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ENHANCED FROST FILTER AND COSINE TANIMOTO CLASSIFICATION BASED NATURAL DISASTER MANAGEMENT WITH SATELLITE IMAGES

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Abstract

Natural disasters are utmost incidents inside the earth's system that lead to sudden demise or bruise to humans, and destruction of precious materials, involving buildings, conveyance systems, farming land, forest and natural environment. Occurrences of economic losses due to natural disasters have resulted owing to the escalated susceptibility of the society globally and also due to weather-related disasters. Satellite image sensing remains the hypothetical instrument for disaster management as it provides information spanning wide-reaching areas and also at short time period. In this work we plan to develop a method called, Enhanced Frost Filter and Tanimoto Similarity Classification (EFF-TSC) for efficient disaster management using satellite images is proposed. The EFF-TSC method for disaster management is split into three steps. They are pre-processing, segmentation and classification. With the input image collected from satellite image database, first pre-processing is performed to preserve important features at the edges and remove the noisy pixel by means of an Enhanced Frost Filter Preprocessing model. Second, to the pre-processed satellite image, Threshold Pixel Segmentation is applied to partition into multiple segments. Finally, to the partitioned images, Tanimoto Similarity Classification is applied to classify the segmented image into two types, namely disastrous image and non-disastrous image. With this, an efficient disaster management is carried out with better accuracy and minimal time consumption. The application of the study is demonstrated using the Disaster image data set collected from Kaggle during the 2017. The results show the capability of the proposed EFF-TSC method for disaster management across time and space from different images with considerable accuracy by also reducing peak signal to noise ratio with considerable time. The findings also suggest that the potential for forensic analysis of disasters using pixel segmentation and classification based on collected images can be utilized to several locations affected by disasters.

Keywords:

Disaster Management, Frost Filter, Threshold Pixel Segmentation, Tanimoto Similarity Classification, Satellite Image

1. INTRODUCTION

Disasters generally take place instantaneously resulting in economic destruction, ecological interference and loss of human life. In the emergence of natural disasters, therefore arises a requirement for prioritizing subsidy endeavors by recognizing the regions that have been affected to the maximum. Uprooting such analytical information via on-the-scene field surveys can result in days or even weeks. In the course of time, satellite images are a valuable information derivation owing to their limitless ground scope and escalating prevalence of accessibility. A bitemporal image classification approach was introduced in [1] to evaluate the pre and post disaster scenes and find whether regions were impacted or not.

A ground truth satellite image from DigitalGlobe with labeled regions identified the issues of Hurricane Harvey to attain higher accuracy and F1-Score. However, segmentation accuracy was not improved by bitemporal image classification approach.

A hybrid machine learning pipeline was employed in [1] with all relevant tweets to uncover disaster events across different locations. The pipeline combined the Named Entity Recognition for identifying the location in posts to extract coordinate and to remove the noise information. A fine-tuned BERT model was used for categorizing the posts with humanitarian categories and graph-based clustering to find the information. However, the time complexity was not reduced by hybrid machine learning pipeline.

1.1 CONTRIBUTION

The most important contributions of this paper are as follows, to increase the disaster management accuracy, a novel Enhanced Frost Filterative and Tanimoto Similarity Classification (EFF-TSC) method is introduced by including the three different processes such as pre-processing, segmentation, and classification.

Initially, an Enhanced Frost Filterative Pre-processing model is applied in EF-TSC method to enhance the satellite image quality by removing the noisy pixels and retaining the edges. As a result, the peak signal to noise ratio is increased and minimize the mean square error.

Threshold Pixel Segmentation model is performed to partition the pre-processed satellite image into different segments for differentiating between the background pixels and foreground object. Followed by, the different image features based on between classes form the threshold with which the segmented portions are formed. This helps in reducing the segmentation time.

Finally, the segmented portions are analyzed by applying Cosine-based Tanimoto Similarity Classification. The analysis results indicate that the satellite images are correctly classified as disastrous or non-disastrous images. Therefore, the machine feature learning process of EFF-TSC method increases disaster management accuracy and reduces the error rate.

Extensive and comparative experimental evaluation is conducted to evaluate the qualitative analysis of the proposed EFF-TSC method with the various machine learning methods to discuss the performance with different metrics.

The rest of this article is categorized as follows: A summarization of related work is provided in section 2. The proposed EFF-TSC method is given in detail in Section 3. Experimental settings are presented in Section 4. Section 5 provides the discussion in detail using table values and graphical representation. Finally in Section 6 concluding remarks and the major findings of the proposed method is provided

2. RELATED WORK

Natural hazards have brought about destructive damage and consequential socioeconomic forfeiture, indicating an escalating tendency. These disadvantageous influences cause ultimatums to disaster response managers. This in turn would results in progressively strained resources and an impoverished workforce. Such ultimatums impact local authorities to re-estimate their policies concerning disaster management.

