

Article

Concentrated Stream Data Processing for Vegetation Coverage Monitoring and Recommendation against Rock Desertification

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Abstract: The vegetation covering regions is confined due to deforestation, mining industries, and environmental factors. The intensified deforestation and industrial development processes impact the vegetation coverage and fail to meet the food demands. Therefore, accurate monitoring of such regions aids in preventing adversary processes and their plant extinction. The monitoring process requires accurate data collection and analysis to identify the root cause that can be due to human/climatic/environmental changes. This article introduces a concentrated stream data processing method (CSDPM) assisted by an extreme learning paradigm. The different causes are analyzed using the extracted features in different learning perceptron layers. In this learning, the accumulated data is analyzed for similar features and trained for the consecutive or lagging input data streams. The monitoring process concluded with the learning output by classifying the plant extinction reason. Therefore, the identified reason is addressed through official policies with new recommendations or alternate vegetation improvements. More specifically, the data concentrated towards deforestation are the fundamental data required for feature matching. The features are initially trained from the existing datasets and previously acquired data from the converted landscapes. This proposed method is analyzed using the metrics analysis rate, analysis time, recommendation rate, and complexity.

Keywords: data processing; extreme learning; feature analysis; matching; vegetation coverage



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1. Introduction

Vegetation is an area that plants cover. Vegetation is an assemblage of plant and ground cover that they provide. Vegetation coverage is calculated based on the leaf area index (LAI), which provides the correct vegetation coverage area percentage. Vegetation coverage monitoring systems are widely used for analysis and prediction [1]. Satellites and wireless sensors are used in monitoring systems that provide correct information for analysis. Satellite imaging produces optimal data for monitoring systems that reduce latency levels in identification and calculation processes [2,3]. Normalized difference vegetation index (NDVI) is identified based on data provided by satellites and sensors. Single-date classification detects the correct index and details from NDVI images [4]. NDVI images improve the accuracy ratio in vegetation coverage monitoring systems. Vegetation coverage monitoring is mostly used to indicate the effects required for ecological environment management systems. The main aim of vegetation coverage monitoring is to improve the quality assessment level of the environment and ecological systems [5,6].

Plant extinction leads to severe ecological damage and damage to other organisms. Plant extinctions mostly occur due to invasive species, loss and degradation of habitat, nitrogen pollution, deforestation, and climate change [7]. Plant extinction data analysis is an important task to perform in the environmental management system. Plant extinction is calculated based on fossil records that provide correct details about plants and species [8]. Plant extinction data analysis is mainly used to identify the species that are about to become extinct from the environment. Data analysis produces accurate information related to the causes and types of species. Information about plants and species is stored in a

secure database containing monitoring and analysis data [9]. Data analysis identifies the major diversity loss ratio of the environment that produces necessary information for further assessments and recovery processes. Data analysis systems detect the correct plant extinction coefficients of vegetation based on factors and features of species [10]. Satellite images are used here to provide appropriate information about species and plants. Satellite images reduce computation time and energy consumption levels, which enhances analysis systems' performance and efficiency [11].

Vegetation land area analysis is an important task to perform in the environment and ecological management systems. Vegetation land areas are evaluated and calculated based on space images that are generated via satellites [12–14]. Normalized difference vegetation index (NDVI) images are produced by satellites containing accurate information about vegetation lands. Machine learning (ML) techniques are used in land area analysis systems to improve accuracy in detection and prediction processes [15]. The support vector machine (SVM) algorithm is commonly used in land area analysis systems. The classification method is used in SVM to identify the correct regions and amounts of land covered with vegetation [16]. NDVI produces factors and patterns of the area from space that reduce the latency ratio in identification and classification processes. The random forest regression (RFR) method is also used in vegetation land area analysis systems. RFR predicts correct meteorological factors and features of vegetation lands that provide relevant information for evaluation and calculation [17]. The back propagation neural network (BPNN) algorithm is used in vegetation land area analysis. BPNN uses NDVI images to obtain information, providing indexes and plant species patterns. BPNN improves data analysis systems' overall performance and efficiency [18–20].

2. Related Works

Liu et al. [21] introduced a dual-channel fully convolutional network (D-FCN) for land cover classification. D-FCN is mainly used to identify images taken via channels' color, shape, and texture. Multi-feature information in D-FCN provides proper data for classification and detection processes. The proposed D-FCN reduces the complexity ratio in computation, which enhances the performance and efficiency of land cover classification.

Zafari et al. [22] designed a random forest kernel (RFK) for land cover classification. A support vector machine (SVM) is used here to detect the number of features for the classification process. Random forest (RF) structures and features are analyzed using SVM, which provides optimal information for classification. Experimental results show that the proposed RFK method maximizes accuracy in land cover classification, improving the systems' effectiveness.

Zerrouki et al. [23] developed a new desertification detection method using a variational autoencoder (VAE). The proposed method's main aim is to identify land cover changes. The feature extraction technique here extracts important features and patterns of lands based on satellite images. Feature extraction detection of both spatial and temporal multi-features from images reduces latency in identification. The proposed VAE model achieves high accuracy in desertification detection, enhancing the analysis systems' performance and efficiency.

Gbodjo et al. [24] introduced a multi-branch convolutional neural network (CNN) approach for Multisensor Land Cover Classification (MSLCC). Per-source encoders identify important features and input signals from the database. CNN is a deep learning approach that uses encoders to predict information for classification. CNN maximizes classification accuracy, which improves analysis systems' efficiency level. The proposed CNN approach reduces the computation complexity ratio, improving the reliability and feasibility of land cover classification.

Manninen et al. [25] designed a soil moisture observation approach using synthetic aperture radar (SAR) data for the heterogeneous subarctic catchment. SAR provides necessary information with high-resolution images that reduce latency in classification. Soil moisture ratios are calculated based on forest land cover and the condition of forests.

Compared with other approaches, the proposed approach achieves high accuracy in the prediction, which increases the performance and significance levels of the systems.

Belda et al. [26] proposed decomposition and analysis of time series software (DATimeS) to detect gap-filling and vegetation phenology trends. The Gaussian process regression algorithm is used here to identify features and patterns of vegetation. Gap-filling solutions provide the necessary information for identification and classification processes. The proposed DATimeS method improves accuracy in the gap-filling prediction that maximizes the performance of systems.

Charbonneau et al. [27] introduced a spatially explicit process-based grid model named DOONIES for coastal dune vegetation. DOONIES mainly aims to identify abiotic and biotic processes of vegetation growth in coastal areas. Patterns, features, and factors for plant species are detected via information stored in a database. The proposed DOONIES model achieves high accuracy in vegetation cover areas that improve the dynamic of coastal restoration management systems.

Daryaei et al. [28] developed a new fine-scale vegetation detection method using unmanned aerial vehicles (UAV) and sentinel-2 data. A random forest land cover classification method is used here that utilizes UAV data. High-resolution UAV and sentinel-2 data are used here that reduce unwanted time consumption levels in identification. Compared with other methods, the proposed method improves classification accuracy, reducing the complexity ratio in further management processes.

Zhou et al. [29] introduced a new evaluation model for ecosystem service value prediction. Normalized difference vegetation index (NDVI) images are used here that provide necessary information for the evaluation model. The principle component analysis (PCA) approach is also used in the evaluation model to reduce correlation among images and patterns. The proposed evaluation model provides better performance and feasibility ratios in ecosystem management systems.

Achour et al. [30] developed a landslide susceptibility model based on a machine learning (ML) approach for land degradation neutrality (LDN). A random forest (RF) algorithm is used here that validates necessary information for further processes. RF reduces latency and energy consumption levels in computation. Factors and features of lands are analyzed via RF, providing accurate data for the evaluation process. The proposed model provides the correct information about landslides for management and analysis systems.

Thomsen et al. [31] developed a new vegetation dynamic monitoring system for tidal marsh restoration sites. Remote sensing and integrating field methods are used here to obtain feasible information for monitoring systems. Through wireless sensors, soil sampling and vegetation colonization are detected based on remote sensing. Unoccupied aircraft systems (UAS) imagery provides data that reduce latency in classification and identification. The proposed monitoring system maximizes effectiveness and performance levels in the restoration process.

