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RESEARCH ARTICLE

Artificial Intelligence Techniques for Landslides Prediction Using Satellite Imagery

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ABSTRACT In hilly areas, landslides can occur due to natural factors such as heavy rainfall, earthquakes, moisture in soil, or man-made factors like unplanned constructions. Landslides can be disastrous leading to a huge loss of property and lives which can be avoided using automatic prediction. Recently, machine learning algorithms have been applied to automatically identify landslides. Numerous feature extraction and classification-based approaches have been implemented on satellite images for semiautomatic detection and prediction of landslides. However, limited research has been done on fully automatic detection with acceptable accuracy. The most challenging task in the classification and prediction of landslides from satellite images is to find an appropriate database for training and yield highly accurate testing results. The primary agenda of a comprehensive study of various techniques used for the detection and classification of landslides using satellite images is to identify the research gap. The secondary objective aims to propose a prototype of novel approach for the same task. Fifty papers based on machine learning and deep learning algorithms from reputed journals are considered for analysis. This article summarizes the performances of different classification techniques from recent literature followed by comparison and discussion with respect to accuracy. Based on the gap identified an effective prototype of the landslide classification approach is proposed. A slightly modified version of the deep learning model ResNet101 is proposed which yields an accuracy of 96.88% when tested on an augmented Beijing dataset of 770 satellite images. The article also offers the researchers the latest status, overview, and potential avenues of machine and deep learning algorithms for landslide detection. The techniques discussed will serve as a valuable resource for identifying research gaps, guiding new researchers, and fostering innovative exploration in the field of landslide classification using satellite images.

INDEX TERMS Landslide classification, satellite image classification, support vector machine, fuzzy-based classification, landslide prediction, landcover classification.

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I. INTRODUCTION

In today's era, the utmost importance is to protect life and infrastructure from natural disasters like landslides and earthquakes. As more mountain areas are getting populated, there is an increase in national initiatives towards the safety of lively beings in the landslide susceptible areas. Landslides can cause tremendous amounts of damage to life as well as property. Landslides pose significant demographic and economic concerns in diverse countries, underlining the need for proactive risk management and international collaboration to avoid disaster-related losses [1]. In India, 12.6% of covered land except snow-covered areas is prone to landslides. About 0.32 million sq. km area falls under the Himalayan range which is further categorized into Northeast Himalaya and North West Himalaya. Darjeeling and Sikkim fall under the North East Himalayas and cover 0.18 million sq. km area prone to landslides. North West Himalaya covers Uttarakhand, Himachal Pradesh and Jammu and Kashmir comprising 0.14 million sq. Km. Western Ghats cover Tamil Nadu, Kerala, Karnataka, Goa, and Maharashtra contributing 0.09 million sq. km and Eastern Ghat contributes 0.01 sq. km of total landslide-prone area [2]. Himalayan range lies in earthquake Zone IV and V, these areas are susceptible to landslides initiated by earthquakes [3]. The estimated loss of infrastructure due to landslides is 1-2 % of the gross national product in most developing countries [4]. Estimating and minimizing the damage caused by landslides is a challenging task for the government authorities and technical teams in developing countries as approximately 80% of the casualties due to landslides are reported from these countries [5].

Developing counties follow a steep increase in construction. Remote areas are connected to roads, railway tracks, bridges, tunnels etc. Constructions in the morphological area cause a problem in the ecosystem environment and create hazards like landslides. The danger of landslides along road alignments in North Sikkim Himalayas is evaluated by geospatial analysis utilizing thematic weighting. The results show that 65.3% of landslides occur in very high-hazard zones, which informs construction design to reduce the likelihood of future disasters [6]. A landslide is a natural and manmade disaster that causes loss of life. Being a developing country, construction cannot be stopped and natural parameters that trigger landslides cannot be controlled. Therefore, an early alarm system can save lives from such hazards. Satellite image databases can be pre-processed to extract the feature to train the model for the detection of landslides with artificial intelligence. AI and machine learning are essential in the digital age for utilizing a variety of data sources and supporting spatial information analysis for catastrophe risk reduction. Recurrent and convolutional neural networks, for example, have achieved above 90% accuracy in their analyses [7]

Landslide classification has three main stages, the first stage is the collection of images or creating datasets from satellite data. Initially, a landslide-prone area is selected, and satellite images of landslides and non-landslides related to those areas are collected and created a database. There are few ready-to-use data sets available for training and testing algorithms [8]. The next step is to preprocess the collected data by removing noise, increasing brightness, and segmenting the area of interest. The image segmentation process is an important step in image pre-processing. The result of segmentation depends on the quality of the images. High-resolution images and machine learning algorithms provide reliable results of segmentation that are useful for selecting interest objects [9].

Satellite remote sensed data is highly effective for the prediction of landslides and reducing the risk of disaster. Data acquired by remotely sensed satellites help in support of keeping inventories of landslides, majorly in periods of risk assessment and during the prevention of landslides [10]. Satellite data is also useful for creating an alert during emergencies and observing current ground situations [11]. Machine learning can allow easy, yet accurate classification and prediction of landslides based on satellite images. Timely prediction of landslide incidents can help the disaster management team to save human lives and avoid loss of property. Machine Learning techniques are extensively used for landslide susceptibility mapping due to the complex relationships between landslides and causative factors. Many ML techniques achieve high reliability in generating susceptibility maps, with an Area Under the Curve (AUC) value exceeding 0.90 [12].

Landslide detection have traditionally relied on a combination of geological surveys and satellite imagery analysis.

The major primary objectives of this article are as follows.

1. To analyze and categorize different machine and deep learning techniques and compare them in terms of performance with diverse types of datasets and types of satellites from where data is collected with accuracy.
2. To identify the research gap from the literature on machine learning classification of landslides available in the last few years.
3. To test and verify whether artificial intelligence techniques can provide a better classification for landslide and non-landslide data.
4. To propose a prototype of a new artificial intelligence-based technique for the classification of landslides with better accuracy.

This study identified several key concerns regarding this work, which encompass

1. Selecting appropriate and latest articles from the available literature.
2. Identify common ground and parameters for evaluating and comparing performances of existing solutions.
3. Use a common strategy to compare different machine learning techniques.

In this article, we have selected 50 research papers based on machine learning techniques for automatic and semi-automatic classification of landslides from various sources such as IEEE Explore, Springer, Remote Sensing Journal, landslide Journal, IEEE and Science Direct etc. Enough care is taken to ensure that the research articles cover a variety of datasets from various landslide-prone countries all over the world. This will allow the researcher to understand the changing trend of datasets and techniques so that a new robust technique can be developed to predict the landslide from any dataset accurately.

The contribution of this article lies in the performance analysis of different classification techniques from recent literature followed by comparison and discussion with respect to accuracy for identifying research gaps, and guiding new researchers in the field of landslide classification using satellite images. The article also contributes by proposing an effective prototype of the landslide classification approach based on the gap identified. The major contribution of the work proposed is the slightly modified and appropriately tuned version of the deep learning model ResNet101 which yields an accuracy of 96.88% when tested on an augmented Beijing dataset of 770 satellite images.

The remaining part of this article is arranged as follows. Section II summarizes the research work categorized according to the type of algorithm. The important findings and research gaps are identified in Section III. Based on the research gap identified, Section IV proposes an optimized artificial intelligence-based classification algorithm. Section V concludes the articles.

