Chapter 2
Literature Review

2.1 Introduction

Authors (Vyas et al., 2011) evaluate the performance of an Artificial Neural Network, Spectral Angle Mapper, and Support Vector Machine over highly diverse tropical forest vegetation utilizing hyperspectral (EO-1) data. The Stepwise Discriminant Analysis resulted in identifying the 22 best bands to discriminate the eight identified tropical vegetation classes. According to the authors, the ANN classifier gave the highest OAA value of 81%. The image classification done with the help of SVM showed an OAA of 71% and SAM showed the lowest OAA of 66%. SVM showed the highest OAA of 80% in classifying spectra coming from 165 processed bands.

In this study authors (Prasad et al., 2017) investigates the correctness and consistency of the Support Vector Machine (SVM) classifier and compare its performance with the Artificial Neural Network (ANN) classifier for multispectral Landsat- 8 images of the Hyderabad region. Fuzzy Incorporated Hierarchical clustering is used for clustering the images. According to the authors, the experimental results indicate that overall precisions of Land used and land cover classification are approximately 93.159% for SVM and 89.925% for ANN. The corresponding kappa coefficient values are 0.893 and 0.843. According to experiment results, SVM has better classification accuracy.

Authors (Prasad et al., 2011) proposed a technique for classification of the multispectral satellite images using SVM in land cover and land use sectors. Pre-processing steps include Gaussian filtering and RGB to Lab colorspace image conversion. Segmentation is done using a fuzzy incorporated hierarchical clustering technique. The cluster centroids are subjected to the trained SVM to obtain the land use and land cover sectors. According to the authors, analysis ensures that the performance of the proposed technique is improved compared with the traditional clustering algorithm.

Authors (Da Silva et al., 2013) proposed a methodology for pattern classification from multispectral images acquired by the HSS airborne sensor. Artificial Neural Network Classifiers and Principal Components Analysis have been used. After performing the tests, according to the Kappa index, the Artificial Neural Networks are capable of being employed as pattern classifiers in multispectral images.

(Cetin et al., 2004) collected image data from Landsat ETM+ and Terra ASTER images. Maximum Likelihood (ML) and Artificial Neural Network (ANN) classifiers are used. Image band combinations are given to the neural network for training and the success of the classification. According to the results, the ANN classifier yielded more accurate results than the ML classifier, Artificial Neural Network approach effective way of extracting land cover information using multi-spectral, multi-temporal, and multi-sensor satellite images. ML algorithm dominated road class over the image whilst the ANN classifier was slightly sensitive to inland water class.

Authors (Beeresh et al., 2014) adopted the spectral mixture modeling. Data SMA (Spectral Mixture Analysis) to map coconut land cover. SMA was executed and assessed based on Landsat-8 ETM (Enhanced Thematic Mapper Plus) data. According to the authors, this technique gives more accurate results. It can be used successfully to classify different plant covers in severe agricultural areas. And the method is easy to implement and has a low computational cost.

Authors(Huang et al., 2010) examined three different types of multispectral imaging systems (ranging from low-cost to relatively high-cost, manually operated to automated, multispectral composite imaging with a single camera and integrated imaging with custom-mounting of separate cameras)to support management in agricultural application and production. According to their study: 1) Low-cost systems can also sacrifice performance. 2) High-cost systems such as MS 4100 and TTAMRSS may be more difficult to mount. 3) Practical applications indicated that field shapefile polygon-based triggering was suitable for imaging from fixed-wing aircraft.4) Image processing automation is necessary for processing a large number of images, such as in the case of canal leak detection using 5) manual exposure should be used in imaging instead of automatic exposure.

In this study authors (Islam et al., 2019) represent a multispectral analysis of the natural target behavior of an area. They used satellite LANDSAT 5 TM sensor images (Thematic Mapper). According to the authors, their work showed possible cartography of soil occupation. The spectral classification was done using spectral reduction by the Minimum Noise Fraction (MNF) transformation followed by spatial reduction by the Pixel Purity Index (PPI) and manual identification of the end members using the N-dimensional visualizer which allowed the identification of different minerals and vegetation.