McNellie et al. [32] proposed an artificial neural network (ANN) model for pattern prediction in plant functional groups. The main aim of the proposed model is to predict patterns and features of plants and species. ANN is used to verify types and vegetation classes that reduce computation complexity. The proposed model achieves high accuracy in the prediction that enhances the performance ratio in the landscape-scale disturbance.

Satti et al. [33] proposed a new climate change prediction method on vegetation using moderate-resolution imaging spectroradiometer (MODIS) data. Snow cover prediction is a complicated task to perform in environmental management systems. Both spatial and temporal parameters are detected from MODIS that produce necessary information for climate change prediction. Land surface temperature (LST) and soil moisture level are calculated based on MODIS data.

Xu et al. [34] analyzed the relationship between the karst rocky desertification ground monitoring and remote sensing observation using the environmental reference system. The system's intention is to minimize the uncertainty issues in the desertification process.

This process uses the Guizhou–Guangxi Mountain region in China for analyzing the rocky desertification. The collected information is processed by moderate-resolution imaging spectroradiometer (MODIS). The algorithm predicts the non-linear relationship between the regions to perform the desertification. The method successfully investigates the vegetation region characteristics such as temperature, albedo, and surface, which improves the overall desertification process with minimum cost.

Guo et al. [35] introduced the Optimal Monitoring Model (OMM) to perform the rocky desertification by creating the feature space model from the LANDSAT_8 OLI images. Here, the desertification process was performed by creating two models such as the point-to-line model and point-point model. During the analysis, vegetation area information is collected, which is processed to create the feature space model. The point-line model is applied to analyze the large-scale region and the rock bare index is computed for each feature space. From the feature space, the rocky desertification is identified with 88.5% of precision compared to other methods.

Dai et al. [36] assessed the karst rocky desertification process from the unmanned aerial images in the Yunnan Province in China. Initially, the unmanned aerial images are collected, which are processed by regression model to extract the back rock region. Then, the images are analyzed to extract the band reflectivity information, which helps to predict the rocky desertification process with up to 0.865% accuracy.

3. Proposed Concentrated Stream Data Processing Method

The intensified process of vegetation coverage and rock destruction is controlled based on mining industries and deforestation. Despite progress in identifying the root cause affecting the vegetation coverage and complexities in meeting the food demands, due to accurate data collection, human, climate, soil, vegetation, and environmental changes have not been mentioned in many conditions. A major objective in concentrated stream data processing for vegetation coverage monitoring and recommendation against intensified deforestation and industrial development processes is accurate monitoring of such regions, reducing adversary processes and their plant extinction. Concentrated stream data processing uses the stream processing procedure that analyzing each piece of data. Instead of patch processing, here data point processing covers the entire vegetation region. This streaming process is able to analyze the large volume and variety of data, which helps to minimize the computation difficulties. Due to the effective utilization of the streaming data procedure, this helps to improve the overall desertification process with minimum computation difficulties.

Geo-hazards severely buried and damaged a large area of vegetation coverage, and rock destruction due to plant and rock debris maximizes the porosity of such regions. These geo-hazards can be identified through geographical data and image data analysis to detect lag in performing the feature mapping. Intensified deforestation and industrial development processes with high porosity are specifically unstable. The accurate monitoring of that region reduces their plant extinction and improves the accuracy of data collection and analysis. The proposed method is schematically represented in Figure 1.

Due to growing food demands and adversary processes, deforestation, landscape monitoring, and environmental factors are becoming unstable. Amid challenges in CSDPM using extreme learning, existing datasets and deforestation data are analyzed to identify similar features. Similar feature analysis is conducted in this proposed method for achieving maximum food demands and vegetation coverage through extreme learning. The features of an Extreme Learning Machine (ELM), a single-layer non-iterative learning model, are experimentally verified and appropriate for real-time applications. The accumulated data are analyzed for similar feature identification and trained for the sequential and lagging input streams that require diverse feature extraction. Therefore, regardless of the vegetation coverage and maximum food demands, lagging in input data streams and feature matching are the prominent computations. CSDPM focuses on this computation by monitoring overall vegetation coverage regions with feature extraction through official

policies with new recommendations. In this proposal, the identified feature extraction reason is noticed through a new policy with recommendations or modified vegetation improvements that are administrable for feature matching and their plant extinction with the available vegetation landscape.

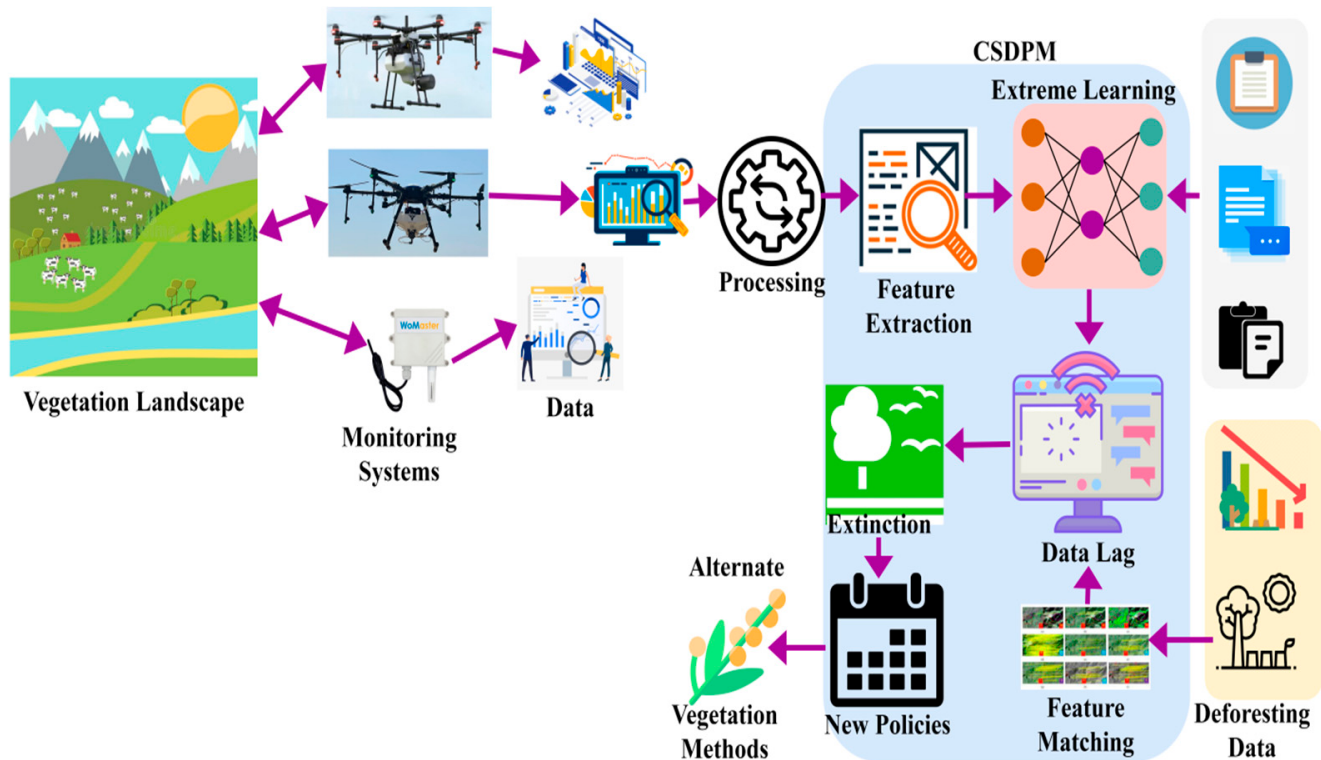


Figure 1. Proposed method representation.