The study presented in [2] provided an elaborate review in the disaster management domain and classifies them according to three different dimensions, paving way for early warning and detection of significant events, coordination between events after occurrences or post-disaster management and finally assessing the damage. With these analyses automated techniques can be structured with which the disaster coordination resulted in the significant decision making in the case of disaster.

One of the most destructive disasters is floods causing huge damage not only to human but also to land, buildings and so on. This is owing to the most dynamic and complicated nature; accurate and precise flood is highly complicated. In [3], two new hybrid ensemble models, namely Dagging and Random Subspace (RS) coupled with Artificial Neural Network (ANN), Random Forest (RF), and Support Vector Machine (SVM) were proposed for designing flood susceptibility maps. With this ensemble method, mitigation strategies were designed that in turn could mitigate future damages to greater extent. A comparative analysis of manual and deep learning techniques for real time disaster management was studied in [4].

Natural hazards possess the latent to bring about calamitous destruction and consequential losses involving both socio and economic factors. The clear-cut destruction and forfeiture observed in the recent decades has shown a growing inclination. Owing to this reason, disaster managers require to lay hold of a heightening control to proactively safeguard by evolving effective management techniques.

An overview of current methods of Artificial Intelligence (AI) for disaster management based on four distinct phases, namely, mitigation, preparedness, response, and recovery were proposed in [5]. Moreover, example applications employing distinct AI techniques and their advantages for aiding disaster management was provided in detail in [6]. Also owing to the emergency nature, a taxonomy of disaster management based on response by means of deep learning-based classification and object identification was proposed in [7] with the purpose of making timely decision making. Also, a card sorting method was designed with the purpose of validating absoluteness and definiteness of the disaster taxonomy.

Over the past two decades, natural disasters have become more persistent and more acute, emerging in greater economic losses and death tolls. Despite application of satellite imagery has resulted in tremendously valuable data source for managing emergency situations however certain drawbacks are still said to persist for remote sensing-based monitoring systems.

An enhanced narration of a latterly proposed technique methodology with the purpose of identifying areas affected with disaster by integrating both semantic and geospatial machine learning methods were proposed in [8]. Automated influenced area identification using semi-supervised topic models for different types of natural disasters were also proposed.

A study showing social media data by AI techniques, can be efficiently utilized in tracking flooding phase transition and identify emergency incidents in an efficient manner. Also for tracking phase transition, a computer vision model to classify images provided in social media data based on four distinct classes, called, preparedness, impact, response, and recovery to provide different phases of disaster event development was proposed in [9]. To locate emergency incidents, we use a deep learning based natural language processing (NLP) model to recognize locations from textual content of tweets. Content analysis and disaster management model using multi correspondence analysis was proposed in [10] for multi-class classification.

The consequences of risk disinclined view point of both participators and individual preferences between airport and nonprofit organization was designed in [11]. Initially, two methods based on reputation cooperation and bidding competition on the basis of the prevailing aviation joint emergency mechanism in China was proposed in [12]. Second, two preferences called altruism and selfishness was also included. Finally, replicator dynamics equations were constructed with the aid of conditional value-at-risk (CVaR) for analyzing was proposed in [13].

A systematic review using multi-source multi-model data using deep learning for disaster management was investigated in [14]. A review of deep learning practices using AI for natural disaster management was reviewed in detail in [15]. One of the most evaluative classes of natural disasters is landslide causing huge havoc to both human life and therefore the overall economic system. To minimize its negative influences, prevention of landslides has become an emergency chore. Machine learning has been extensively utilized in the prevention of landslides.

A holistic review of pertinent research on machine learning for prevention of landslides was investigated in [16]. A systematic review and analysis of machine learning for disaster management was provided in [17]. A novel framework that classifies the present-day research that has been performed on flood management systems using machine learning was presented in [18]. An analysis using social media as the main factor was proposed that in turn classified the tweets related to hurricanes in an accurate manner.

Though numerous studies have been presented on utilizing machine learning techniques for classifying satellite images to analyze disaster management in a precise and accurate manner, few works have been done on further analysis using machine learning to measure the error rate or peak signal-to-noise ratio during disaster management. To address on this aspect, a novel method called, Enhanced Frost Filterative and Tanimoto Similarity Classification (EFF-TSC) for is proposed. The elaborate description of the EFF-TSC method is provided in detail in the following section. used numerous data mining tasks to create qualitative predictive models to predict the students' grades from a collected training dataset. During the survey, university students were aimed and collected multiple personal, social, and academic data of them. Preprocessing of the collected were done to make it suitable for data mining tasks. Third, the classification models were tested on the preprocessed data. On the whole this study motivated the universities to do data mining tasks on their students' data regularly to get interesting results and patterns which in turn can be more effective and helpful for university as well as the students in many ways.