II. RELATED WORK

This section takes a comprehensive review of different machine-learning algorithms and methodologies for landslide detection and classification using satellite data.

The literature studied reveals that the entire Machine learning algorithm used for landslide detection or classification can be divided into four main categories: supervised learning-based algorithms, unsupervised learning-based algorithms, Fuzzy classification algorithms and combination or hybrid classification algorithms. Hence, we have grouped the methodologies and their summaries in four different sub-sections as below.

A. SUPERVISED LEARNING-BASED TECHNIQUES

This subsection summaries all Machine learning techniques under supervised learning-based algorithms as below:

Malviya and Gupta [13] used learning-based Extended Local Binary Patterns [ELBP] and SVM for the classification of 24 different class satellite images. Two major issues with satellite image processing were discovered in this paper: noise is more noticeable in satellite images and different satellite images have unique properties. The SVM algorithm is used to estimate the noise pattern and Local Binary Pattern used for segmentation. In this research, the researcher considers only four different classes of pictures for training the framework with three algorithms; Radial Kernel-based Support Vector Machine (RKSVM), Linear Kernel base Support Vector Machine (LKSVM), extended Local Binary Patterns (ELBP). Extended Local Binary Patterns (ELBP) is preferred which correctly classify all 24 images. The overall 94% accurate result was obtained by the ELBP SVM algorithm for satellite image classification. Satellite images are of unique features and have varieties in texture and quite difficult to propose one strategy for all images. Still, work needs to be done to design a more accurate algorithm to give improved results for the classification of different classes of satellite images. Only a few images for training cannot guarantee better accuracy. The robustness of technique with more dataset is not attempted which may be the bottleneck in its applicability.

Byun et al. [14] proposed a landcover classification multispectral image approach based on the Seeded Region Growing (SRG) approach. Efficient image segmentation techniques and high-resolution pan-sharpened images were used. The modified SRG approach combines the multispectral and gradient information of images for homogeneous image regions with accurate and close boundaries. In the noise removal process of multispectral images multi-valued anisotropic diffusion method was used to collect edge information for extracting seed points local minima. Two datasets Quick Bird image and GeoEye-1 were used for experimental results. The result of the proposed technique was compared with three algorithms: the conventional region growing algorithm, the toboggan watershed algorithm, and the mean shift algorithm. At a threshold value of 0.5 and mean square spectral error, the proposed algorithm provided the best result and has an accuracy of 91.15% and the kappa coefficient is 96.70%. MSRG can use multi-feature information including edge and multi-spectral information. This proposed method uses a threshold value for seed selection which cannot provide the best result of seed section for every image. The work needs to be done in an area that is more efficient in segmentation.

Sukawattanavijit et al. [15] developed GA SVM algorithm for the classification of multi-frequency images from RADARSAT-2 (RS2), Synthetic Aperture Radar (SAR) and Thaichote (THEOS) MS images. SVM classifier was used for the classification of land cover. To obtain the best input feature GA was used. Function classification accuracy and the number of features in the selected subset were used to define the fitness of the function. Two datasets THEOS & LANDSAT8 of MS images were used for experiments. To convert the intercorrelated MS band into a set of non-correlated components PCA was used. Training sets and testing sets were developed by using the ENVI program GA-SVM algorithm was compared with the grid search algorithm based on parameter searching.GA-SVM algorithm has 85.02% accuracy for THEOS images and 95% accuracy with combined RS2 and THEOS images. The genetic algorithm along with SVM provides better results as compared to grid search but the Genetic algorithm can be computationally intensive and time-consuming for large datasets. High classification accuracy was achieved with fused RS2 and THEOS images and performance might be different with other testing datasets.

Huang and Zhang [16] proposed a multi-feature model-based SVM that combines multiple spatial and spectral features both for object and pixel levels. Differential morphological profiles Gray-level, co-occurrence matrix and an urban complexity index, are three features that were used.

Probabilistic fusion, object-based semantics and certainty voting three algorithms were proposed to add multiple features. Two WorldView-2 datasets and DC Mall dataset were used for training and testing. In DC Mall 50 samples were used in the training process and 19332 in testing. WorldView 2350 samples were used for training and 68706 samples were used for testing. For the classification of high-resolution imagery data, one optimal feature for different images was impossible to select. In the proposed multi-feature, SVM was based on multi classifier system that contain a series of spatial and spectral features for high-resolution image classification. Newly developed SVM has 94.4% accuracy with GLCM on DC Mall dataset. With the Worldview-2 dataset developed SVM has 92.8% accuracy. This work is limited to training sets and knowledge base rules for construction. Two datasets used in the experimental result used a limited number of datasets for training does not provide efficient results. Semantic analysis was used for the post-processing feature system and depended on segmentation quality which can reduce the overall classification accuracy.

Shukla et al. [17] discussed the survey of different LSZ map approaches for preparing landslide susceptibility zonation maps with support vector machine by considering one case study on the area of Garhwal. The datasets were prepared from the survey of India toposheet. To finalize the tectonic map of the selected area, Landsat satellite images of 30 m resolution were used. Data is pre-processed with ArcGIS software to generate parameters such as soil, aspect ratio, drainages, and elevation of the study area. The vector layer of 30*30 m resolution data set was converted into Raster data and raster to ASCII format to use Matlab for SVM. To test the trained SVM Model Ukhimath river basin data were used which was prepared by the geologic survey of India. The trained proximal SVM model to classify more area in landslides susceptible zone have classification higher accuracy of 84.2% and prediction accuracy of 81.15%. Landslide susceptibility zonation maps play an important role in assessing the risk in those zones. Preparing landslides susceptibility zonation map for an area that is sensitive to landslide is most important. The focus of such kind of map prepared with a Support vector machine is to identify the landslide-prone areas.

Sabanci et al. [18] compared the results of K-Nearest Neighbor Algorithm and multilayer perceptron (MLP) for the classification of varied forest types to classify the dataset data mining methods used. A dataset of ASTER satellite images was created and the collected images were processed in three parts: Classification, regression, and clustering along with association rules. Advanced Spaceborne Thermal Emission and Reflection Raido meter Satellite images with a resolution 15m in forest land were used in creating training and testing datasets. To train the model, training sets of ASTER Satellite images were used to classify the sample images into different classes. The collected ASTER Satellite data from the University of California, Irvine (UCI) forest is divided into two classes one was for training and the other one was for testing the model. A total of 524 images were used of which 38% data was used for training and 62% was for testing. The machine learning algorithm MLP yielded a classification accuracy of 90.43% and KNN produced 89.10% accuracy. KNN and MLP have the best classification accuracy. In this research training set is only 38 % and by increasing the ratio of a training set the result can be further improved.

B. BAYESIAN MODEL BASED LANDCOVER CLASSIFICATION TECHNIQUES

This subsection area summarizes all Machine learning techniques under Bayesian model-based algorithms as below.

Mianji et al. [19] proposed a modified supervised classification method in which the feature reduction technique combined with Bayesian learning-based probabilistic spare kernel method. To increase the distance between the classes, hyperspectral data was first transferred to low-dimensionality feature space and processed with a multiclass RVM classifier. The proposed method uses a dataset of AVIRIS with a resolution of 10nm and wavelength of 0.4 to 2.5micro m images for training and testing the model. This dataset used contains two datasets Indian Pine and San Diego dataset. The experiment was performed for both Linear [FLDA+RVM] and nonlinear [GNDA+RVM] and the performance of the proposed methods was evaluated on varying trains to test the sample. The overall accuracy of Linear FLDA+RVM and GNDA+RVM was 98.01% and 99.04% when the train-to-test sample ratio is 1:30 respectively. Real Hyperspectral data is used for verifying the effectiveness of this proposed supervise classification method. The result is compared with the SVM algorithm and this proposed method gives better performance over SVM.