The vegetation landscape is continuously monitored through accumulated data processing and analysis using satellites, sensors, etc. The proposed method operates between vegetation landscape monitoring and recommendation. In this method, adversary processes and their plant extinction for the vegetation coverage and rock desertification assessment are easier for satisfying accurate data collection output for the varying layers and regions. Further, this concentrated stream data processing aims to reduce the complexity and maximize the analysis rate and time. The proposed method minimizes the recurrent data lags and their plant extinction. The extreme learning output is used for classifying the feature extraction reason and data concentration towards deforestation and landscape to meet the food demands and vegetation coverage. The initial vegetation coverage region is monitored through geographical means, and image data are computed as in Equation (1).

$$\max_{i \in at} V_L \forall Geo_{data} = Image_{data}, \quad (1)$$

$$\min_{j \in Geo_{data}} at_{ij} \forall V_L, \quad (2)$$

Such that

$$at_{ij} = at_{Geo_{data}} - at_{Image_{data}}, \quad (3)$$

$$\min_{i \in at} D_c \forall i \in M_S \quad (4)$$

In Equations (1)–(4), the variables $V_L, Geo_{data}, Image_{data}$, and at are used to denote the concentrated stream data processing based on the i th row and j th column of the intensified deforestation and landscape image pixels analysis at any time at . The accurate data collections D_c and monitoring systems M_S are used for identifying vegetation cov-

erage regions and rock desertification in an open environment. In the next analysis, the variables ar , $at_{Geo_{data}}$, and $at_{Image_{data}}$ denote analysis rate, geo data accepting time, and image accepting time, respectively. The third objective of this proposed method is to minimize the adversary processes, and their plant extinction is represented using the condition $D_c \forall i \in M_S$. If $L = \{1, 2, \dots, l\}$ is the set of varying layers in the vegetation landscape, then the number of data processing points in the analysis time at is $Geo_{data} \times at$, whereas in the geo data analysis it is $L \times Geo_{data}$. The analysis for D_c is illustrated in Figure 2.

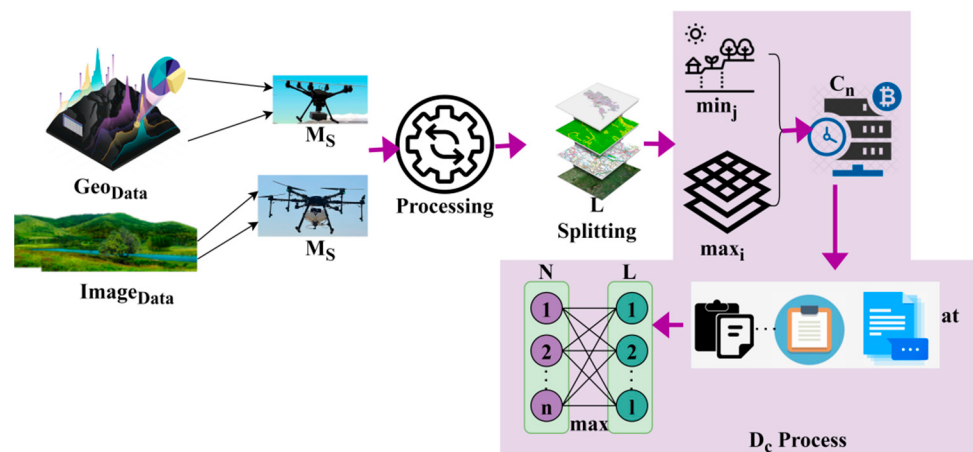


Figure 2. Analysis for D_c .

The inputs from Geo_{data} and $image_{data}$ are analyzed by categorizing them into L . The min_j and max_i as in Equation (1) are the prime classifications for maximizing C_n . Considering $n \in N$, the at is classified between i and j . This relies on the available data; however, the classification for learning takes the maximum possibilities for $L \times Geo_{data}$ and $Geo_{data} \times at$, such that $L \times at = \frac{1}{Geo_{data}^2} \forall n$ is used for D_c processes. Therefore, $i \in M_S$ relies on the maximum data accumulated for V_L (refer to Figure 2). For the overall environmental factor analysis, $L \times Geo_{data}$ and $Geo_{data} \times at$ are considered for accurate data analysis based on vegetation coverage and rock destruction. The plant extinction and adversary processes are feasible through data lag and feature mapping in the following vegetation coverage. In this process, the classification of different learning perceptron layers using feature extraction is prominent to identify lagging in input data streams. The food demand is the capacity C_n of the n vegetation landscape alongside environmental factors; the analysis time needed for accumulated data processing is the computing factor for improving the vegetation coverage monitoring and recommendations for such regions. The classification of the extraction reason is addressed in the available N vegetation landscape and is processed using an extreme learning paradigm. Later, depending on the identified feature extraction reason, the similar feature analysis is the improving factor. Based on the classification process, the various learning perceptron layers are analyzed using the feature extracted as the prevailing sequence for computing feature matching. The perceptron layers can change any time based on climate/human/environmental changes. The accumulated data are analyzed for similar features and trained for the consecutive important factors in the following manner.

3.1. Continuous Data Processing

In this data processing, the analysis of $Geo_{data} \times at$ for all the vegetation landscapes based on C_n is the data collection estimation. The probability of data processing (ρ_{dp}) continuously is computed as

$$\rho_{dp} = (V_L + M_S - 1)^{i-1}, \quad (5)$$

where

$$\rho_{V_L} = \left(1 - \frac{\text{Geo}_{data} \in n}{\text{Geo}_{data} \in at}\right), \quad (6)$$

As per Equations (5) and (6), the continuous data processing through different monitoring systems maintains the constant probability of n vegetation covering regions. So that there are no adversary processes, the accurate monitoring of deforestation and landscape identified in such regions is computed as in the above equations. Therefore, the collection of data for ρ_{dp} follows

$$\text{Collection}_{data}(n) = \frac{1}{|\text{Geo}_{data} + \text{Image}_{data} - 1|} \cdot (\rho_{dp})_{ij}, \quad (7)$$

However, the accurate data collection for n vegetation landscapes is computed as per Equation (7), as it is valid for both Geo_{data} and Image_{data} analysis identifying the root cause due to vegetation coverage and rock destruction. The different causes are analyzed based on different learning perceptron layers and are processed using feature extraction at any time intervals at for reducing the impact of vegetation coverage based on the condition $(L \times \text{Geo}_{data}) > (\text{Geo}_{data} \times at)$. The continuous data processing is presented in Figure 3.

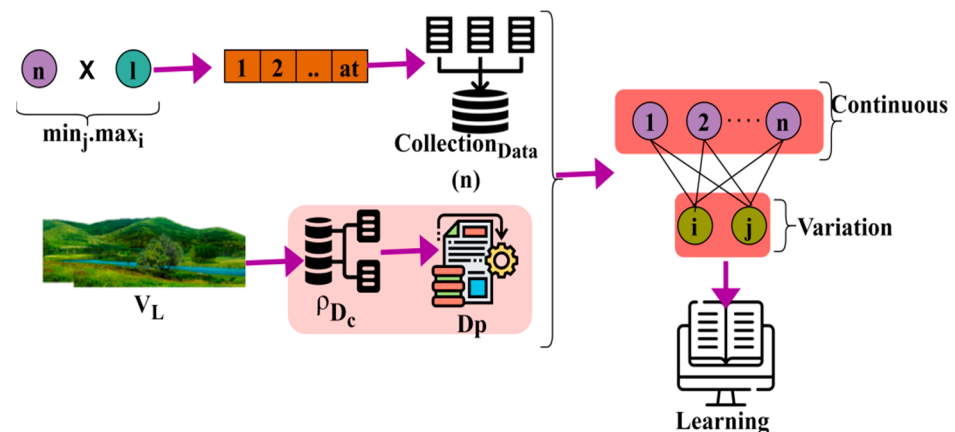


Figure 3. Continuous data process.

The $N \times L$ with distinguishable at is required for $\text{collection}_{data}(n)$. The input V_L is used for $D_C \forall (\text{Geo}_{data} \times at)$, which is used for ρ_{dp} , such that new or existing at is performed. If this ρ_{dp} is true (maximum), then D_c is required for figuring out i and $j \forall n$. If this is sequential (i.e., $n \in at$), then it is continuous; otherwise, a variation is observed. These combinations are used by extreme learning for identifying feature matching and data lags (Figure 3). The concentrated stream data processing is performed with the help of an extreme learning process. Hence, in identifying root cause for deforestation and landscape using the condition $L > at$, ρ_{V_L} is less to satisfy Equations (1), (2), and (4). Contrarily, the output for similar feature analysis is the prolonging ρ_{V_L} and, therefore, the analysis time for accumulated data results in data lag.