3. METHODOLOGY

In this section, we discuss our proposed Enhanced Frost Filterative and Tanimoto Similarity Classification (EFF-TSC) for efficient disaster management using satellite image. The Fig.1 shows the proposed EFF-TSC method framework. It is divided into three main parts, which are preprocessing, segmentation and classification.

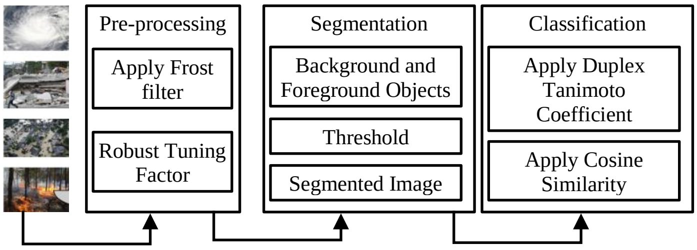

Fig.1. Block diagram of Enhanced Frost Filterative and Tanimoto Similarity Classification-based disaster management

As shown in the Fig.1., with the input images acquired from disaster images dataset, the first part is the pre-processing phase, which includes two steps. First, the input image collected from satellite image database is applied with the frost filter function. Second, a robust tuning factor is introduced into filtered image pixels that in turn remove the noisy pixel while preserving features at the edges, therefore improving peak signal to noise ratio.

The second part is segmentation. This is performed by applying Two-Dimensional Threshold Pixel Segmentation, which includes two steps. The first step involves the segmentation to produce coarse segmentation results by differentiating between the background and foreground object. Then, the threshold is evaluated by maximizing the between class variance to partition into multiple segments in a computationally efficient manner.

In the last one, the classification model is modified by incorporating the cosine similarity to the duplex tanimoto coefficient to produce fine-tune segmentation results. The parts are discussed in detail in the following subsections.

3.1 ENHANCED FROST FILTERATIVE PRE-PROCESSING

Satellite-derived information by oneself does not cut the mustard to produce a significant and relevant analysis of a given disaster situation. For several disaster-related image analyses the accessibility of relevant and precise topographic elevation data on the strained portion of the image is of greatest significance. Also, while suppressing the noise edges are also said to be affected. To preserve the edges while suppressing noise, in this work, an Enhanced Frost Filterative Pre-processing model is designed.

An Enhanced Frost Filterative Preprocess is used to denoise the input satellite image for removing the noisy pixel from the database. Enhanced Frost Filter minimizes the noise and preserves the important image features at the edges. Figure 2 shows the structure of Enhanced Frost Filterative Pre-processing model.

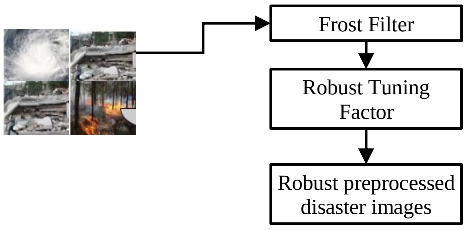

Fig.2. Structure of Enhanced Frost Filterative Pre-processing

As shown in the Fig.2 with the four distinct types of images provided as input, the objective here remains in designing a robust pre-processing model that removes the noise in the image while preserving their edges. The Frost Filter is initially stated as given below:

$$PI(i,j)=\frac{\sum_{i}\sum_{j}P_{ij}Q_{ij}}{\sum_{i}\sum_{j}Q_{ij}} \tag{1}$$

$$Q_{ij}=e^{-RTF\,R(\mu,\sigma)Dis_{ij}} \tag{2}$$

From the Eq.(1), $PI(i,j)$ refers to the pre-processed image with i, j representing the location of prevailing pixel (i.e., referring to the rows and columns), P_{ij} denoting the value of pixels among sliding window centered at i,j. In addition, from Eq.(2), Dis_{ij} represents the distance between pixels in the prevailing sliding window and prevailing pixel, RTF referring to the robust tuning factor with $R(\mu,\sigma)$ denoting the ratio of mean to standard deviation respectively.