(Zhang et al., 2003) studied the detection of stress in tomatoes by applying hyperspectral remote sensing. Airborne Visible Infrared Imaging Spectrometer (AVIRIS) images with 224 bands were used. They developed an approach using Minimum Noise Fraction (MNF) transformation & Spectral Angle Mapper (SAM) to process the hyperspectral image for the identification of diseased tomato plants. Classification of plants with SAM technique spectra showed that the diseased tomatoes could be separated from the healthy plants while the less infected plants were difficult to separate from the healthy plants. It also demonstrated that the spectra-based classification approach is an applicable method to crop disease identification.

Authors (Vyas et al., 2013) develop canopy level estimation of chlorophyll and Leaf Area Index (LAI) for tropical species using the Hyperion data. Hyperion data were collected with a cloud cover of less than 25%. ACORN 1.5 software is used to collect atmospheric correction. ENVI V.4.6 software was used to subset extraction and image processing. Predictive performances of the developed simple ratios (SRs) gave the best result for the prediction of chlorophyll with the Leave-One-Out Cross Validation (LOO-CV) method. The best results for the prediction of LAI with the LOO CV method were achieved using the ND ratio.

Authors (Sprintsin et al., 2013) represent an approach for low-cost mapping of tree heights at the landscape level. Multi-Spectral space-born images were used. The proposed model was implemented for mapping mean tree height on a per-pixel basis by using high-spatial-resolution satellite imagery. The model integrates parameters related to landscape, tree size, and competition, and determines the mean stand tree height as a function of tree competitive capability. The validation of the model shows a high and significant level of correlation between measured and modeled datasets ($R2 = 0.86$; $P < 0.01$), with almost negligible (less than 1 m) levels of absolute and relative errors.

(Kulkarni et al., 2019) analyzed land Use and Land Cover change for the remotely sensed images using Spectral Angle Mapper Algorithm. The data set was obtained from BHUVAN (NRSC, ISRO) for the period 2008-2016. LISS-3 Images were downloaded for analysis. The classification is Land (Built-up), water bodies (Lakes), Vegetation (Gardens), and Soil (Barren and fertile). Different band combination 4-3-2 and 3-2-1 was used to train the pixels. The result obtained using the satellite images and the accompanying classification algorithms indicate that the percentage of water bodies has drastically shrunk (from 2.9% in 2008to1.8% in 2016) in the area of study.

Authors (Ramchandra & Kumar, 2004) discusses land use and land cover change & analysis techniques. GRASS (Geographic Resources Decision Support System) is used. Multispectral data (1998 and 2002) of the IRS 1C / 1D (Indian Remote Sensing Satellites). The change analysis-based period of four years using supervised classification showed an increasing trend (2.5 %) in an unproductive wasteland and a decline in the spatial extent of vegetated areas (5.33 %).

Authors (Xie et al., 2008) surveyed remote sensing applications in vegetation mapping and the selection of accurate remote sensing products. They also cover, the various techniques of image preprocessing and classification methods. And also discussed how to extract foliage features from space-born images and the results.

This study (Xue et al. 2017) conducted a review for more than 100VIs (Vegetation Indices) and discussed their applicability according to the vegetation of interest, implementation precision, and environment based on hyperspectral and UVA platforms.

In this paper (Ennouri et al., 2019) conduct a review and reveals that it is possible to create new opportunities for scientist and agronomist to explore features of biological spectacles that cannot be accessed through machines and processes, and also make planning and observing crop condition cost-effective.

Authors (Sprintsin et al., 2013) proposed a method that integrates landscape parameters, tree size, and competition factors like age, etc., and determines the mean tree heights by using a combination of landscape, stand, and canopy characteristics and high-spatial-resolution satellite imaginary.

Authors (Macintyre et al., 2020) examine that the Sentinel-2 platform can be used for classifications of target units at considerably higher levels by comparing several multi-temporal feature sets as input to four ML classifiers (SVM, NN, RF, and CT) to separate target classes, and achieved best results with SVM (74%) and NN (72%) classifier compared to RF (65%) and CT (50%).

Authors (Ali-Sisto et al., 2020) presented a height adjustment algorithm that can correct vertical misalignments in Digital Arial Photogrammetry (DAP) data and achieved major increases in the prediction accuracy of key forest variables.

In this study, the author (Kwan, 2019) conduct a review of some current and demonstrative algorithms in change detection using Multispectral (MS) and hyperspectral (HS) images and highlighted their advantages and disadvantages.