3.2. Extreme Learning Process

In this extreme learning paradigm, the lagging input data stream condition of $L > at$ is maximum, and hence the accurate data collection of identifying the different causes is time-invariant. Along with the varying environmental factors at a constant time for N , the data lag and plant extinction occurrence are the identifying root causes here. The probability of extreme learning (ρ_{E_L}) performance is computed as

$$\rho_{E_L} = \frac{\text{Exf. Collection}_{data}(n) \cdot \left[\left(\frac{\text{Geo}_{data} - \text{Image}_{data}}{n} \right) \rho_{V_L} - \frac{D_{lag} * \text{ext}}{at \text{Image}_{data}} \right]}{F(M) * n}, \quad (8)$$

Such that

$$F(M) = \int_0^{at} Ex_f^{at-1} (ext - 1)^{at-1} d(at) \quad (9)$$

$$F(M) \in \text{Collection}_{data}(n) = \int_1^{Gep_{data}} Ex_f^{at-1} \cdot \frac{D_{lag}}{at_{Image_{data}}} (1 - \rho_{dp})^{at-1}, \quad (10)$$

In Equations (8)–(10), the variable $F(M)$ illustrates the feature matching for at instances. From the overall data processing, the plant extinction and adversary processes are identified with the help of vegetation landscape images, and data for the n analysis are the data lagging problem. The data collection based on vegetation landscape information and images, as in the above analysis, requires high analysis time, thereby maximizing the complexity. The learning process is illustrated in Figure 4.

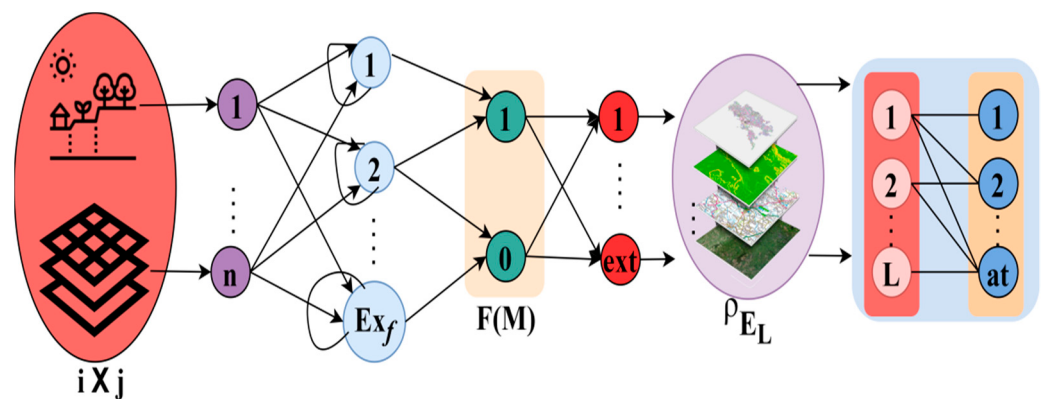


Figure 4. Learning process.

Extreme learning is performed using distinguishable L for $n \in Ex_f$. This generates two possibilities (i.e., 1 (or) 0 for $F(M)$). If the $F(M)$ is successful, then ext is used for validating ρ_{EL} , otherwise at is forwarded in L . Considering the forward $L \forall at$ the ρ_{EL} varies, and then $i \times j$ is updated for maximum and minimum. Depending on the available Ex_f , the $collection_{data}(n)$ is increased (refer to Figure 4). From the data analysis, if identifying similar features in the extraction process, the learning is trained for the consecutive process, and lagging in data streams is the identifiable factor in the proposed method. This factor is addressable using an extreme learning process to mitigate the impacts of intensified deforestation and industrial development through a monitoring process. The following session represents the extreme learning output by classifying the feature extraction reason for the similar feature identification in data processing to mitigate the above-discussed problems.

3.3. Feature Matching Using New Recommendation

The data processing output is concluded with a monitoring process for classifying and extracting features that rely on extreme learning. It aids in meeting the maximum food demands for both geographical data and images of vegetation landscapes. The existing dataset matches the resolving factors using extreme learning. The perceptron layers depend on different causes for analyzing the data lagging and plant extinction probabilities at a similar time of accurate data collection. Hence, the perceptron layers for vegetation landscape improvements are changed and follow new recommendations with official policy to avoid plant extinction. The plant extinction of rock desertification is defined in deforestation and landscape by computing n probability and accurate data processing for

increasing analysis time. The first feature matching relies on maximum data lag (D_{lag}) and $F(M)$ as

$$F(M, D_{lag}) = \left[Geo_{data} - \left(\frac{ext}{at_{Geo_{data}} + at_{Image_{data}}} \right) \times \frac{1}{n} \right] - Collection_{data}(n) + 1, \quad (11)$$

Such that

$$n = \sum_{i \in at} \sum_{j \in Image_{data}} at_{ij} - \sum_{Q \in Geo_{data}} at_Q, \quad (12)$$

$$= \sum_{i \in at} Collection_{data}(n) - \rho_{dp}, \quad (13)$$

Using Equations (11)–(13), the maximum data lag in the vegetation coverage process depends on data processing and feature extraction, as in ρ_{VL} and $Collection_{data}(n)$. Here, the chances of identifying the root cause are computed as

$$\rho_{VL}(at/ext) = \frac{1}{\sqrt{2n}} experssion \left[\frac{Geo_{data} - \rho_{VL}}{\delta} \right] \quad (14)$$

where

$$\delta = Geo_{data} - \rho_{VL} * n, \quad (15)$$

Based on the probability of vegetation landscape, the aim is to compute L and at to reduce the analysis time and, therefore, the actual Geo_{data} is given as

$$Geo_{data} = \max \left[\frac{\rho_{EL}}{Collection_{data}(n) + \rho_{VL} - ext} \right], \quad (16)$$

By using Equation (16), the alternate vegetation improvement or new recommendations with official policy are computed, and the layer changing in the vegetation landscape is analyzed at any time interval for both Geo_{data} and $Image_{data}$. The lag estimation using extreme learning is illustrated in Figure 5.

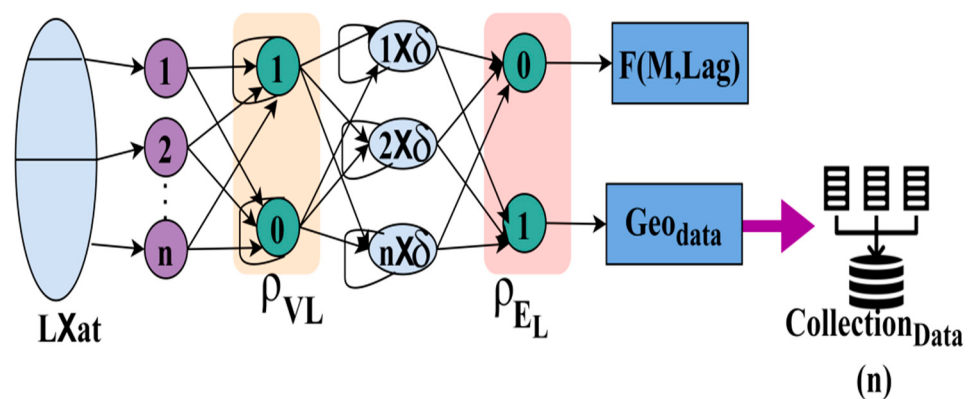


Figure 5. Extreme learning for lag estimation.