Li et al. [20] investigated an active sampling supervised Bayesian approach with active learning for the segmentation of Hyperspectral images. A multinomial logistic regression model based on logic regression was used for class posterior probability distribution learning Unbiased multilevel logistic prior (MLP)was used to encode spatial information and segment the hyperspectral images. Active learning is useful for reducing number of labelled samples. The performance of the proposed algorithm was assessed by simulating a real hyperspectral dataset. Gaussian RBF kernel is applied for all experiments to normalize the input hyperspectral data. The LORSAL algorithm was used to learn MLR (multinomial logistic regression). The Multilevel logistic (MLL) prior model was adopted for smooth segmentation. The researcher designed an algorithm that combines LORSAL, MLL and active learning. To evaluate proposed algorithm datasets Indian pines, AVIRIS and ROSIS Pavia were used for experimental results. The proposed algorithm yielded 86.72% accuracy on 3921 labelled sample. Overall accuracy Based on experimental results MBT approach gives unbiased sampling and better classification. In this paper, the main dominating factor is a limited dataset for training and testing of the algorithm. The result can be modified with more training samples.

Ruiz et al. [21] proposed a method for Remote sensing image classification based on nonparametric & interference paradigms. This approach allows dealing with infinite dimension features. For both fine and infinite dimension feature space this method is useful. This scheme provides point-wise class prediction and confidence interval prediction. This method is efficiently used for supervised and active learning. The experimental result of this proposed algorithm was performed over two multispectral images for supervised and active learning classification. Landsat images of Rome city were acquired for supervised classification and ROSIS images of Pavia city were used for active classification. Multispectral and synthetic aperture radar data is used to test this algorithm and Hyperspectral images are used for multiclass land cover classification. The proposed method has 96.80% overall accuracy in supervised mode. For active learning minimum normalized distance (BAL-3) has 97.34% accuracy and running time is 9s. In the supervised mode, proposed algorithm provides the same result as compared to SVM but an improvement is observed in active learning. This work can provide pointwise class prediction and confidence intervals. To an extent this work can use multitemporal image segmentation for better results.

Cui et al. [22] suggested a novel classification method for multispectral (MS) images and this approach was based on nonparametric supervised classification. To provide a digital vector number of different class statistic distributions were followed. In MS image high posterior probability was calculated only when an unknown pixel digital number is the same as this pixel in a training class. In accordance with the statistical characteristics of the DN vector, each class vector must follow Gaussian mixture distribution. To estimate the maximum posterior optimized simulated algorithm was used in the proposed method. Spectral classification of the proposed approach yielded 85.30% accuracy and 0.799 Kappa coefficients for the first dataset. Spectral Spatial classification of the proposed approach yielded 94.78% accuracy and 0.92 Kappa coefficient for the first dataset. Three datasets of multispectral images acquired from the SPOT6 satellite have four bands and each band has a spatial resolution of 2m. The overall accuracy result of the proposed classification model was compared with the state–of–the–art classification methods and suggested that the proposed approach outperformed in kappa coefficient and overall accuracy. The proposed Bayesian approach has good results in comparison with the traditional approach. This approach uses the Gaussian Mixture model for fitting the training dataset instead traditional single Gaussian model to provide better results.

C. DECISION TREE BASED LANDCOVER CLASSIFICATION TECHNIQUES

This subsection area summaries all Machine learning techniques under Decision tree based algorithms as below

Duro et al. [23] explored a multiscale object-based image analysis (MOBIA) approach based on an RF classifier for EO imagery. MOBIA can produce more than a dozen variables for classification as compared to the pixel-based approach. The use of object features to evaluate information from multispectral bands vegetation index and digital elevation model or other input layers is possible with MOBIA. For object-based classification, object features are used for calculating individual image objects and provide a segmentation process. Maximum likelihood classification (MLC) and K-nearest neighbor (k-NN) are traditional classification algorithms used for MOBIA classification. As compared to modern or parametric algorithms MLC gives poor classification results. In nonparametric algorithms, the RF classifier is more faster and reliable for MOBIA. Two datasets from SPOT-5 high-resolution geometrics sensors and LANDSat-5's thematic mapper sensor were used for testing and training. For multi-source, multi-sensor data RF classifier accuracy is 90%. This approach consistently gives 85% accuracy with RF algorithm. The data used is of high resolution of 10 m and quite complex to collect data for the training process. This algorithm can be implemented with more datasets to improve the result.

Albert et al. [24] introduced a classification approach for land cover and land use (LCLU). This classification approach focuses on spatial and semantic context for LCLU classification simultaneously. In land cover land use classification conditional random field was applied. Nodes are used as super-pixels in the land cover layer and nodes represent the object in the land use layer. An iterative inference procedure was introduced to enable inference in high-order Conditional Random Forest (CRF). Aerial images were used as input for this proposed classification approach. Two test sets located in Germany were used for testing the algorithm and all these pictures were of orthophoto with four channels and 0.2m ground sampling distance. The result is homogenous for land cover classification and the classification result is improved for similar land use. The overall accuracy for the first test set is 83.7% and for the second set is 82.5%. The size of the super-pixel is very useful for good classification results. As compared to the non-contextual classifier proposed approach gives better experimental results.

Zegarra et al. [25] proposed approach is multi-class semantic segmentation with class-specific for high-resolution aerial images. This research includes prior knowledge about the layout in the CRF model. The first step starts with a Pixel-wise prediction of the class likelihood. For better results, the appearance feature sampled from the neighborhood of each pixel was considered. From object specifies the assumption high-level representation at the level of the object was added. The hypothesis was for road segments and buildings. In the classifier stage, all pixels that belong to the hypothesis were assigned the same level. Experimental results were performed on 1000 × 1000 pixels file generated from dense matching from Vaihingen dataset. This model consists of three steps: The first step is the input of aerial data, then passes through a multilevel classifier with good appearance feature extraction and the last is the recovery step. In the second step large window of the classifier is used because of this building boundaries get blurred and boundaries get mixed even if buildings are close enough. Overall 82.42% accuracy was achieved with experimental results. This classifier Accuracy is given by CRF for buildings, roads, grass, tree and background. Classifiers give more than 80% accuracy but the boundaries of roads and buildings were blurred. The proposed approach is useful for urban planning and environmental monitoring. The complexity, computational cost, and sensitivity to extreme variations of objects are a few disadvantages that can be improved by improving datasets.

D. NEURAL NETWORK BASED LANDCOVER CLASSIFICATION TECHNIQUES

This subsection summaries all Machine learning techniques under Neural Network supervised learning based algorithms as below.

Mahmon and Ya'acob [26] surveyed different algorithms which were backpropagation and K mean algorithm for the classification of satellite images with different classification methodologies. ANN's classifier approach was compared with convolutional classifier techniques which are Maximum Likelihood (ML) and unsupervised (ISODATA). To cover the different types of area, present work categorized the LU/LC into three different classes. Either output of k means clustering image output or ground truth data samples were used as a training set. The training set was selected randomly in this research. Accuracy and kappa coefficient were used to compare the result of image classification. Overall accuracy is 89.3% and the kappa coefficient is 0.820.