From the Eq.(3), RTF represent the robust tuning factor that is represented by the probabilistic value $Prob(t_0)$ of t_0 and the gray features of proximity pixels $GP(i,j)$ respectively. Here, the robust tuning factor refers to the initialization of tuning factor values on the basis of the geographical features (i.e., cyclone '1', earthquake '2', flood '3' and wild fire '4'). The probabilistic value is mathematically stated as given below.

$$\text{Prob}(t_0)=\frac{CP(t_0)-\mu(t_0)}{\sigma(t_0)} \tag{4}$$

From the Eq.(4), the probabilistic value $Prob(t_0)$ is obtained based on the centered pixel $CP(t_0)$, mean of the pixel $\mu(t_0)$ and the standard deviation of the pixel $\sigma(t_0)$ centered at t_0 respectively. The gray features are mathematically stated as given below.

$$GP(i,j)=\frac{CP(i,j)-CP(t_0)}{\sum_{m=1}^{M}\sum_{n=1}^{N}CP(m,n)-CP(t_0)} \tag{5}$$

From the Eq.(5), the gray features with location of prevailing pixel $GP(i,j)$ is estimated based on the centered pixel location $CP(i,j)$ and the centered pixel $CP(t_0)$ centered at t_0 respectively. Obviously, the above tuning factor is robustly altered on the basis of the four distinct geographical features, therefore resulting in better performance upon comparison with the conventional Frost filter.

$$RTF_{ij} = \text{Prob}(t_0),GP(i,j) \tag{3}$$

The pseudo code representation of Enhanced Frost Filterative Pre-processing is given below.

Algorithm 1: Enhanced Frost Filterative Pre-processing

Input: Dataset *DS*, Image $I=I_1,I_2,\ldots,I_n$, location of prevailing pixel *i, j*, distance Dis_{ij}

Output: Robust noise-reduced pre-processed images

Step 1: Initialize tuning factor *TF*

Step 2: Begin

Step 3: For each Dataset *DS* with Image *I*

Step 4: Formulate Frost Filter as given in Eq.(1)

Step 5: Estimate robust tuning factor as in Eq.(3)

Step 6: For each pixel with *i* rows and *j* columns

Step 7: Estimate probabilistic value centered at t_0 as in Eq.(4)

Step 8: Evaluate gray features as in Eq.(5)

Step 9: Return pre-processed images *PI*

Step 10: End for

Step 11: End for

Step 12: End

As given in the above of Enhanced Frost Filterative Pre-processing, the objective of the algorithm remains in improving the peak signal to noise ratio for the respective four different images provided as input. First the traditional frost filter is formulated and applied to the raw natural image. Followed by which second, a robust tuning factor is designed where the robust here refers to the initialization of its according to the type of natural image. Finally, with the aid of the probabilistic and the gray value representation, enhanced and robust pre-processed images are obtained with improved PSNR.

3.2 THRESHOLD PIXEL SEGMENTATION

In this section, phase, the image is segmented according to the pre-processed features. So, this section comprises of coarse and fine segmentation steps. First, the natural images have certain limitations, including redundant information, similarity with respect to color, intensity or texture. Also, the traditional methods have drawbacks, such as ignoring intra-class intensity variance. While using traditional pixel segmentation model most of the background patches are until now perpetuated in the segmentation results. To solve this issue, problem, Threshold Pixel Segmentation model is presented that forces the search extent of the ideal segmentation threshold to extract foreground object inside the image.

Therefore, Threshold Pixel Segmentation model in our work take into consideration of the minimization of intra-class intensity variance that in turn maximizes inter-class variance of super-pixels. So, the Threshold Pixel Segmentation model coarse segmentation partition the pre-processed image into multiple segments based on the pixel and reduces the computational time and number of iterations to a greater extent. The Fig.3 shows the Threshold Pixel Segmentation model.

As shown in the Fig.3, In the gray level range the initial segmentation threshold *Thres* is calculated based on the number of pixels at gray level *i* for the pre-processed image denoted by PI_i and the total number of pixels. The gray level histogram for the pre-processed image is normalized and assessed as a probability distribution formulated as given below.

$$Prob_i = PI_i/TP \tag{6}$$

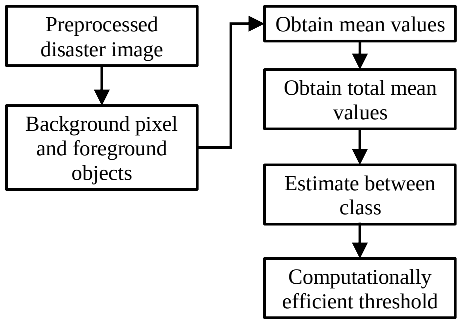

Fig.3. Structure of Threshold Pixel Segmentation model

From the Eq.(6), the initial segmentation threshold with the probability distribution $Prob_i$ is evaluated based on the pre-processed images PI_i and the total pixels *TP* respectively. Let us suppose that the pixels are split into two categories Cl_0 denoting background pixels and *BP* and Cl_1 denoting foreground objects *FO* respectively. Then, these two background pixels and foreground objects for each category is mathematically stated as given below.