The $L \times at$ (post output) is used for designing the extreme learning for ρ_{VL} . If $\rho_{VL} = 0$, then $F(M, Lag)$ is estimated for $(M \times \delta) \forall n \in N$; otherwise $Geo_{data} \in n$ is used for collecting D_C . Therefore, the continuous processing for Geo_{data} is used for ρ_{EL} , such that the $F(M)$ is performed. This is non-recurrent until $L \times at$ identifies min_j and max_i . If the identification is accurate, then $(n * \delta)$ is used for Geo_{data} extraction (Figure 5). The excluding environmental factor based on $[Geo_{data} * F(M, D_{lag})]$ is the maximum monitoring process requiring feasible data collection, so the analysis time for the intensive process of vegetation coverage and rock destruction is demandingly high. The adversary process monitors $(Geo_{data}, Image_{data})$ and $(Go_{data_{at-1}}, Image_{data_{at}})$ are based on analysis time from the

vegetation coverage and rock destruction. The probability of ρ_{V_L} , ρ_{d_p} , and ρ_{E_L} is the final computing factor for preventing data lag and plant extinction. The extinction occurrence in both $(Geo_{data}, Image_{data})$ and $(Geo_{data_{at-1}}, Image_{data_{at}})$ is found. Instances are alternating based on D_{lag} for $F(M)$, computed as

$$Collection_{data}(n) = \begin{cases} \frac{n - \rho_{V_L}}{n + \rho_{E_L}} \forall Geo_{data} = Image_{data} \\ \frac{n - (\rho_{V_L} * F(M))}{n + (\rho_{d_p} + \rho_{E_L} - D_{lag})} \forall Geo_{data} < Image_{data} \end{cases} \quad (17)$$

Using Equation (17), the continuous plant extinction of $(\rho_{d_p} + \rho_{E_L} - D_{lag})$ is identifiable with the help of $Collection_{data}(n)$. Therefore, the actual N for accumulated data identifies the different causes in perceptron layers for similar feature analysis (i.e., the concentration towards deforestation data until identifying the converted landscapes). Here, the analysis rate and time for concentrated stream data processing is the sum of two or more vegetation landscape analyses for better data collection. Therefore, the lagging in a data stream is detected at the time of feature matching through extreme learning without increasing the complexity and reducing adversary processes and their plant extinction at at instances.

4. Numerical Results

The experimental analysis is performed using the data in [37] to verify the proposed method's efficiency. This dataset provides the vegetation cover of the Sudano-Sahel region over 32 years. The vegetation change and landscape modifications are analyzed using pixel-dependent images and dry land data. This study selects 30 images for examining the vegetation analysis. The productivity is determined using rainfall and a pixel value < 0.05 , such that 5.5 km^2 is used for analysis, as shown in Equations (1)–(4). The wood, vegetation, and herbaceous features are analyzed in this analysis. Based on this information, the following analysis is performed. In Figure 6, the landscape for the considered region is presented.

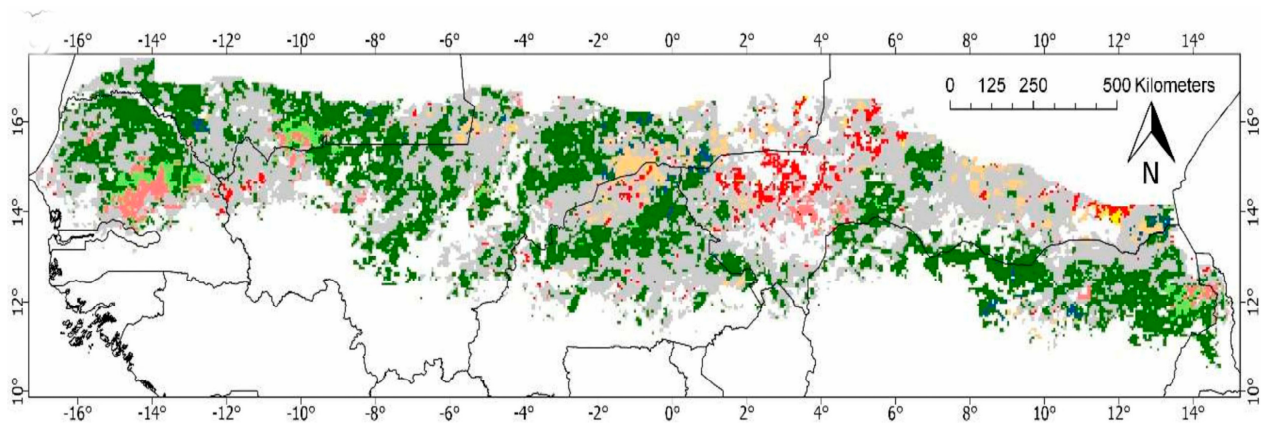


Figure 6. Considered landscape from the data source.

The above landscape was observed from 1991 to 2013 in the region mentioned above. The color markings in the above figure are classified as in Figure 7. This shows the recent improvements and desertification of the lands through deforestation. Considering the sensor data observed from different landscapes, the proposed method is analyzed specifically for vegetation gain, woody loss, and no-change instances. The data based on the above mapping is used for analysis and consists of latitude and longitude information, vegetation growth, and rain efficiency determines the landscape changes. Based on rain

efficiency computed as cumulative wet index/rainfall per year, the plant extinction and improvements are computed. This calculus-based representation is given in Figure 7.

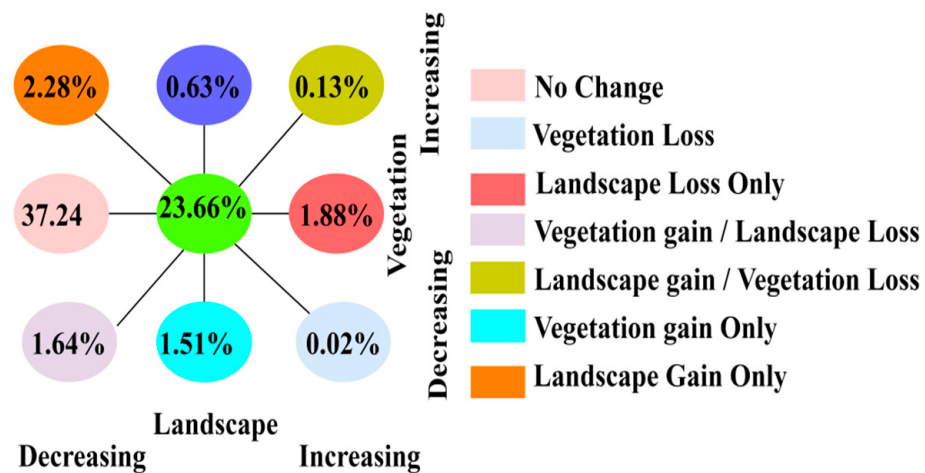


Figure 7. Vegetation and landscape changes.

Distinguishing the above variations, the increase or decrease in landscape and vegetation is analyzed. The rainfall index, the variations in cumulative wetlands, and deforestation are used for estimating the values. The above representation is to be correlated with the mapped region presented in Figure 6. The further analysis of vegetation loss for the varying ρ_{EL} and V_L over the varying years is presented in Figure 8.

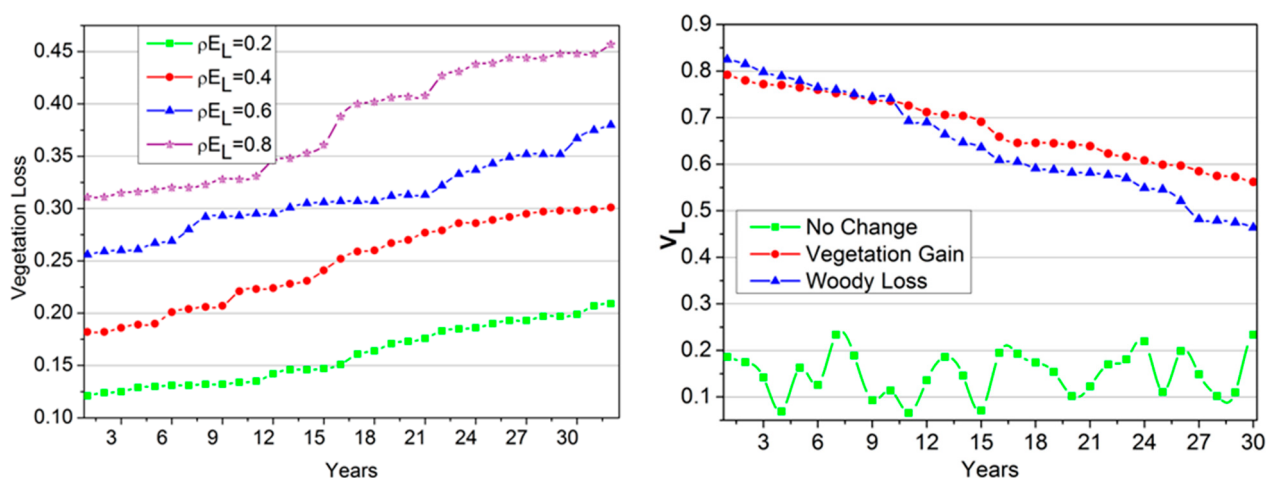


Figure 8. Vegetation loss and V_L analysis.