In this study researchers (Shi et al., 2020) conduct a study that explores how multi-temporal digital Color-infrared CIR) orthophotos can be used to improve LiDAR (light detection and ranging)-based individual tree species mapping and achieves 69.3% overall accuracy.

Author (Bórnez et al., 2020) have done a broad comparison of vegetation variables and methods to retrieve land surface phenology of Copernicus Global Land products and explored the sensitivity of phenology to Input Vegetation Variable, NDVI (normalized difference vegetation index), LAI (leaf area index), FAPAR (fraction of absorbed photosynthetically active radiation), and FCOVER (fraction of vegetation cover).

Authors (Suneetha et al., 2020) proposed object-based Classification for remote-sensing satellite images. Segmentation, training, and classification of the multispectral image are done using the Convolution Neural Network (CNN).Deimos-2 and Cartosat-1. The Overall Accuracy (OA) was 93.6% and the Kappa coefficient was 87% effectiveness of the proposed method for Deimos-2 Data. Cartosat-1 Data accuracy values were observed as 87.33% and 81%.

Authors (Venkatalakshmi et al., 2005) focused on the classification of RS multispectral images on hybrid clustering. Hybrid clustering includes PSO and K-Means. Classification is done using SVM and ML classifiers. The results of classifiers are combined in the decision fusion center using XNOR Boolean logic. SVM produced 90% accuracy and decision fusion produced 92% accuracy.

Authors (Shnain., 2019) proposed a Support Vector Machine (SVM) used as a supervised classification with the aim of the Minimum Noise Fraction (MNF) method to eliminate the noisy bands to increase the accuracy. Achieved accuracy of 95.23%. The MNF transform method gave a good reduction of the spectral band and reduced the percentage of noise.

Authors (Santosh et al., 2019) present a classification method for an extremely various subtropical landscape at a sub-regional scale). The study area is divided into 4 agricultural regions which include pastures, forest plantations, sugarcane, and annual crops. The overall accuracy was high at the more detailed level (0.84). Many classes that are highly represented in the region, mostly perennials, were well-classified.

Authors (Raeva et al., 2019) introduced the application of UAVs. A total of 12 flights were carried out – 6 with a multispectral camera and 6 with a thermal camera from March to August 2016. This study presents an extended analysis and a reflective approach to the processing. 3 basic indices were computed – NDVI, GNDVI, and NDRE. Thermal maps are also computed based on thermal imagery. The vegetation value indices observed with actual growth of crops as known from reality. The potential of UAV photogrammetry in agronomy and precision agriculture is getting higher.

(Perumal et al., 2010) have matched the performance of various classifiers. They tried both supervised and unsupervised classification and found that the Mahalanobis classifier outperforms even advanced classifiers. This classifier shows the status of considering the data set - classifier relationship for successful image classification and performed the best in classification.

Authors (L. Li et al., 2021) proposed a deep learning semantic template matching framework for remote sensing image registration and achieves a high matching accuracy. The image-matching accuracy in this study is sensitive to the size of reference images.

Authors (Soimarti & Ketcham, 2016) proposed an adaptive hybrid of pixel-based and region-based segmentation for remote sensing. Land-use, water-use, and cloud-use segmentation can be applied to geology exploration. And achieved an accuracy of land-use=89.76%, water use=86.73%, and the cloud-use=82.32%.

(Qin et al., 2018) proposed a classification system by combining location-based social media photos (SMPs) and high-spatial-resolution remote sensing images using deep neural networks and achieved OAA of 78.91 % (with SMP), 71.23 % (without SMP) using FCN and 74.85%(With SMP), 65.72%(without SMP) using CNN.

Authors (Dou et al., 2021) proposed the Deep–shallow Learning (DSL) framework for remote sensing (RS) image classification. A study performs on 3 RS datasets (LandsatOLI, Spot-5, and GaoFen-2) indicate that the DSL effectively results in higher classification accuracy. DSL secures 85.54%, 85.28%, and 75.89% for dataset-1, 2, and 3, respectively.

Authors (Wu et al., 2020) propose a deep neural network, named a classified adversarial network (CAN), for multi-spectral image change detection and achieved 97%,95%, and 78% for 3 different datasets Mingeng, Yandu Village, and Hongqui canal respectively.