Sammouda et al. [27] introduced a Hopfield Neural Network for agriculture satellite images. Pixel clustering-based segmentation was performed on Satellite images which is quite difficult due to poor resolution, poor illumination and environmental conditions. Characteristics such as population density, ecological distribution etc. were used to find exact bee forage locations with Hopfield Neural Network. Geo Eye satellite images dataset with 0.5m resolution was used for clustering. Hopfield Neural Network is giving good results when using three, four and five clusters in terms of classification sensitivity and accuracy.

Zhao et al. [28] presented a Convolutional Neural Network (CNN) model for multispectral and panchromatic image classification. The convolutional Neural Network (CNN) model introduced in this paper was a super pixel-based multiple local CNN. A very high-resolution multispectral and panchromatic images were fused together to achieve results. The introduced CNN model was valid for two datasets one was prepared from the DEIMOS-2 satellite for Vancouver images and the other was prepared from Quick Bird Satellite for China images. Both dataset images were MS remote-sensing and panchromatic images. For the segmentation of MS images and to collect super pixel linear clustering algorithm was used. Super-pixel multiple region joint representation method was introduced to collect all spatial and environmental information of super-pixel. Super pixels were taken as basic units. To improve the classification performance of the proposed algorithm that combines detailed information and semantic information. The overall accuracy for classification was 94.4% and kappa coefficient was 0.92. Further, this experiment can be extended to semi-supervised and unsupervised deep learning. The processing time may increase due to the complexity of the SML-CNN model. This work will be more helpful in urban planning, environment monitoring and vegetation.

E. FUZZY BASED CLASSIFICATION TECHNIQUES

This subsection area summaries all Machine learning techniques under Fuzzy based algorithms as below:

Lei et al. [29] proposed an unsupervised change detection using fuzzy c mean clustering for landslide mapping. For VHR remote sensing image change detection approach based on image segment was used for landslide mapping. Gaussian pyramid-based fast fuzzy c mean clustering algorithm is used to get better spatial information for landslide regions and for accurate landslide region difference of image structure information. Three datasets of biotemporal images of 0.5 m resolution were prepared from aerial survey system. The result was compared with existing three algorithms in terms of higher accuracy, fewer parameters, and short execution time. The proposed CDFFCM model yields 79%, 80%, and 62% accuracy for three data sets, respectively. The proposed approach work on spatial information to achieve better difference image and also have better computational time due to Gaussian pyramid method. This algorithm also reduces the sensitivity to a threshold for segmentation and requires fewer parameters. Post-event images have complex information and still this algorithm needs to be modified for post-event images. More landslide images and ground truth are required to improve the accuracy.

Stavrakoudis et al. [30] developed a classification approach for VHR multispectral images based on Boosted Genetic Fuzzy Classifier. The classification procedure followed two stages, one was fuzzy rule-based which is followed by the genetic tuning stage. The fuzzy rule is useful in local feature selection and it is allowed to select the feature by repeating Boosted Genetic algorithm. The next stage was the tuning stage used to improve the classification by using an Evolutionary Algorithm. An IKONOS satellite database with 1m spatial resolution was used for experimental results. The testing performance of BGFC is 84.87%. The main aim was to increase the overall classification performance of the algorithm and the proposed algorithm was good in handling complex multidimensional classification.

Sinh Mai et al. [31] proposed a method that combines the fuzzy probability theory and fuzzy clustering classification algorithm to overcome the disadvantages like low accuracy and instability of other satellite image classification algorithms. This proposed method initially calculates the number and coordinates of cluster-based Fuzzy probability and then for classification applies a fuzzy algorithm.

Landsat 7 Satellite datasets were used for experimental results. The experimental results show that the developed fuzzy clustering algorithm gives a Classification entropy of 0.13 and a kappa coefficient of 0.9156 for one dataset and a Classification entropy of 0.14 and a kappa coefficient of 0.8599 for the second dataset. This method yields high classification accuracy on multispectral satellite images as compared to the various developed algorithms.

Ngo et al. [32] developed an Interval Type 2 C-mean clustering scheme for multi-spectral satellite imagery. The dataset for experimental results was taken from LANDSAT7 imagery which includes rivers, rocks, fields, jungles planted forests. To generate NDVI image of the chosen study area, two channels were used: Near Infrared and the other is visible red. NDVI is classified by IT2FCM to define different types of land covers. For some undefined pixels, the IT2FCM algorithm can handle uncertainty. Further, this algorithm can be implemented with a hyperspectral image for better results.

F. DEEP LEARNING TECHNIQUES

Many literature surveys and comprehensive reviews on deep learning and its application applications carried out in number of researches are available [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], and [43]. This research discusses the challenge of high quality datasets, impact of model complexity on computational resources and limitations of model interpretability. This subsection summaries all Deep learning techniques under hybrid algorithms as below:

Ji et al. [35] presented a large-scale landslide dataset based on Bijie City to address the problem of an accurate remote sensing dataset along with a boosted attention module to enhance the feature map in CNN. Experimental results show that ResNet50 boosted by the 3D attention module yields the best performance in landslide detection with a 96.62% F1 score. To extend this work, need for more sophisticated CNN architecture is required to recover different representations of landslides from complicated backdrops.

Ullo et al. [36] presented a Mask R-CNN pixel-based segmentation model trained with transfer learning and ResNet101 ResNet50 as a backbone network. Experimental results claim precision 1 and 0.97 FI of the model with ResNet101 as a backbone network. The dataset used in model training was only 160 samples collected from open-source landslide UAV photographs. Sridharan et al. [37] evaluated landslide near debris scars. Three deep learning algorithms ResNet, AlexNet, NASNet-large yields 96%,92%,98% accuracy. The findings suggest potential for modifying and deploying these algorithms to develop landslide hazard risk maps globally.

Zhang and Wang [38] undertook a theoretical comparative framework of Artificial intelligence, Machine learning, and Deep learning emphasizing their major component and learning approaches. Catani [39] Discussed the implementation of convolutional neural networks (CNNs) for discerning mass movement patterns using transfer learning to attain higher classification than existing architectures Chang et al. [40] discussed the application of deep learning model in landslide recognition. This work emphasizes the incorporation of a transformer into ResU-Net to improve context modeling utilization of large and different sources of data for better identification. This study shows deep learning with InSAR shows promise for early landslide prediction.

Yang et al. [41] proposed a semantic segmentation model for automatic landslide detection. Three semantic models: U-Net, DeepLab3+, and PSPNet were combined with different deep learning models (ResNet50, ResNet 101) to evaluate experimental results. Among all combinations, PSPNet with ResNet50 as the backbone network yields 91.18% mIoU. This paper indicates high accuracy in landslide recognition but further needs to improve landslide boundary segmentation and dataset. DEM data and remote sensing data can be integrated to enhance segmentation accuracy. Liu et al. [42] developed a landslide detection mapping model based on three networks: Convolutional neural network, residual neural network, and dense convolutional neural network. DenseNet with RS images and CF's reveals the promising experimental result on landslide detection. Fu et al. [43] proposed a study to evaluate the size of post-earthquake seismic landslides with unmanned air vehicle remote sensing images. Mask R-CNN uses ResNet50, ResNet101, and Swin Transformer as the backbone network was trained with post-quake UAV images that claimed 0.93 precision. To reduce training time and increase generalization transfer learning was used in this research.