Over the varying years, the probability of extreme learning increases as vegetation loss increases. The vegetation loss is estimated by considering the available data and varying inputs from different years. Similarly, the identifiable features for landscape improvements and woody losses are identified for further V_L . Depending on the estimated $Collection_{data}(n)$, the variants are identified. Therefore, the no-change cases are less feasible due to rain, humidity, and other indices. Therefore, consecutive learning is required based on data processing probability, and feature matching is required for further cause detection. In Figure 9, the gain and $F(M)$ for the varying classifications are analyzed.

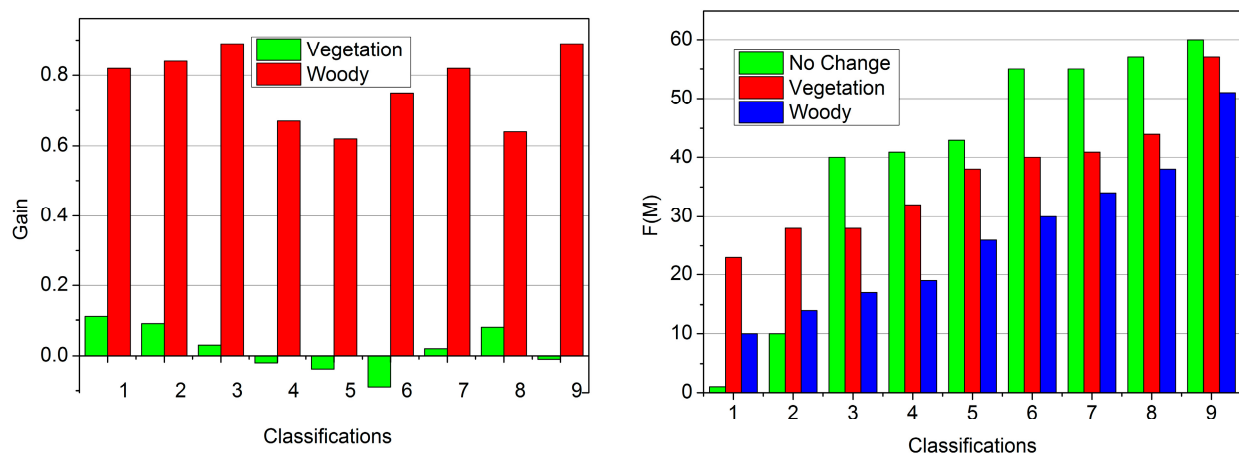


Figure 9. Gain and $F(M)$ analysis.

The gain and feature matching analysis are represented in Figure 9 for the varying classifications. The classifications are presented in Figure 7 are considered as the different observations for the above figure. The gain is estimated as the feature-matched inputs across various data collection instances. The V_L is required for improving the observed probability analysis. Probability analysis is used first for identifying different validation instances. The modifications are based on the learning layers for computing the gain factor. Therefore, the feature matching increases for the various changes across distinguishable *at*. The analysis for vegetation gain and woody loss for the varying p (from the dataset) is analyzed in Figure 10.

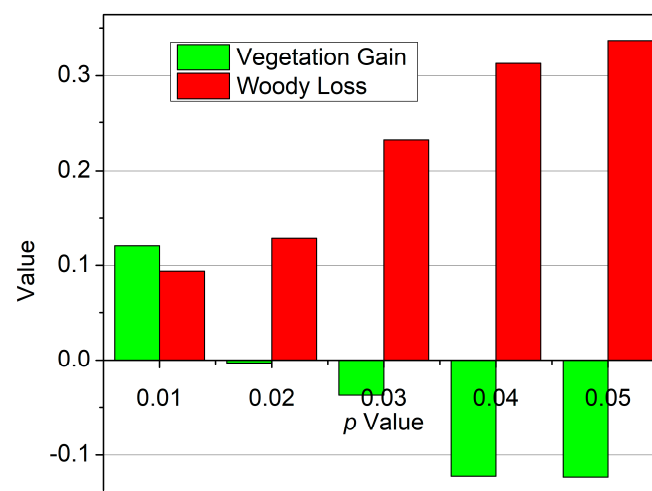


Figure 10. Vegetation gain and woody loss for p .

The p values impact the variations in the vegetation coverage and rain efficiency-based improvements for preventing multiple computations. The computations across different probabilities and varying *at* are induced by $L * n$ for the Geo_{data} observed. This is required for improving the estimation of vegetation gain. The landscape coverage is predicted using V_L and d_p probabilities for $F(M)$.

4.1. Comparative Analysis

The comparative analysis is performed using the metrics analysis rate, analysis time, recommendation rate, complexity, and matching ratio. The input data streams are varied from 2 to 28, and features are varied from 2 to 60. The methods DTimeS [26],

DOONIES [27], MSLCC [24], and OMM [35] are used in this comparison along with the proposed CSDPM.

4.1.1. Analysis Rate

The intensified vegetation coverage and rock destruction process is monitored for accurate data processing and satisfies a high analysis rate using the proposed method. The adversary processes and their plant extinction are identified due to intensified deforestation and industrial development processes at any data analysis time interval. Official policies used for addressing the identified feature extraction reason rely on new recommendations and are analyzed for preventing data lag and finding the root cause in the proposed method (refer to Figure 11). Classifying the extraction reason by using the extreme learning output is alleviated due to deforestation and mining industries in an open environment. Accurate data collection and processing rely on monitoring the accumulated data and plant extinction analysis in vegetation-covering regions to reduce the data lag. The feature extraction reason is identified through a monitoring process for similar feature analysis with an existing dataset based on $L \times Geo_{data}$ and $Geo_{data} \times at$, which finds lagging in input data streams. In this article, the data lag and plant extinction are detected in vegetation coverage regions and are trained for consecutive processing, preventing complexity in the data processing. Therefore, the analysis rate is high in this proposed method.

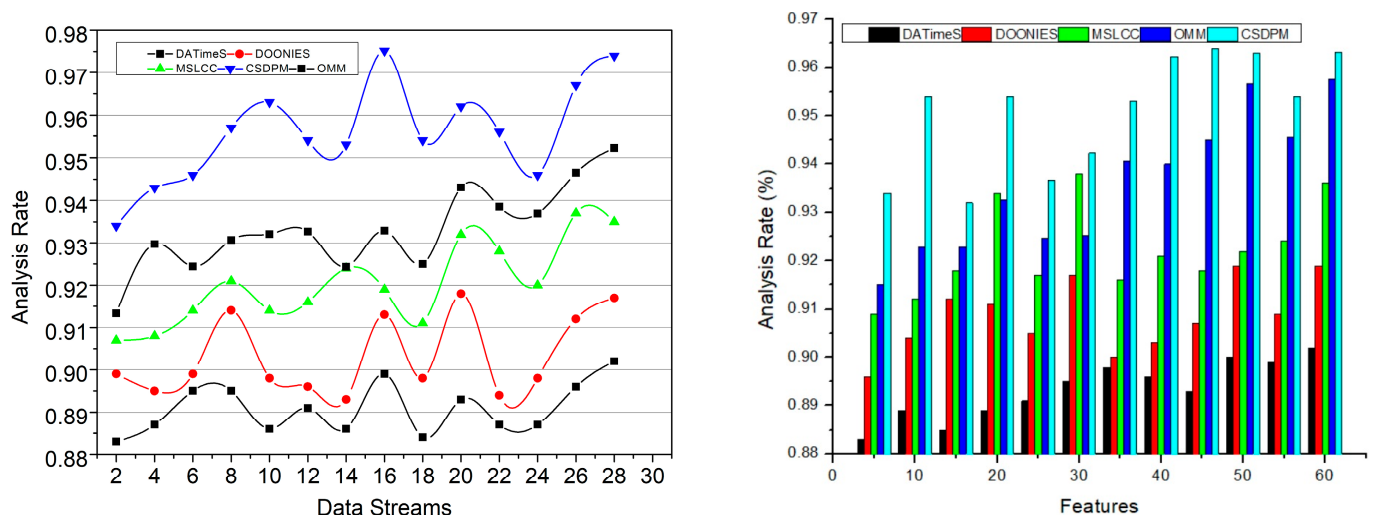


Figure 11. Analysis rate.