$$BP=\mathrm{Prob}(Cl_0) \tag{7}$$

$$FO=\mathrm{Prob}(Cl_1) \tag{8}$$

From the Eq.(7) and Eq.(8), the background pixels *BP* are estimated based on the probability distribution of background pixels $\mathrm{Prob}(Cl_0)$ and the foreground objects *FO* are obtained on the basis of the probability distribution of foreground objects $\mathrm{Prob}(Cl_1)$ present in the pre-processed images respectively. Then, the mean values for the above two categories for each pre-processed disastrous image are obtained as given below.

$$\mu_0 = \frac{\sum_i i\mathrm{Prob}_i}{BP} \quad \mu_1 = \frac{\sum_i i\mathrm{Prob}_i}{FO} \tag{9}$$

With the above two categories of mean values as in Eq.(9), the total mean of gray level histogram for the pre-processed image is represented as given below.

$$Tot = (BP)(\mu_0) + (FO)(\mu_1) \tag{10}$$

The between class variance of gray level histogram is then mathematically formulated as given below.

$$\sigma^2_{Between} = BP(\mu_0 - Tot)^2 + VO(\mu_1 - Tot)^2 \tag{11}$$

Finally, the threshold for segmentation is obtained by maximizing the between class variance as given below.

$$Thres' = \arg\max\left\{\sigma^2_{Between}(PD_i)\right\} \tag{12}$$

Algorithm 2: Threshold Pixel Segmentation

Input: Dataset *DS*, Image $I = I_1, I_2,\ldots,I_n$

Output: Computationally efficient threshold-based segmented images *SI*

Step 1: Initialize pre-processed images *PDI*

Step 2: Initialize categories Cl_0, Cl_1

Step 3: Begin

Step 4: For each Dataset *DS* with Image *I*

Step 5: Evaluate gray level histogram as a probability distribution using Eq.(6)

Step 6: For each pre-processed images *PI*

Step 7: Obtain background pixels as in Eq.(7)

Step 8: Obtain foreground objects as in Eq.(8)

Step 9: Evaluate mean values for two categories Cl_0 and Cl_1 as in Eq.(9)

Step 10: Evaluate total mean of gray level histogram as in Eq.(10)

Step 11: Evaluate between class variance as in Eq.(11)

Step 12: Evaluate threshold for segmentation as in Eq.(12)

Step 13: Return threshold for segmentation *Thres*'

Step 14: End for

Step 15: End for

Step 16: End

As given in the above Threshold Pixel Segmentation algorithm, the objective remains in partitioning the pre-processed images into multiple segments with minimum time. With this objective, gray level histogram is first evaluated. Next, background pixels and foreground objects for each gray level histogram is obtained. Then, for these two categories, mean values of the pixels are estimated. Finally, by maximizing between class variance, updated threshold is obtained with which the pre-processed image is partitioned into multiple segments in computationally efficient manner.

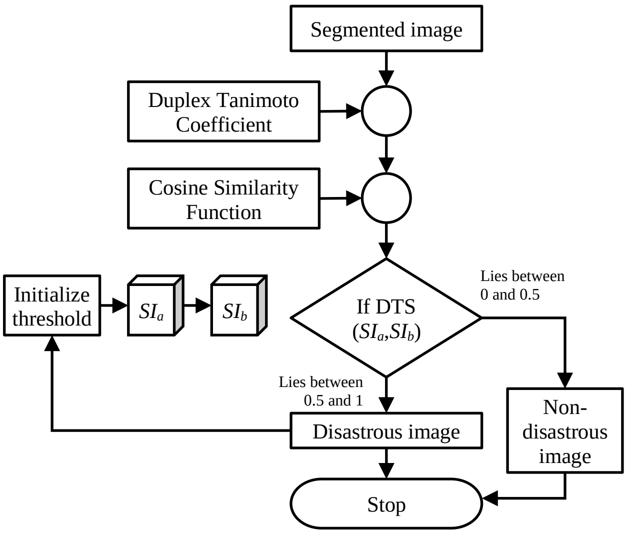

Fig.4. Structure of Cosine Based Tanimoto Similarity Classification

3.3 COSINE-BASED TANIMOTO SIMILARITY CLASSIFICATION

Finally, in this section using the updated threshold partitioned into multiple segments, classification of images into disastrous or non-disastrous is performed by using Cosine-based Tanimoto Similarity Classification model. The Cosine-based Tanimoto Similarity Classification is carried out to correlate the input image and training image (i.e., disastrous image) categorizes the segmented image into two types, namely disastrous image or non-disastrous image. Tanimoto similarity value ranges between 0 and 1. When the similarity value ranges between '0' to '0.5', the image is said to be non-disastrous image. When the similarity value ranges between '0.5' to '1', the image is said to be disastrous image. By this way, an efficient disaster management is carried out with better accuracy and minimal time consumption. The Fig. shows the structure of Cosine-based Tanimoto Similarity Classification model.

