the existing and proposed machine learning models for anomaly detection. This analysis is further justified by performing an XOR operation in computer vision, which also proves that more anomalies have occurred while comparing the train image and test image.

Table 2. Comparison of Wayanadu Landslide -Machine learning model

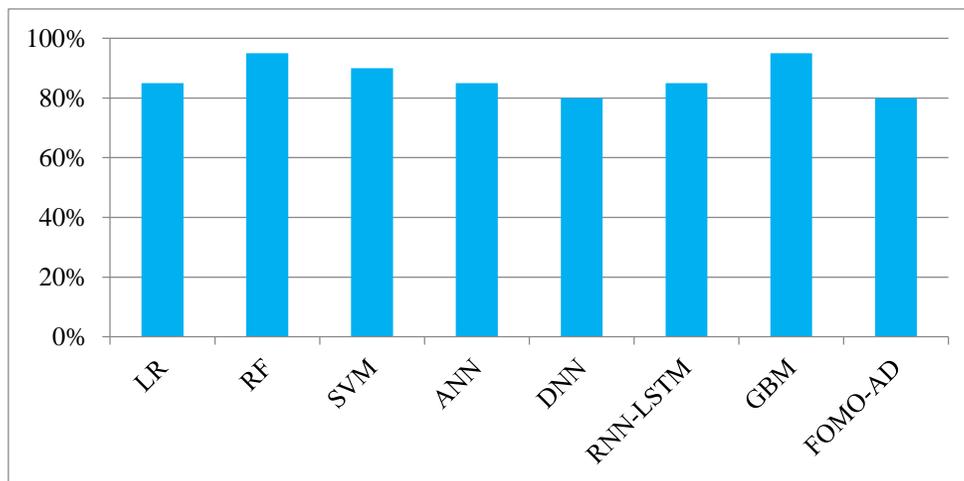| Parameters	Lokesh et al [27] (2025)	Proposed
Accuracy	85%	80%
Algorithm	LR, SVM, ANN, GBM, CNN-LSTM	FOMO_AD
Feature	Time series and Sequential data are not applicable for real-time.	Real-time anomaly detection, memory-efficient visual anomaly detection.
Predictive model	Static	Dynamic (with Edge Impulse platform)

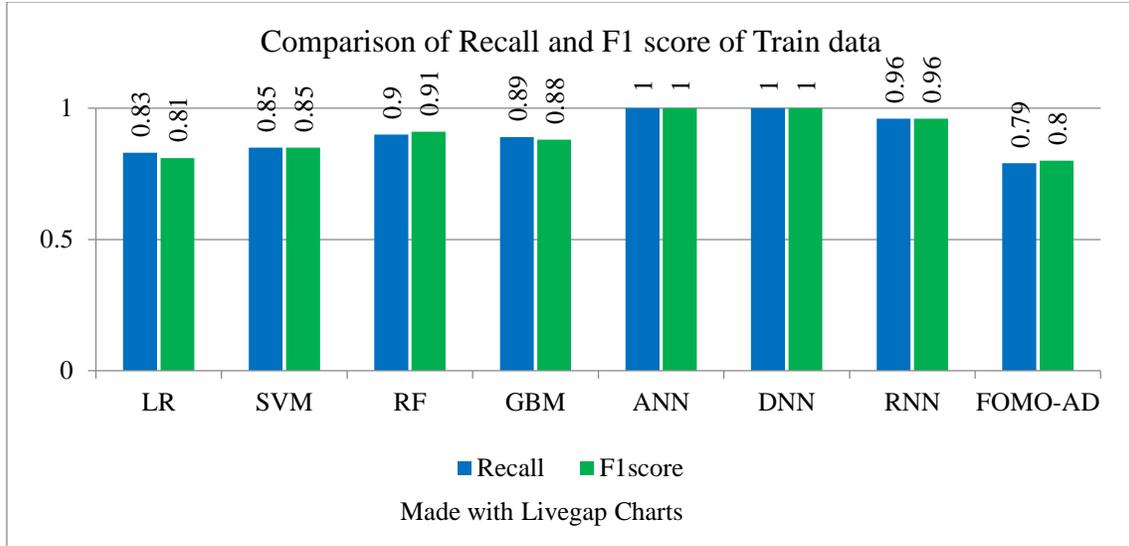**Fig. 19 Comparison of machine learning algorithm with its accuracy employed for Wayanadu landslide detection**