The authors (Liang et al., 2020) propose a two-stream remote sensing scene classification architecture by combining a Convolutional Neural Network (CNN) and Graph convolutional network (GCN) and applied on the AID dataset and NWPU-RESISC45 dataset. The model achieved an overall accuracy of 96.70% and 94.93% for the AID dataset and NWPU-RESISC45 achieved an accuracy of 90.75% and 92.87%.

Author (Remi, 2018) proposes a framework based on Orfeo Toolbox (OTB) and TensorFlow (TF) libraries and effectively RS images using the framework and showed decent computational efficiency, without any restriction on image sizes and hardware configuration.

Authors (X. XU et al., 2021) Experimental classification is based on pixel and object-based classification and achieves 87% accuracy in classification scenes from satellite images.

Authors (Yi Lv et al., 2021) propose a remote sensing image target detection deep learning-based DFS algorithm and compare it with YOLOv2. The data set used in the experiment derives from GoogleEarth and detects a total of 6 objects airplanes, boats, warehouses, large ships, bridges, and ports. Achieved OAA of 85% using DFS and YOLOv2 achieved 72% accuracy.

Authors (Yang et al., 2020) studies the change in land cover in Shenyang urban area. The maximum likelihood method is used for classification in the experiment.

Images obtained by SPOT, ASTER, and Landsat TM. And achieved OOA of 85.33%, 86.67%, 88.33%, and 86.38% for the years 1989,2000,2010 and 2016 respectively

Authors (Elaalem et al. 20113) Studies the performance of the supervised classification. The study used a SPOT 5 satellite image. Maximum likelihood classification (MLC) was used. Study areas were classified into 5 homogeneous (mixed pixels) and 4 heterogeneous (unmixed pixels) land cover classes. According to the authors, 65 % of the study area was classified as heterogeneous and 25 % of the study area was classified into homogeneous land cover classes.

In this study (Mahata et at., 2019) perform LULC classification on the Barakar River Basin (BRB) in West Bengal and Jharkhand states. The Landsat-5 (TM) images were taken for the years 2005, 2010, and 2015. Overall accuracy is 99.99% for 2005 and 2010, and 100% for 2015, with the BTEN classifier and kNN, achieving accuracy at 99.09%, 98%, and 97.89% accuracy respectively. SVM achieved OAA 99.40% and 94.28% for 2005 and 2010 respectively.

Authors (Yang et al., 2019) proposed a quantum entanglement algorithm to improve remote sensing image classification because quantum entanglement has the characteristics of clustering. Kunming city in the Yunnan region is used as the research area. The study compares the classification method with the traditional remote sensing classification method by using the 02C image data of yuanyuan1. The model converts the classification process image into a random self-organization process of quantum particles. The state configuration formed by the entanglement of quantum particles evolves with time and finally joins to an average probability distribution.

In this study (Jenicka et al., 2014) proposed a multivariate texture model (MDLTP) with four discrete output levels for effective classification. Land Use/Land cover classification of the remotely sensed image has been performed using the proposed multivariate texture model MDLTP (Multivariate Discrete Local Texture Pattern) and SVM classifier. Total of 93.46% accuracy was achieved.

Authors (Marghany et al., 2009) presented the mapping of geological features in the United Arab Emirates (UAE) using multispectral remotely sensed data. Image enhancement contrast, stretching, and linear enhancement were performed to acquire visualization. An automatic detection algorithm of Canny was performed to extract linear features, lineaments, and fractures. Digital Elevation Model (DEM) was performed by using a fuzzy B-spline algorithm to map spatial lineament variations in a Three-Dimensional (3D) visualization. Tool for 3D geological features mapping established by integration of the canny algorithm with DEM which was generated by using fuzzy B-spline.

A researcher (El-Khoribi, 2008) proposed a new training algorithm for the discrete HMT. The algorithm uses sufficient statistics of the HMT generative model to form a fixed-length training vector to be used in linear discriminant classifiers (like SVM). The algorithm proves a great amount of perfection over the baseline HMT when applied to land cover images.

In this study authors (Kopco et el., 2013) presents an analysis of the performance of ARTMAP neural networks. Fuzzy, Gaussian, and Extended Gaussian classifiers were compared. Extended Gaussian classifier's best performance.