G. OTHER CLASSIFICATION TECHNIQUES

This subsection area summaries all Machine learning techniques under hybrid algorithms as below:

Martha et al. [44] presented an algorithm uses spectral, contextual and shape information of images for landslide detection. For object-oriented analysis, multispectral images were segmented and objects collected from these images were used as a classifying unit. The main objective was to correctly identify the landslide using OOA. Complex landslides were difficult to segment because of different characteristics like low contrast and overlap shadow. To identify the false positive landslides shape and morphological information were combined. A landslide is categorized by the base material and movement of flow. To identify landslide Resources at 1 and LISS IV multispectral data sets were used. For testing the algorithm images of the area in Himalayan in India were selected and test the algorithm with 5.8 m MS data from Resources at 1 and 2.5 m Cartosat1. 76.4% recognition is possible with the proposed algorithm and classification accuracy is 69.1%. This algorithm yields more efficient and accurate landslide detection by utilizing object-based classification. The main challenge in the work is to distinguish landslides from another object with similar spectral properties like soil and water.

Blaschke et al. [45] used a semi-automated object-based image analysis methodology to detect landslides. Object-based image analysis has gained an important role in remote sensing. IRS-ID and SPOT 5 satellite image database were used for the detection process. For landslide detection NDVI, brightness and textural features of satellite images were fused with slop and flow direction. Digital Elevation and gray-level co-occurrence matrices were used to collect slop and flow directions. In object-based image analysis multi multi-resolution segmentation was applied for selecting the feature and classifying the object. The segmented object was processed with their spatial, spectral, and textural parameters. The landslide class was defined on the base of its morphological characteristics. Research aimed to integrate the spectral, spatial, and morphometric characteristics of landslides. The inventory database of 109 landslide events was used as proof to validate the results and according to rule-based classification, the area above 1600m (about 5249.34 ft) with a slope greater than 7% is considered landslide affected area. The brightness threshold is set for a database created from IRS-ID and SPOT 5 satellite images. The combinations of these parameters indicated that an overall accuracy of 93.07% was achieved for landslide detection. This method will be useful to detect landslides even without proper landslide inventory.

Meena et al. [46] Used U-Net and machine learning approaches for automatic detection of landslides by landslide event-based inventory of triggering events and occurrence landslides. The major issue lies in mapping performances among interpretations in the event-based inventory. In this research, two datasets: Dataset 1 from RapidEye satellite imagery and Dataset 2 combine RapidEye and ALOS-PALSAR. 239 data samples were used in several training zone and one testing zone to evaluate the model. Experiments were performed over fully convolutional U-Net, Support Vector Machine (SVM), Random Forest (RF), K-nearest neighbour. Among all machine learning techniques, U-Net performs best result of 76.59%MCC. The performance of the U-Net model further can be increased by increasing the sample size for training samples.

Wang et al. [47] presented a 11-layer deep convolutional neural network (DCNN-11) model for landslide identification using ML& deep learning. Promising results from a case study of Hongkong City were achieved on three databases: Recent Landslide Database (RecLD), Relict Landslide, Database (RelLD) and Joint Landslide Database (JLD). Experimental result reveals that DCNN-11 is very effective model among Support Vector Machine (SVM), Random Forest (RF), and logistic regression.DCNN-11 has highest area accuracy 92.5% with RecLD database. Further, it is observed that the performance of DCNN can be improved by considering the inconsistency in terrain, landslide, inaccuracy in database and necessity for more complicated CNN's in the future owing to computational restrictions. Saha et al. [48] also investigates landslide susceptibility in the Garhwal Himalaya using machine learning models, with Deep learning neural network (DLNN) demonstrating good accuracy. Ghorbanzadeh et al. [49] compares Artificial neural network (ANN), Support vector machine(SVM), Random forest (RF) Convolutional neural network (CNN) for landslide detection. Optical data from Rapid Eye satellite were used for experimental result. CNNs are used for effective feature representation in image recognition and have better accuracy for small window size.

Naemitabar and Asadi [50] undertook a comparative study on four machine learning techniques: Support vector machine(SVM), the Random Forest (RF), the boosted regression trees (BRT) model and a Logistic Model Tree (LMT) for identification of landslide prone area. The SVM and RF yield higher reliability in assessing landslide susceptibility, with factors like lithology, slope, and land use identified as crucial. Experimental results shows that SVM and RF model have AVC 0.86 and 0.89 respectively.

Dou et al. [51] presented an automatic method for landslide detection. This approach combines three different approaches namely Genetic algorithm, object-oriented analysis, and case-based reasoning. In object-based analysis, segmentation plays a very important role. High resolution of the image provides correct information about the landslide and was helpful in the better result of the segmentation process. To obtain the object of interest in object-oriented analysis multi-segmentation was preferred on collected images. The genetic algorithm was applied for the feature section. Geographical features classify and enhance the accuracy with case-based reasoning. The case-based reasoning is achieved with different techniques like k nearest neighbor etc. In this paper, Quickbird images of 0.6 m spatial resolution were used for image segmentation and feature selection. Roadside landslides were more exposed to high damage due to landslides and caused difficulties in day-to-day life. Spot 5 and DEM datasets were also used for experimental results. All data were rectified to remove the distortion and noise. Object-oriented image analysis gives 75% accuracy for the detection of landslides and fused Object-oriented image analysis with a case-based reasoning and genetic algorithm (GA) yields 87% accuracy in the detection of landslides. The proposed technique provides benefits over a knowledge-based section for the detection of landslides. This technique helps in creating inventory that will be helpful for providing specifications for future landslides.

Martha et al. [52] designed a new approach to detect landslides using bitemporal multispectral images. Multispectral images were used to collect the object from post-landslide images. For the analysis of high-resolution images, a tool is developed which makes input data in a user-defined grid. Multispectral images were collected from the Resourcesat-2 LISS-IV satellite for a defined study area. These two datasets have three bands and are useful for object-based change detection techniques to recognize landslides. For the detection of landslides 10m DEM from Cartosat1 satellite data was used. For good quality images auto-rectified

Resourcesat-2 LISS-IV satellite images are further processed to achieve high pixel match. Top atmospheric reflectance calculations were performed in the preprocessing step of images to overcome weather conditions like sunlight. Pre and post-landslide image reflectance differences identify the landslide. Image segmentation was performed with knowledge-based approach. Object-based change detection was used to detect landslides. The developed graphic user interface (GUI) tool provides overall good accuracy in landslide detection. Combined spectral and morphometric parameters have 89% accuracy in the detection of landslides with 10m DEM from Cartosat-1 satellite images. This work can further be modified for the shadow of clouds in pre-landslide images. Some landslides were not identified due to small clouds over the pre-landslide images.

Li et al. [53], [54] introduces an Attention-attended module. This model filters out irrelevant contexts and emphasizes informative ones for the semantic segmentation of satellite images. They work on the LoveDA dataset and outperform other models in critical categories such as "background," "Building," "Road," "Barren," and "Forest," with top scores in Mean F1 score of 76.18 and Overall Accuracy of 72.60. Li et al. [55], [56] proposed a method consisting of encoder and decoder architecture along with weighted adaptive loss function.