Fig. 20 Comparison of Recall and F1 score of Train Data
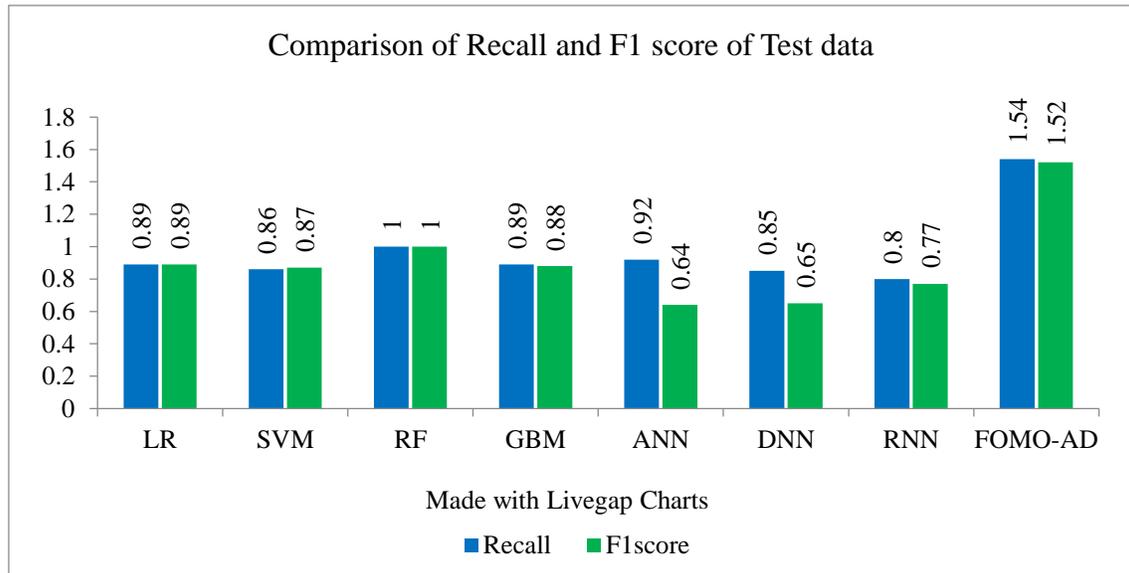

Fig. 21 Comparison of Recall and F1 score of Test Data

Figure 20 shows the comparison of recall and F1 score of the Train data as a part of the performance matrix of the existing algorithms, like LR, SVM, RF, GBM, ANN, DNN, and RNN, with the proposed FOMO_AD. Similarly, Figure 21 shows the comparison of recall and F1 score of Test data as a part of the performance matrix of the existing algorithms like LR, SVM, RF, GBM, ANN, DNN, and RNN with the proposed FOMO _AD. The F1 score of proposed FOMO_AD of the test data, when compared with all other existing algorithms, is higher, which shows the proposed model is better than the other.

6. Conclusion
Thus, this machine model developed in Edge Impulse will act as an alarming system, which has been proven to be more accurate, having better precision in analyzing or predicting the area where the landslide may occur in the near future. In the same way, this could be extended to similar hilly regions with the satellite images taken from the EOSDA software, and prediction helps us save lives from such natural and man made misfortune.

Computer vision-based anomaly detection is also proposed in this article, validating the result obtained in the Edge Impulse software. The work can be further extended by adding more test data by considering other environmental factors like rainfall history data, remote sensing data, etc., apart from Sentinel-2 NDVI data alone.

Table 3 shows the confusion matrix with the F1 anomaly score for the proposed machine learning model in Edge

Impulse Software. F1 score obtained with a max value of 10.33 and a mean value of 1.5, which says there are a few high anomaly points compared to many normal ones, which is not mentioned in other existing methods.

Table 3. Confusion matrix with F1score in Edge impulse software

	Anomaly	**No Anomaly**	**Uncertain**
Anomaly	1	-	-
No Anomaly	-	1	1
F1 score	10.33	1.53	

Table 4 shows the cross-validation of robustness, which further explains how reliable and stable the proposed anomaly detection model is across different data splits (ie, 2014-2024). Here, having 3 train data (ie, 2014, 2017, and 2020) and 1 test data (ie, 2024), the k-fold cross-validation process gives 4 folds. The evaluation model is performed for each fold.

Table 4. Cross validation of Robustness

Fold	**Train Data**	**Test Data**	**Result**
1	2014,2017,2024	2020	Normal
2	2017,2020,2024	2014	Normal
3	2014,2020,2024	2017	Normal
4	2014,2017,2020	2024	Anomalies detected

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