As shown in the Fig. with given two vectors of duplex features SI_a and SI_b (representing two segmented image coefficients), the Duplex Tanimoto coefficient is represented as given below.

$$T\left(SI_a, SI_b\right) = \frac{SI_a \cdot SI_b}{\left(SI_a\right)^2 + \left(SI_b\right)^2 - \left(SI_a \cdot SI_b\right)} \quad (13)$$

From the Eq.(13), the Duplex Tanimoto coefficient $DT(SI_a, SI_b)$, is measured based on two different segmented images SI_a and SI_b. However, with the misalignment nature of segmented images it becomes hard for classifying the images in an accurate manner. To address this aspect, a cosine similarity function is introduced that is in turn said to be robust for misalignment and this is mathematically formulated as given below.

$$\mathrm{Cos}\left(Sim\left[SI_a, SI_b\right]\right) = \frac{SI_a \cdot SI_b}{\left(SI_a\right)\left(SI_b\right)} \quad (14)$$

The Cosine similarity '*Cos*(*Sim*)' as given in the Eq.(14) is employed in our work to measure how similar two segmented images based on threshold are likely to be in terms of their subject matter. Finally, Duplex Tanimoto Significance function fine-tunes the similarity outcome '*Cos*(*Sim*)' based on the number of similar and dissimilar disastrous images into either disastrous image between two segmented images. The Duplex Tanimoto Similarity function is mathematically stated as given below.

$$DTS\left(SI_a, SI_b\right) = DT\left(SI_a \cdot SI_b\right) * \mathrm{Cos}\left(Sim\left[SI_a, SI_b\right]\right) \quad (15)$$

Hence, from the Eq.(15), similarity outcome '*DTS*' acquires both prevalence and the number of similar and dissimilar disastrous images into consideration while calculating similarity between two segmented images, therefore improving accuracy to a greater extent. The pseudo code representation of Cosine-based Tanimoto Similarity Classification is given below.

Algorithm 3: Cosine-based Tanimoto Similarity Classification

Input: Dataset '*DS*', Image $I = I_1, I_2, \ldots, I_n$

Output: Accurate Disaster Management

Step 1: Initialize threshold-based segmented images '*SI*', duplex features SI_a and SI_b

Step 2: Begin

Step 3: For each threshold-based segmented images '*SI*'

Step 4: Formulate Duplex Tanimoto coefficient as in Eq.(13)

Step 5: For each duplex features '$\underline{SI_a}$' and '$\underline{SI_b}$'

Step 6: Evaluate cosine similarity function as in Eq.(14)

Step 7: Evaluate Duplex Tanimoto Similarity function as in Eq.(15)

Step 8: If $DTS(SI_a$ and $SI_b)$ lies between 0 and 0.5

Step 9: Then the given segmented image (i.e., classified result) is non-disastrous image

Step 10: End if

Step 11: If $DTS(SI_a$ and $SI_b)$ lies between 0.5 and 1

Step 12: Then the given segmented image (i.e., classified result) is disastrous image

Step 13: End if

Step 14: Return classified results

Step 15: End for

Step 16: End for

Step 17: End

As given in the above Cosine-based Tanimoto Similarity Classification algorithm, the objective remains in designing an accurate and fine-tune disaster management model based on duplex function. With this objective first, Duplex Tanimoto coefficient is formulated for the segmented images. Followed by which cosine similarity function is applied for each duplex features. Finally, with the obtained results, accurate classification between disastrous image and non-disastrous image are made in a precise and timely manner.

4. EXPERIMENTAL SETUP

The simulation of proposed EFF-TSC method and existing methods, bitemporal image classification [1] and hybrid machine learning [1] are implemented using MATLAB coding for disaster management with minimum time. The number of Images is collected from the disaster images dataset, https://www.kaggle.com/mikolajbabula/disaster-images-dataset-cnn-model. This database contains 4 different types of natural disaster images. Totally 250 images are taken and perform preprocessing, segmentation and finally classification results are arrived at. Followed by, the images are classified as disastrous or non-disastrous images. Experimental evaluation of EFF-TSC method is conducted on different parameters such as peak signal-to-noise ratio, segmentation time, and classification accuracy with respect to a number of satellite images.