4.1.2. Analysis Time

In this proposed method, the intensified deforestation and industrial development process are identified alongside environmental factors through extreme learning, and the existing dataset does not change the perceptron layer in the vegetation landscape in any instance. The identification of similar features in monitoring deforestation data and landscape data in the instances of both Geo_{data} and $Image_{data}$ is analyzed for training the existing datasets for accurate data collection. The analysis of the current dataset from the vegetation landscape based on climate, human, and environmental changes is compared with the existing dataset. Then, a new recommendation is provided with official policies for that region for monitoring systems. The lagging input data streams and extraction reason are identified at intervals for estimating the concentrated stream data processing. Plant extinction is prevented by accurately monitoring such regions in the vegetation landscape. In this proposed method, the different learning perceptron layers extract the features and achieve a lower analysis time, as shown in Figure 12.

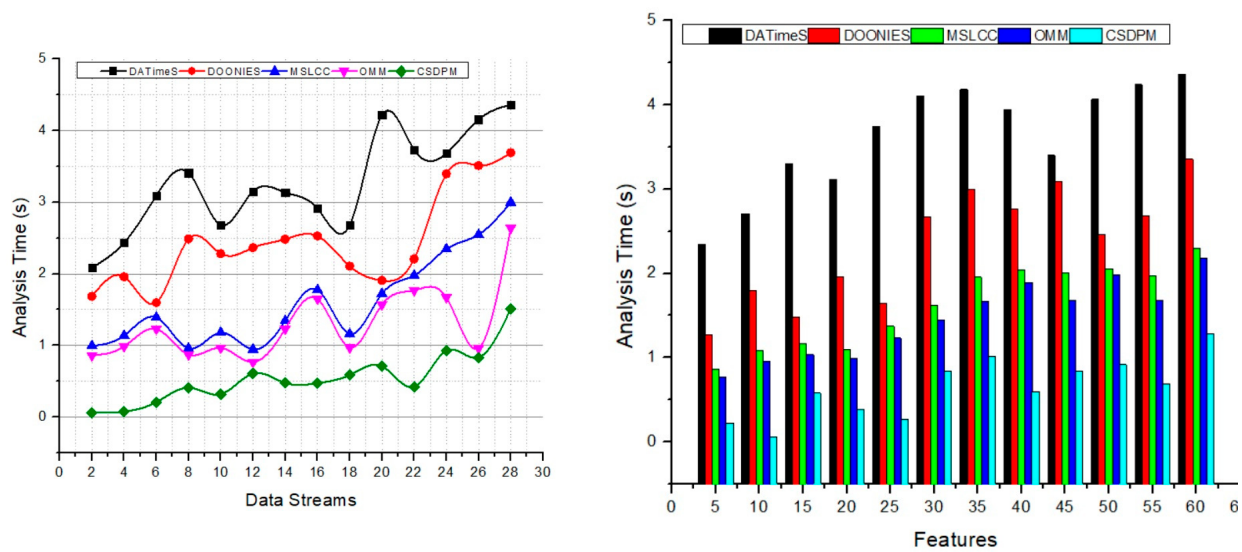


Figure 12. Analysis time.

4.1.3. Recommendation Rate

This proposed method satisfies a high recommendation rate for accurate data processing and feature extraction for identifying lagging in input data streams. The root cause requires feasible data collection (refer to Figure 13). The different layers and feature matching computation are performed to improve alternate vegetation through new policies in an open environment. The plant extinction issue is alleviated for both the instances of ρ_{V_L} and $Collection_{data}(n)$. The maximum vegetation coverage is performed with the help of identified reasons noticed through the new policy for training the consecutive similar features. Based on the monitoring process, the accurate data collection and analysis are estimated with existing datasets and deforestation data exhibited to easily identify data lag in the vegetation coverage analysis. This continuous data processing maximizes the recommendation rate at a similar time of training the features through extreme learning. If any plant extinction occurs in the data processing, it is continuously monitored to achieve a maximum analysis rate. Therefore, the conditions $(Geo_{data}, Image_{data})$ and $(Go_{data_{at-1}}, Image_{data_{at}})$ are computed for improving the recommendation rate along with existing dataset analysis. Hence, the different leaning perceptron layers satisfy alternate vegetation improvements for maximizing the recommendation rate for reducing deforestation in that region.

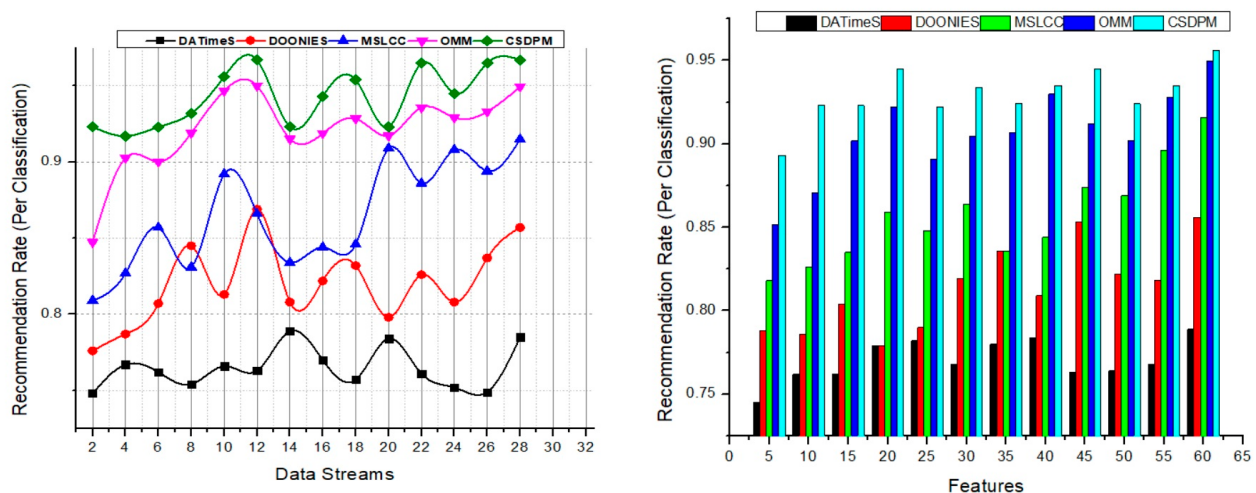


Figure 13. Recommendation rate.

4.1.4. Complexity

In this proposed method for accumulated data processing for vegetation coverage monitoring and recommendation against a rock, destruction is to be computed to classify the extraction feature and achieve a lower data analysis time than the other factors, as illustrated in Figure 14. The maximum recommendation for identifying the extraction reason and improving feature matching by using deforestation data to accurately monitor such intensified vegetation landscape regions is needed. The vegetation covering regions alongside the open environment is monitored for reducing plant extinction and trains the extreme learning until a high recommendation is satisfied. The probability of vegetation coverage is computed based on the existing dataset analysis for reducing intensified vegetation coverage and rock destruction through learning. The existing dataset contains overall vegetation landscape information for future reference. This data analysis improves feature extraction, preventing complexity. The accurate data processing due to deforestation and mining industries' augmentation is mitigated for reducing root causes for plant extinction. The data lag is identified using the existing datasets and previously acquired data analysis as per Equations (14)–(17). Therefore, in this proposed method, the complexity of multiple data processes is lower.