Martha et al. [57] presented a comparison of the pixel-based approach and object-oriented approach for landslide detection. Very high resolutions of 0.5m remotely sensed images were used to compare the results of the two algorithms. An inventory was created with 115 field-based landslides fused with 0.5m spatial resolution for comparative analysis. Unsupervised classification was used in pixel base classification and images were classified in eleven different classes. For non-landslide and landslide pixel binary analysis was used and assigned zero and unity for landslide and non-landslide, respectively. In object-oriented analysis k mean clustering was used to remove regions based on brightness to detect landslides and object properties were used to reduce false positive results. Object-oriented analysis has 96.5% and Pixel-based unsupervised classification has 94.3% accuracy. In this paper, further investigation on challenges associated with OOA needs to be discussed for improvement.

Vecchiotti et al. [58] presented a semi-automatic image classification technique for landslides caused by rainfall. This approach combines pixel-based classification with remotely sensed images multi multi-parameters for landslide detection. Vegetation change in pre and post-image will identify the landslide event. In the method, bitemporal pixel change detection was applied. It was a double classification technique. Terra ASTER L2 data sets were used for the defined study area. 110 landslides which were recognized accurately with this semiautomatic image classification technique. This double classification workflow gives 81.5% producer accuracy coupled with a more than acceptable 68.9% accuracy and 72.9% kappa coefficient. With its data set cloud detection was not performed but it can be overcome with SPOT and SENTINEL-2 for a better view of scenes.

A comparative analysis of the review is shown in Table 1.

III. FINDINGS AND RESEARCH GAP

The primary tendency of all research papers that have been reviewed in this paper is to observe the performance of classification on landslide detection. In this literature survey the analysis is based on the accuracy of the classification, satellite-based datasets used for detection and algorithms used for classification. During this study, we find different observations that will be helpful for future research directions, concluded in this section.

A. CHALLENGES WHICH ARE DISCUSSED

Numerous researches have been done with semi-automatic classification of landslides and a few with automatic detection. The most important stage is the data collection. The high-quality image provides a better result for feature extraction. The review concludes that two different images are fused to give a better feature selection. Earth-observing satellites are two types: active satellites and passive satellites [59]. Satellite data provides images and features are extracted based on the following points:

- Active satellites are microwave remote sensing and have their own source of energy. Active satellites have controlled illumination and have the least effect of weather.
- In Active satellite Day and night operations are possible. ESA satellite, Canada RadarSet, Indian satellite (RISAT) and Japanese satellite (ALSO) is a type of active satellite. ESA's sentinel-1 is an active microwave remote sensor and is useful in providing data for all types of disasters like floods, earthquakes, and landslides.
- Passive remote sensing is more useful nowadays and does not assign any external source of energy. These types of satellites measure either reflected radiation from the sun or emitted radiation from the earth. Reflected radiation depends on sunlight so it works on the daytime only and suffers various illumination conditions like weather play a major role. NOVA AVHRR, LANDSAT, SPOT, IRS, Cartosat, and IKNOS are some examples of passive satellites.
- To image segmentation, compare object-based and pixel-based image classification.
- To classify multispectral images and multi-frequency images.

B. CHALLENGES WHICH ARE NOT DISCUSSED

There are few challenges which are not discussed:

- Real-time remote sensing data: Automatic detection of landslide require real-time data which based on satellite imagery need highly efficient algorithms for real-time computation.
- Limited training data set: Acquiring large-scale data sets for training the model in a machine learning algorithm

TABLE 1. Performance analysis of classifiers for landslide detection.

REF No.	Technique	Data Set	Type of Images	Accuracy
[12]	SVM &ELBP	Different class images	All type satellite images	94% accuracy
[13]	Seed Region Growing Approach	1.Quick Bird 2. Geo Eye	Pan sharpened High Resolution satellite image.	accuracy 91.15% and the kappa coefficient is 96.70%.
[14]	GA-SVM	RADARSAT-2 (RS2), Thaichote(THEOS) & LANDSAT 8	MS images	95% Accuracy with RADARSAT-2 (RS2) THEOS
[15]	Multi feature Model Based SVM approach	DC Mall data set World View -2 data set	Hyper spectral digital imagery	Improved accuracy 1-4%
[17]	MLP&KNN	ASTER Satellite Image 15m resolution	524 images	MLP has 90.43% classification rate and KNN has 89 %
[18]	Feature reduction technique combined with Bayesian Learning sparse kernel model.	San Diego and Indian Pine data set	Hyperspectral images	Real time hyperspectral images give better result over SVM
[22]	Non parametric RF classifier for multiscale object based image analysis.	LandSat 5, Spot .5	Landsat 5 thematic mapper sensor, Spots high resolution geometrics .	85% RF classifier accuracy
[34]	The automatic method fused three techniques: OOIA),GA, CB technique.	High-resolution Quickbird, SPOT 5	Spatial resolution 0.6 m	Proposed OOIA-GA-CBR gives 87%
[35]	Multi-resolution segmentation (MRS) technique	Resoursesat -2 LISS-IV	Multispectral Images	80.9% accuracy
[36]	Compare pixel-based and object-oriented analysis for landslide detection	aerial images	Very high-resolution (VHR)	OOA gives 96.5% accuracy and pixel-based unsupervised has 94.3%accuracy

is a challenging task, which can hinder the ability of the trained model to detect landslides accurately.

- Feature extraction: for automatic detection and classification of landslides, need to extract the feature from the database and the feature should be relevant so that model can accurately differentiate between landslide and non-landslide images.
- Environmental factor: landslide depends on various environmental factors like rainfall, soil type, topography etc. By considering these parameters machine learning model require a more careful feature selection algorithm.

C. RESEARCH GAP

For natural areas like soil hills and forests, experimental segmentation results are good. Overall accuracy is good due to feature testing but if the number of samples increases accuracy will decrease, it is relative accuracy than the actual accuracy. For the seed selection process threshold value is used, it gives a suitable result but also limits the best results [16]. A combination of high spectral and spatial resolution images was used. It is challenging to classify images that have the same spectral properties and spectral reflection as water and shadow. The suggested C voting and P fusion technique must ensure that the high-resolution picture knowledge base rule is accurately interpreted [18].

The SVM-based approach for landslide segmentation could not provide better results due to dependency on the threshold. SVM and RF learning methods could not achieve classification accuracy [60], [61] For the seed selection process threshold value is used, it gives a suitable result but also limits the best results. Three algorithms random forest (RF), classification and regression tree (CART) and multivariate adaptive regression spline (MARS) were compared in testing, training, and validity accuracy. Random forest gives high accuracy in testing but does not give high accuracy in validating runs. The result shows that one model that provides good results in testing does not provide high accuracy in validating runs. Preference is always provided to the one mode that gives high accuracy in the prediction of events [62], [63].

D. OBSERVATIONS

This article covers a review of 50 research papers out of which 70% papers used passive sensor-based satellite databases for training and testing, 22% of papers used active sensor-based satellite databases while 8% of papers used aerial images for experimental results. The different types of satellites used in different research work as shown in Figure. 1.