Authors (Hashemi-Beni & Gebrehiwot, 2020) used deep learning methods for remote sensing image classification for agriculture applications. The U-Net and FCN-8s models were used to classify the image into three classes (soil, crops, and weeds). The U-Net and FCN-8s models achieved an overall accuracy of 75.2% and 72.1%. FCN8s model achieved 75.1% and U-net achieved 66.72% accuracy in detecting weeds The U-net achieved 60.48% accuracy and FCN-8s achieved 47.86% accuracy respectively.

The researcher (Nurwauziyah, 2018) compares the performance of the Decision Tree, SVM, and k-NN classification method to find. The study shows the SVM method performs better than the Decision Tree and k-Nearest Neighbor method. SVM achieved overall 78.6% and 83.30% accuracy for high and low-resolution satellite imagery respectively.

The author (Guliyeva, 2020) used satellite images taken from satellites AZERSKY, RapidEye, and Sentinel-2B for Land Use/Land Cover supervised and unsupervised classifications performed on images. This study was carried out based on the software application of ArcGIS Pro 2.5. The kappa coefficient and overall accuracy were used to assess the classification accuracy. SVM achieved an overall accuracy of 93.65 % in AZERSKY and 81.25 %, and 92.06 % in RapidEye and Sentinel respectively. MLC achieved 93.85%, 92.19%, and 84.37%. RTC achieved 95.31%, 90.62 %, and 84.12% in AZERSKY, RapidEye, and Sentinel respectively.

In this study authors (Nanyam et al., 2011) applied unsupervised, supervised, and hybrid classification methods for land use and land cover classification to determine the best-suited method for classification. Maximum likelihood used supervised classification used and minimum distance classifier for better accuracy. And in Hybrid classification, the features of both supervised and unsupervised classification were combined. Supervised classification achieved 85.00 % accuracy unsupervised classification achieved 81.25% and Hybrid classification achieved 82.5 %.

Authors (Lowe & Kulkarni, 2015) classified multispectral images using a maximum likelihood classifier, neural network, support vector machine (SVM), and Random Forest and analyzed two Landsat scenes acquired with Landsat-8 OLI. And compare their results. And according to the authors, the random forest gives a better result than other supervised classifications. The overall accuracy of Random Forest is 96.25%, Neural Network 76.87%, SVM 86.88%, and Maximum likelihood 83.13%.

Authors (Chitwong et al., 2004) compare the result using a back-propagation neural network (BPNN), and maximum likelihood classifier with principal component analysis (MLC-PCA). Classification using the three-layer back-propagation neural network with principal component analysis (BPNN-PCA) is better than MLC-PCA.

In this study, researchers (Cao et al., 2017) propose a difference image (DI) creation method for unsupervised change detection in multi-temporal multispectral remote-sensing images based on deep learning. The proposed model tested on three data sets and performed better compared to the traditional pixel-level and texture-level-based approaches.

In this study author (Suneetha et al., 2020) proposed object-based Classification for remote-sensing satellite images. Segmentation, training, and classification of the multispectral image are done using the Convolution Neural Network (CNN). Deimos-2 and Cartosat-1. The Overall Accuracy (OA) was 93.6% and the Kappa coefficient was 87% effectiveness of the proposed method for Deimos-2 Data. Cartosat-1 Data accuracy values were observed as 87.33% and 81%.

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The author (Shanin) used Support Vector Machine (SVM) supervised classification with the aim of the Minimum Noise Fraction (MNF) method to eliminate the noisy bands to increase the accuracy. Achieved accuracy of 95.23%. The MNF transform method gave a good reduction of the spectral band and reduced the percentage of noise.

The author (Hichri et al., 2012) proposes to solve the CD problem using interactive segmentation. A support vector machine (SVM) classifier is used for remote-sensing image classification. Two interactive segmentation methods combination of SVM and MRF (Markov random field) methods and a combination of SVM and LS (level-set) methods were used. The experimental results achieved accurate CD results with minimum interaction.

Authors (Hasan et al., 2019) proposed a model for the classification of hyperspectral images using Support Vector Machine (Linear SVM and RBF (radial basis function) SVM) and convolutional Neural Networks (CNN). The proposed model contains steps like (1) dimensionality reduction with principal component analysis (PCA) (2) classification by using SVM (3) the extraction using CNN (4) comparison between SVM and CNN. 98.84 % accuracy was achieved in the SVM-RBF model, and 94.01% accuracy is achieved in CNN.