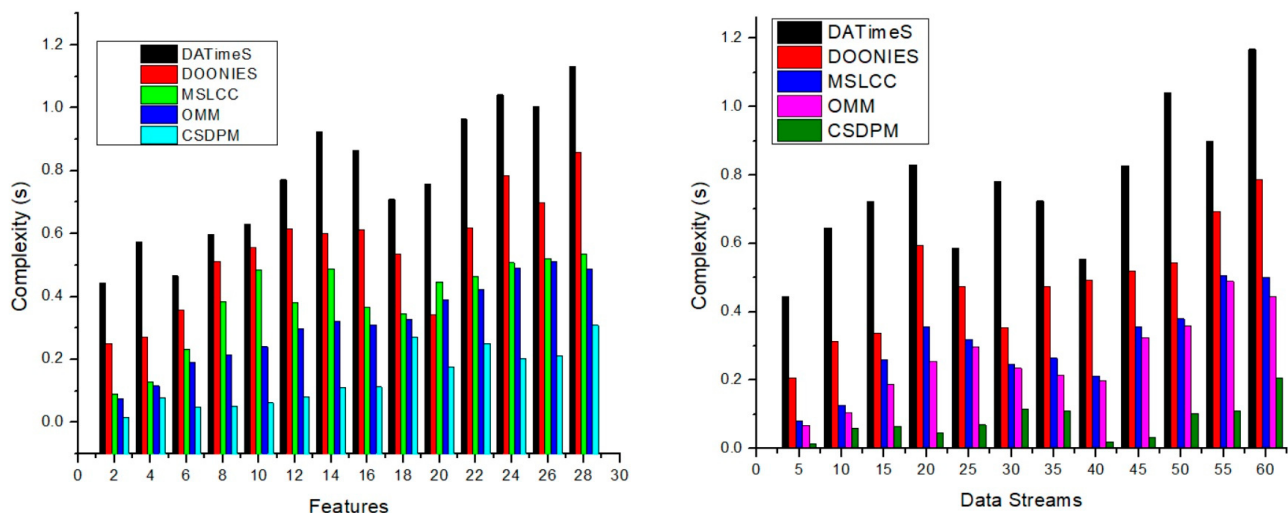


Figure 14. Complexity.

4.1.5. Matching Ratio

This proposed method for monitoring deforestation and landscape based on previously acquired deforestation data and existing datasets with current vegetation-covering region data is compared for similar feature analysis. The initial extreme learning is trained from the existing dataset, achieving a high feature-matching ratio in this proposed method compared to the other factors that fail to meet the food demands and vegetation coverage (refer to Figure 15). In this method, deforestation and landscape data are analyzed and then the similarity features are verified for accurate data collection and analysis for different learning perceptron layers. By using the learning process, the adversary processes and their plant extinction are reduced using Equations (8)–(10), and the new recommendation is addressed through official policies based on $(L \times Geo_{data}) > (Geo_{data} \times at)$ in both the instances of Geo_{data} and $Image_{data}$, respectively. The multiple data processing outputs in lagging issues are addressed using an extreme learning process for maximizing recommendations and improving vegetation coverage monitoring with accurate data collection. In this proposed method, the intensified vegetation coverage and rock destruction region are identified and prevent plant extinction for an accurate monitoring process. Therefore, the vegetation coverage regions control the deforestation and mining industries with previously acquired data analysis, leading to less data lag.

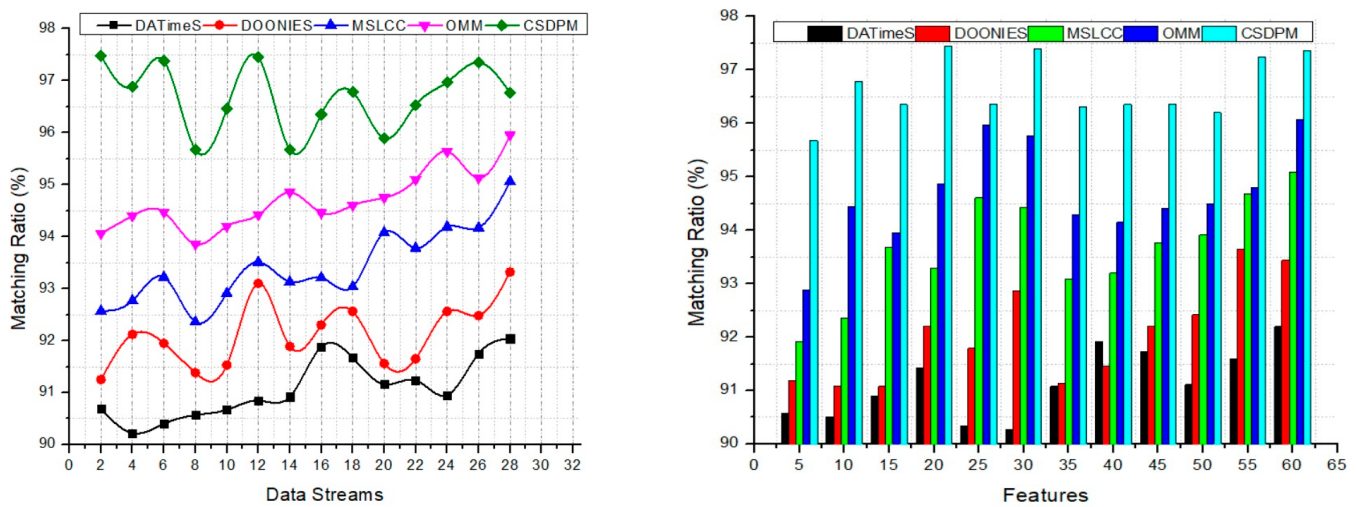


Figure 15. Matching ratio.

4.2. Discussion

This article uses an extreme learning paradigm to present the concentrated stream data processing method (CSDPM). The collected features are then used in several layers of a learning perceptron to examine the various potential causes. This type of training examines the collected data for patterns, then adapts to the leading or following input streams. The last step of the monitoring procedure was identifying the cause of plant extinction using the acquired knowledge. For this reason, new recommendations or alternate vegetation enhancements are implemented as part of government plans to combat the recognized cause. For feature matching especially, the data with emphasis on deforestation are the most basic data. Existing datasets and previously gathered data from the altered landscapes are used to initially train the features. Metrics, including analysis rate, analysis duration, recommendation rate, and complexity, are used to analyze the suggested technique. Based on the survey, there are several issues with existing methods in achieving a high analysis rate, a lower analysis time, a high recommendation rate, less complexity, and a high matching rate, such as decomposition and analysis of time series software (DATimeS), spatially explicit process-based grid model (DOONIES), Multisensor Land Cover Classification (MSLCC), and the Optimal Monitoring Model (OMM). The comparative analysis results are presented in Tables 1 and 2 for the varying data streams and features.

Table 1. Comparative analysis for data streams.

Metrics	DATimeS	DOONIES	MSLCC	OMM	CSDPM	Findings
Analysis Rate	0.902	0.917	0.935	0.933	0.956	3.24% High
Analysis Time (s)	4.362	3.692	2.997	1.29	0.54	46% Less
Recommendation Rate (per Classification)	0.785	0.857	0.915	0.92	0.943	8.48% High
Complexity (s)	1.131	0.857	0.535	0.313	0.142	79.9% Less
Matching Ratio	92.04	93.32	95.06	94.7	96.68	3.09% High

Table 2. Comparative analysis of features.

Metrics	DATimeS	DOONIES	MSLCC	OMM	CSDPM	Findings
Analysis Rate	0.902	0.919	0.936	0.935	0.951	4.9% High
Analysis Time (s)	4.361	3.354	2.296	1.49	0.64	36% Less
Recommendation Rate (per Classification)	0.789	0.856	0.916	0.90	0.929	7.1% High
Complexity (s)	1.168	0.786	0.501	0.265	0.0789	92.1% Less
Matching Ratio	92.2	93.44	95.08	94.67	96.65	2.98% High

5. Conclusions

The ratio of vegetation coverage due to rock desertification and deforestation has been significantly reduced in recent years. The data observed from different time intervals and sensors improve the detection of such divergences. This requires intense data processing and recommendations using smart computations. This article introduced a concentrated stream data processing method to meet this process. The geographical (sensed) and image data acquired from the landscapes are used for identifying input variations. This is required for identifying data lag and probability for analysis. In this process, extreme learning is induced by varying its layers across multiple decisions. The decisions on computation probability analysis and recommendations are performed by changing the features extracted. The feature-matching process performs a data similarity check for designing new guidelines. In particular, the data concentration is used for detecting changes in landscapes without increasing complexity or analysis time. Therefore, from the experimental analysis, this method improves the analysis rate by 4.9%, recommendations by 7.1%, and matching ratio by 2.98%. Contrarily, it reduces the analysis time and complexity by 36% and 92.1%.

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Conflicts of Interest: The author declares that there are no conflict of interest.

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