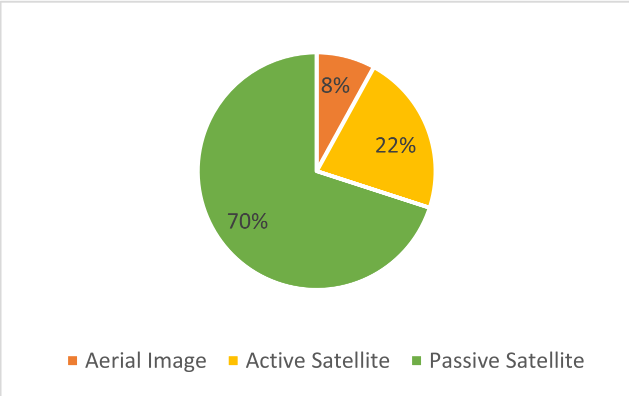


FIGURE 1. **Classification of images used for landslide monitoring.**

Analysis carried out on the basis of accuracy shows that an accuracy range between 95%-100% is obtained in three research papers, 90%-94% is obtained in seven research papers, 85%-89% is obtained in seven research papers, 80%-84% is obtained in four research papers and below 80% is obtained in two research papers as shown in Figure 2.

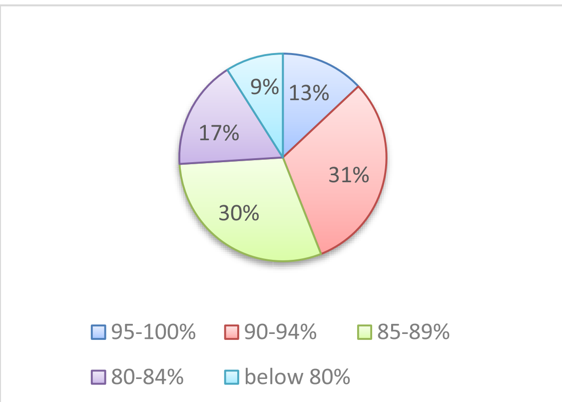


FIGURE 2. **Classification accuracy of ML/DL based techniques.**

Classification algorithms are categorized into seven different classes. This article reviewed fifty research papers, six papers are based on SVM classifier, four papers are based on Bayesian classifier, three papers are based on a decision tree classifier, three papers are based on neural networks, four papers are based on fuzzy, fourteen papers are based on deep leaning technique and the remaining are hybrid algorithms that combine different classifier algorithms. Figure 3 shows the different algorithms-based research papers.

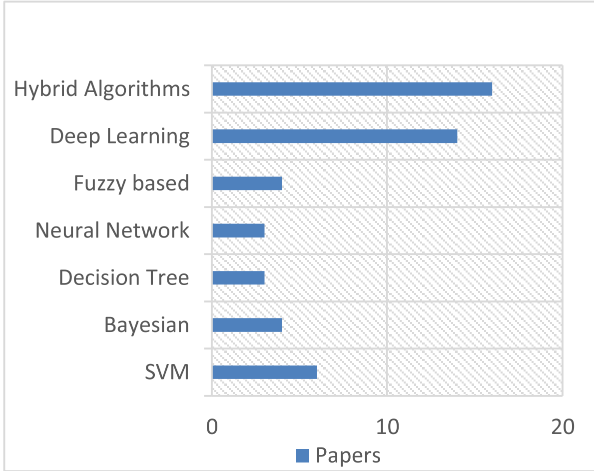


FIGURE 3. **Number of classifiers and types used in literature review.**

IV. PROPOSED CLASSIFICATION ALGORITHM

Automatic detection and classification of landslides using satellite images play a very important role. Classification has two approaches: The classical machine learning based approach and the Deep Learning model-based approach. For feature extraction and feature selection Machine learning uses an explicit whereas deep learning uses an implicit approach for classification. Deep learning model extracts and selects the features automatically without any supervision using hidden network layers so the results are more accurate. Based on the results of previous research work, automatic detection and classification of landslides using satellite images need tuning of trainable parameters during the training phase. The optimization algorithm used in deep learning will improve the model efficiency in terms of accuracy and learning speed in the training process. Figure 4 presents a flow chart describing the proposed prototype model for landslide detection. This proposed work uses the Bijie dataset which contains 770 landslide and 2000 non-landslide satellite images. The dataset is prepared with the preprocessing of images. Image augmentation is used to increase the sample size in the database. All the images are kept in the same size and format. The data set is divided into two classes: landslide and non-landslide. 70% of data is used to train the model and 30% of the data is used to test the model. Images in the training dataset are not included in the testing set to maintain the originality of the result. The train and test ratio impacts the model's learning rate which is the response of estimated error when updating the weights of the model. We consider hyperparameters: batch size, learning rate, momentum, epoch, to train the network. In the proposed model we use an attention mechanism to emphasize the feature map with ResNet101 as a backbone convolutional network.

V. EXPERIMENTAL RESULT

A. DATASETS

Dataset plays an important role in deep learning CNN algorithms. In the proposed work we select Bijie Landslide dataset. This dataset is first open remote sensing dataset

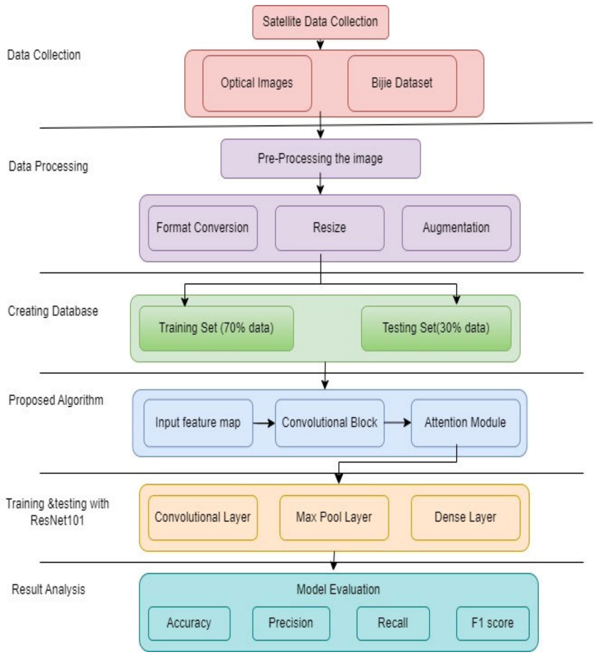


FIGURE 4. Stages of the proposed work.

based on landslide and non-landslide images [33] This dataset contains images of Bijie City, China and covers 26,853 square km area. These images were from TripleSat satellite with 0.8m resolution. More than 2770 images were classified into two sets, the landslide set contains 770 images and the non-landslide images contain 2003 images. In our experiment, 70% images from the Bijie dataset are used for training and 30% of images are used for testing the model. Figure 5 shows some images of landslides in our training set.

FIGURE 5. Examples of landslide instances from Bijie dataset.

B. EXPERIMENTAL RESULTS AND ANALYSIS

A deep learning-based CNN model along with optimization algorithms are used to modify the loss function, learning rate, weights, bias, and accuracy. The model is shown in Figure 6.