The authors (Yan et al., 2015) used Wangyedian Forest Farm in Inner Mongolia as the study area. Back propagation artificial neural network (BPANN) for classification. The proposed model achieves an accuracy of 95.36%.

The author (El-Khoribi, 2008) proposed an approach to the supervised classification of multispectral images. The training algorithm for the discretely hidden Markov tree (HMT) System is applied and tried on Landsat 7-band images having eight different land cover classes. Experimental results show superior performance in land cover classification.

Authors (Dian-lai et al., 2020) proposed deep neural networks (DNN) for the classification of medium-resolution remote sensing images and achieved high accuracy of 96.53% in land cover classification in Miyun District.

Authors (Mahdianpariet al., 2018) present deep learning tools for the classification of wetland classes for Canada country and examine DenseNet121, InceptionV3, VGG16, VGG19, Xception, ResNet50, and InceptionResNetV2. The classification results are compared with Random Forest and Support Vector Machine. InceptionResNetV2, ResNet50, and Xception achieved 96.17%, 94.81%, and 93.57%, respectively. Support Vector Machine and Random Forest achieved an accuracy of 74.89% and 76.08%, respectively

Author (Ara, 2021) applied land use land cover classification in the eastern Sone River Basin of Bihar, India. The LandsatETM+satellite dataset was used for classification. Image processing software ERDAS imagine 9.0 was used. Maximum Likelihood (ML) Supervised classification was used and obtained an accuracy of 80% with kappa statistics of 0.749.

Authors (Ben-Romdhane et al, 2016) proposed a spectral-spatial method that contains multilevel segmentation, feature analysis, and ensemble learning methods. Dataset acquire from habitat maps published by the Environment Agency-Abu Dhabi. The spectral-spatial method achieved an accuracy of 96.41% and SVM achieved 94.17% of accuracy.

Authors (Minaei,& Kainz, 2016), examine the LCLU classification of the watershed for the years 1972, 1986, 2000, and 2014, using Landsat MSS, TM, ETM+, and OLI/TIRS images. LCLU maps created using pixel-based classification methods and Geographic Object-Based Image Analysis (GEOBIA) with the data-mining and J48 machine-learning algorithms were used. The overall accuracy ranged from 89% to 95%.

Researchers (Haack, 2015) employed four different classification methods. Traditional visual interpretation, segmentation, visual labeling, digital clustering, and supervised signature extraction with the application of a decision rule followed by analyst editing. Accuracies range from 85 to 89%.

Authors (McIver& Friedl, 2002) has applied remote sensing image information extraction and land utilization coverage classification. In America, USGS and EPA, etc. departments have united taken out the USA land coverage database plan, and decision tree classification technology has not only applied in land classify but also urban density information and crown layer density information extraction. The land classify precision has reached 73%-77% and urban density information extraction precision has reached from 83% to 91% and tree crown precision has reached 78%-93%.

The author (Sanusi et al., 2019) uses CNN to classify remote sensing images using the Alexnet dataset and then fine-tuned images. The proposed model achieved a high level of classification accuracy of 99.99% against CNN with an accuracy of 99.91%, stacked auto-encoders SAE with an accuracy of 93.98%, and deep belief network DBN with an accuracy of 95.91%.

Authors (Naushad et al., 2021) use VGG16 and Wide Residual Networks (WRNs), by replacing the final layer with additional layers, for LULC classification and achieved accuracy from 98.57% to 99.17%.

Authors (Danneels et al., 2007) developed a procedure for the detection of landslides using multi-spectral remote sensing images. The maximum likelihood classification method and the results are compared with ANN classification. Segmentation double threshold technique in combination with histogram-based thresholding.

Authors (Sanusi et al., 2019) use CNN architectures in Alexnetand conclude that the model achieves a high level of accuracy. Proposed CNN achieved 99.99% as against the existing conventional CNN with an accuracy of 99.91%, stacked auto auto-encoders SAE with an accuracy of 93.98%, and deep belief network DBN with an accuracy of 95.91%.

The author (Choubik et al., 2021) proposed an automatic earthquake detection model based on the FCN classifier using STanford EArthquake Dataset (STEAD) and achieved an accuracy of 83% on raw data. The model detects 75 out of 77 earthquakes.

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