4.1 DISCUSSION

The simulation results of proposed EFF-TSC method and existing methods bitemporal image classification [1] and hybrid machine learning [1] are described in this section. The effectiveness of the proposed and existing methods is compared with certain metrics such as peak signal-to-noise ratio, segmentation time, and classification accuracy over different numbers of satellite images. The efficiency of the proposed EFF-TSC method and existing methods are discussed along with the results is explained using tables and graphical representation.

4.1.1 Case 1: Peak Signal to Noise Ratio:

Peak signal-to-noise ratio is measured based on the mean square error also referred to as the difference between original satellite images (i.e., for disaster management) and pre-processed image. The peak signal to noise ratio is mathematically formulated as given below,

$$PSNR = 10 * \log_{10}\left(\frac{M^2}{MSE}\right) \quad (16)$$

$$MSE = [I_i - I_{PI}]^2 \quad (17)$$

From the Eq.(16) and Eq.(17), the peak signal-to-noise ratio *PSNR* is measured based on the maximum possible pixel value *M*=366 and the mean square error (i.e., the difference between original satellite image size I_i and the pre-processed satellite image size I_{PI} respectively. The PSNR is measured in terms of decibel (dB). The effectiveness of the proposed DCDCT method extensive experimental results is reported in Table.1.

The proposed EFF-TSC method is compared against the existing bitemporal image classification [1] and hybrid machine learning [1] method. The simulator MATLAB is used to experiment the factors and measure the result values with the help of table and graph values. Results are presented for different satellite image sizes considering the peak signal noise ratio. The results provided here states that increasing the values of image sizes and number of images, the PSNR value is also increased, though the increase observed is not linear because of the image size.

Table.1. Tabulation for PSNR

Number of images	PSNR (dB)		
	EFF-TSC	Bitemporal Image Classification	Hybrid Machine Learning Pipeline
50	39.04	37.3	35.85
100	45.85	39.25	33.55
150	51.35	41.25	35.25
200	55.25	43.55	38.15
250	58.15	48.35	45.35
300	62.35	51.55	47.35
350	69.15	55.85	51.23
400	71.35	65.15	60.15
450	75.85	68.35	60.25
500	83.25	72.45	65.45

Let us consider the original satellite image size is 21.5KB and the size of the image after removing the noise is 12.5 KB. The Mean square error is 81 and the peak signal to noise ratio is 39.04dB using EFF-TSC. By applying the bitemporal image classification [1], hybrid machine learning pipeline [2] the observed peak signal to noise ratio are 37.3 dB and 35.85 dB. Similarly, various runs are carried out with respect to different sizes of the input satellite image. The observed value of EFF-TSC method is compared to the peak signal to noise ratio of the existing methods. The averages are taken for the comparison of ten results. The average value indicates that the EFF-TSC method increases the peak signal to noise ratio by 6% and 7% when compared to existing [1] [2] respectively. The Table.1 illustrates the performance results of the peak signal to noise ratio versus various sizes of the satellite images taken from the input dataset. The Table.1 shows the performance results of bitemporal image classification [1] and hybrid machine learning pipeline [2] method. The inputs of numerous sizes are given to the horizontal axis and the output results of the PSNR are observed at the vertical axis. Among three different methods, the EFF-TSC method outperforms well. The Enhanced Frost Filterative model is applied to eliminate the unwanted noises. This in turn results in the increasing of the visual quality of satellite images. The proposed filtering technique with the assistance of the robust tuning factor remove the noise and accurately preserves the edges on the images hence it reduces the mean square error and increases the peak signal to noise ratio using EFF-TSC method by 17% compared to [1] and 30% compared to [2].

4.1.2 Case 2: Segmentation Time:

The second parameter of significance is the segmentation time. It is evaluated according to the time consumed in performing the segmentation process i.e., segmenting the pre-processed satellite images for disaster management into background pixels and foreground objects. This is mathematically stated as given below.

$$Seg_{time} = \sum_{i=1}^{n} I_i * Time\left[(BP)(\mu_0)+(FO)(\mu_1)\right] \quad (18)$$

From the Eq.(18), the segmentation time Seg_{time} is measured based on the sample images involved in the simulation process I_i and the time consumed in performing the actual segmentation $Time[(BP)(\mu_0)+(FO)(\mu_1)]$. It is measured in terms of milliseconds (ms). The results of 7 different image sizes for disaster management are listed in Table.2. As listed in Table.2. , the EFF-TSC method measures the segmentation time which is measured in terms of milliseconds (ms). The segmentation time using EFF-TSC method offer comparable efficiency measures than the state-of-the-art methods.