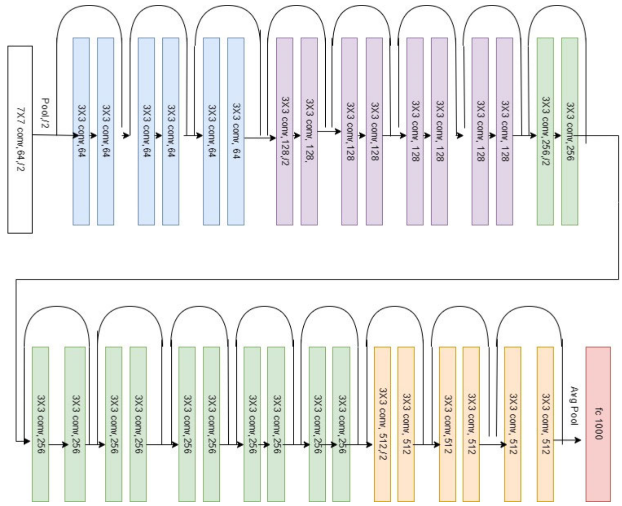


FIGURE 6. ResNet101 neural network architecture.

Different deep learning optimizers like adaptive gradient descent, Stochastic Gradient descent, Adam, and Root mean square can be used for increasing the efficiency of deep learning-based CNN models for detecting and classifying landslides.

Google Collaboratory is used for python code. First, the original training images were resized to 150 × 150 × 3 and augmented (original, rotated and shifted versions of images) with 32 batch size. ResNet101 is trained as backbone network model and is tested on the chosen dataset to measure its accuracy. Then, the random search optimization technique is applied on the ResNet101 model with maximum number of trials=20 and number of epochs=3. The ResNet101 model is then trained to optimize the hyperparameters as mentioned in Table 2.

TABLE 2. Range of ResNet101 trained hyperparameters.

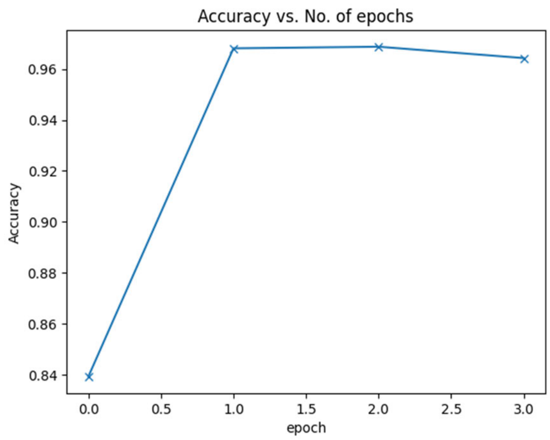
Hyperparameter	Range
Version	101
Batch size	32, 64
Epoch	3
Optimizer	adam
Pooling	‘max’, ‘avg’
Learning Rate	0.02

The main advantage of ResNet’s is that it allows the training of very deep networks through its skip connections, which mitigate the problem of vanishing gradient. The architecture of ResNet101 is quite straightforward and computationally efficient compared to others such as DenseNet. Finally, the features are extracted using the optimized hyperparameters and then the fully connected layer was used for calculating the performance of classification and different scores. Experimental results of ResNet101 are shown in Table 3.

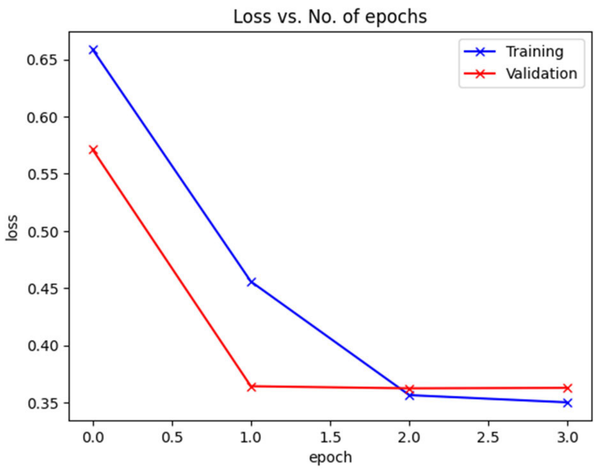
TABLE 3. Performance of proposed model.

ResNet-101Parameter		Precision	Recall	F1-Score	Accuracy
Training Set 70	Batch Size 32	96.4%	96.36%	96.36%	96.88%
Testing set 30	Batch Size 64	91.40%	90.90%	90.88%	92.86%
Training Set 80	Batch Size 32	95.2%	94.86%	95.14%	94.86%
Testing set 20	Batch Size 64	90.85%	91.36%	91.18%	91.24%

The proposed model is producing the best landslide recognition results with an accuracy value of 96.4% and obtain the highest precision index 96.4%. The graphical representation of experimental results is depicted in Figure 7a and 7b.



(a)



(b)

FIGURE 7. (a). Experimental results of ResNet101. (b). Experimental results of ResNet101.

VI. OBSERVATIONS AND DISCUSSION

The batch size is an important hyperparameter in deep learning which works as a trade-off between speed and accuracy. If batch size is large, it may lead to faster training. However, this may result in less accuracy and overfitting. A special care is taken to implement Regularization Techniques such as dropout and weight decay to prevent overfitting, which can be particularly problematic when training with less size. On the other hand, if batch size is smaller it can yield better accuracy, but it is computationally expensive as well as time-consuming.

It is observed that a smaller batch size than 32 is leading to few random fluctuations in the training data. Whereas, the larger batch size than 64 is found more resistant to the fluctuations and converges very slowly.

Another important hyperparameter "number of epochs" is found yielding maximum accuracy of 96.4% at epoch = 1 with moderate loss around 0.45 as shown in Figure 7b. The accuracy is slightly declining with the increased number of epochs. As shown in Figure 7a, at epoch=3, accuracy is declining and showing as 96% but the loss is also minimal. At epoch =1 onwards, the loss is almost constant and not reducing which indicates that the model stops improving on the validation set. Thus, the experiment has been stopped at maximum 3 epochs.

This paper uses satellite images based Bijie landslide dataset for landslide detection and analysis. Images used in this work provide extensive and precise spatial coverage but it does not directly incorporate crucial environmental characteristics and parameters such as soil moisture, precipitation, and seismic activity which have a substantial impact on landslide susceptibility. Soil moisture has impact on soil stability and have valuable insights into landslides but can not be detected only through image analysis. The image-based analysis is also not able to detect precipitation and seismic activity as they change over time and space. Hence, these environmental parameters are not incorporated in the proposed model. However, the accuracy of the proposed technique may increase substantially if these parameters are incorporated in the feature vector.

VII. CONCLUSION AND FUTURE SCOPE

This article analyses, and provides detailed comparison of different machine and deep learning techniques using various datasets of satellite images for landslide detection. Among the selected articles, 22% articles used active sensor based satellite database and 70% used passive sensor based satellite database. The accuracy in selected articles was found between 90% to 95%. This review survey reveals that a hybrid combination of different algorithms gives better classification results as compared to a single algorithm. The research gap is identified and a prototype model is proposed. The proposed model uses deep learning CNN network ResNet101 as the backbone to produce the best landslide recognition effect with an accuracy value of 96.88% and obtain the highest precision index of 96.4% with well-thought-tuned hyperparameters. Thus, the results yielded conclude that the proposed technique can provide classification of landslide data with better accuracy.

Of course, there are a few limitations in this work. To alleviate the restrictions future research could combine satellite image processing with meteorological data and provide more accurate understanding of landslide detection and prediction. The environmental parameters such as soil moisture, precipitation, and seismic activity can also be incorporated in the feature vector for better accuracy of prediction. The Further to enhance models performance attention module can be used. The attention mechanism helps to focus on essential characteristics of satellite photos as well as environmental factors. This could improve model's capacity to generalize across different areas and conditions, making it more resilient and adaptable.

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