Table.2. Tabulation for Segmentation Time

Number of images	Segmentation time (ms)		
	EFF-TSC	Bitemporal Image Classification	Hybrid Machine Learning Pipeline
50	72.5	92.5	102.5
100	89.35	115.35	145.55
150	105.25	135.85	190.35
200	135.55	170.25	215.35
250	140.25	195.35	235.85
300	148.35	205.45	295.35
350	165.25	235.15	325.55
400	170.45	280.45	380.15
450	205.35	305.35	405.35
500	225.15	335.15	435.15

The Table.2 describes the segmentation time of different methods with respect to number of satellite images for disaster management. With an increase in the number of images, the segmentation time for three different methods also increases. Comparatively, the EFF-TSC method is lesser than the other two existing methods. As a simulation, with ‘50’ input images considered for experimentation, the segmentation time was found to be ’72.5 ms’ using EFF-TSC, ‘92.5 ms’ using [1] and ‘102.5 ms’ when applied [2]. However, performance analysis on an average was found to be comparatively reduced by 28% and 44% than [1] and [2] This is achieved through the Threshold Pixel Segmentation model. The segmentation process splits the pre-processed satellite image into different regions based on the minimization of intra-class intensity variance that in turn maximizes inter-class variance of super-pixels pixel intensity. Then background pixels and foreground objects for each gray level histogram is obtained and by maximizing between class variance, updated threshold region are obtained for segmentation. The updated threshold region utilized for segmentation process using EFF-TSC method in turn reduces the segmentation time considerably upon comparison with [1] and [2].

4.1.3 Case 3: Classification Accuracy:

Finally, the third parameter of significance is the accuracy involved during the classification of segmented satellite images for disaster management. The classification accuracy is measured as given below.

$$CA = \sum_{i=1}^{n} \frac{I_{CA}}{I_i} \quad (19)$$

From the Eq.(19), the classification accuracy CA is measured based on the images involved in the simulation process I_i and the images classified accurately I_{CA}. It is measured in terms of percentage (%). Finally, Table.3 provides the robustness of EFF-TSC method in terms of classification accuracy for five hundred different image sizes that is measured in terms of percentage (%). The robustness or the classification accuracy in EFF-TSC method refers to the ability of the method to cope with errors. With higher robustness observed using EFF-TSC method, the objective is being achieved. The robustness or the classification accuracy metric is measured in terms of percentage (%).

Table.3. Tabulation for Classification Accuracy

Number of images	Classification accuracy (%)		
	EFF-TSC	Bitemporal Image Classification	Hybrid Machine Learning Pipeline
50	88	84	82
100	86.35	83.15	76.45
150	86	81	76
200	85.45	80.45	74.35
250	84	79.55	73.25
300	83.55	79	71.45
350	83	77.35	70
400	81.45	76.15	68.45
450	81	75	66
500	80.25	73.35	64.35

The Table depicts the performance results of classification accuracy of three different disaster management algorithms. The above plot illustrates the EFF-TSC method achieves higher accuracy in the disaster management. The numbers of satellite images are collected for disaster management is affected by some unwanted noise resulting in minimizing the visual quality of images. This causes incorrect identification of disaster management present in the satellite images. Therefore, the Enhanced Frost filtering model is applied to improve the quality of the image by removing the noise pixels and retaining the edges. In addition, the segmentation of the satellite image is used to vary the illustration of different regions based on between class variance values instead of processing the entire images. Moreover, the segmented image pixels are analyzed by means of Cosine-based Tanimoto Similarity function. This in turn improves the classification accuracy for the EFF-TSC method by 6% compared to [1] and 16% compared to [1] respectively.

5. CONCLUSION

The Satellite imagery can provide disaster response officials an abundance of information for evaluation, analysis and keeping an eye on natural disasters like, hurricanes, earth quake, flood, wild fire from small to large regions globally. Judgement of the specific earth quake classes that may be saturated by a natural disaster can enable planners to better evaluate their region's likelihood of threat and susceptibility. This information in turn obviously would permit for categorizing target alleviation and awareness activities for their area. Therefore, the disaster management via satellite images is highly important globally. A novel EFF-TSC method is developed for precise disaster management from the input satellite image with higher accuracy. The input satellite images are preprocessed to get a quality improved image by applying the Enhanced Frost filtering model. Followed by, the Threshold pixel segmentation is carried out to obtain the background pixels and foreground objects by maximizing between class variance. Finally, the Cosine-based Tanimoto Similarity function analyzes the extracted segmented feature and classifies the input satellite image into disastrous or non-disastrous image. The comprehensive experimental assessment is carried out with satellite image dataset. The quantitative results discussion shows the EFF-TSC method has received better performance in terms of achieving higher disease classification accuracy with lesser time consumption and error rate when compared to other related works.

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