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Fire images classification using high order statistical features

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Abstract

Wildfires and forest fires have devastated millions of hectares of forest across the world over the years. Computer vision-based fire classification, which classifies fire pixels from non-fire pixels in image or video datasets, has gained popularity as a result of recent innovations. A conventional machine learning-based approach or a deep learning-based approach can be used to distinguish fire pixels from an image or video. Deep learning is currently the most prominent method for detecting forest fires. Although deep learning algorithms can handle large volumes of data, typically ignore the differences in complexity among training samples, limiting the performance of training models. Moreover, in real-world fire scenarios, deep learning techniques with little data and features underperform. The present study utilizes a machine learning-based approach for extracting features of higher-order statistical methods from pre-processed images from publicly available datasets: Corsican and FLAME, and a private dataset: Firefront Gestosa. It should be noted that handling multidimensional data to train a classifier in machine learning applications is complex. This issue is addressed through feature selection, which eliminates duplicate or irrelevant data that has an effect on the model's performance. A greedy feature selection criterion is adopted in this study to select the most significant features for classification while reducing computational costs. The Support Vector Machine (SVM) is a conventional machine classifier that works on discriminative features input obtained using the MIFS, feature selection technique. The SVM uses a Radial Basis Function (RBF) kernel to classify fire and non-fire pixels, and the model's performance is assessed using assessment metrics like overall accuracy, sensitivity, specificity, precision, recall, F-measure, and G-mean.

1. Introduction

Millions of hectares of forest have been destroyed by wildfires in recent years (Bhujel, Maskey-Byanju et al. 2017, Mannan, Feng et al. 2017, Nolan, Boer et al. 2020). Nature's balance is protected by forests. Forest fires are usually identified after they have spread across a large area, making management and extinguishment difficult, if not impossible (Alkhatib 2014). Computer vision-based fire detection is gaining active research attention in categorizing surface and crown fires (Guan, Min et al. 2022). Surface fires in the forest can be easily identified with smoke sensors, making classification difficult. Crown fires occur when a surface fire is not controlled immediately. No sensor can withstand the tremendous heat produced by a crown fire, making sensing difficult (Chowdary, Gupta et al. 2018). To detect crown fires early, satellites or unmanned aerial vehicles must continuously monitor the forest landscape. Vision-based techniques also help firefighting teams locate their destination by classifying video or picture information. Apart from preventing flames from spreading, this strategy aims to minimize economic and financial losses to human and forest life. The classification of fire pixels in an image or video can be done using either standard machine learning or deep learning (Bot and Borges 2022, Bouguettaya, Zarzour et al. 2022, Majid, Alenezi et al. 2022).

The conventional machine learning paradigm necessitates feature extraction and selection. Alternatively, deep learning can be used to automatically extract and select features for classification (Farhana Thariq Ahmed, Ahmad et al. 2019). Manual feature extraction is inefficient at capturing discriminative feature information in large data sets. Handcrafted approaches also perform inefficiently and are unreliable as data size increases. While deep learning methods may handle enormous data volumes, they could not account for the variation in complexity across samples. Thus reducing the efficiency of their training models and increasing misclassification (Guan, Min et al. 2022). Moreover, in complex fire scenarios, deep learning with minimal data and features underperforms.

Thus, the current study employed machine learning to extract higher order features (Swami, Mendel et al. 1998) from the image dataset for fire pixel classification. Higher order cumulant features were used since they are resistant to Gaussian noise in the original data. In remote sensing applications like fire monitoring and detection, higher-order statistical features are rarely used (Vijithananda, Jayatilake et al. 2022). The present study evaluates higher order cumulants (order 3) that extract the cumulant coefficients from images using an unbiased approach. Handling multidimensional data to train a model is difficult in machine learning. Through removing redundant or irrelevant data, the model's performance can be improved. To lower the computational cost, information theoretic feature selection approaches have been used in this work with a predefined set of significant feature inputs. Later, the discriminative features are fed into the SVM classifier. To assess the model's performance, the images are classified as either fire or non-fire using an SVM classifier with a Radial Basis Function (RBF) kernel. The current approach uses fire photos from publicly available datasets, notably the Corsican (Toulouse, Rossi et al. 2017) and FLAME (Shamsoshoara, Afghah et al. 2021) datasets. Fire detection was indeed conducted using images from the, Firefront Gestosa , a private dataset.

2. Proposed framework

Figure 1 depicts the current work's process for categorizing fire pixels with handcrafted feature extraction and selection. Three publicly available image datasets have been used in this study: Corsican (Toulouse, Rossi et al. 2017), FLAME (Shamsoshoara, Afghah et al. 2021), and Firefront Gestosa. Furthermore, the present work, combined the three distinct datasets to increase the number of training examples for the presently proposed machine learning model. In this work, the pictures of the adopted datasets are manually labelled and annotated using the data partitioning technique. Prior to the classification task, the images in the image dataset are pre-processed using mask creation and flame localization. Cropping and resizing the photos to 300*300 pixels is then performed using the patch creation approach. Following that, the resized images are divided into training, testing, and validation test sets. The downsized images are then modified using the Radon transform, which reduces the image's dimensionality from two dimensions to one dimension.

The present work applied a projection angle of 0^0 to 360^0 and a step size of 10^0, for performing the Radon transform. As a result, each image is formed contributes to 37 angles. The current study extracts HOS cumulant features from each angle and then concatenates all 37 angles' extracted features into a single feature vector. Since it is impractical to input a larger feature vector to the learning algorithm, the present work incorporates a feature selection approach to reduce computational complexity. The current work examined the extracted features experimentally using a greedy feature selection criterion - Mutual Information Feature Selection (MIFS), with a predefined set of optimal features (30, 50 and 80). Finally, the reduced set of optimal features is sent into the SVM classifier, which performs fire pixel classification. Finally, the machine learning model is used to localize the fire pixels and the classification performance of SVM is evaluated using the following metrics: overall accuracy, sensitivity, specificity, precision, recall, f-measure, and g-mean.

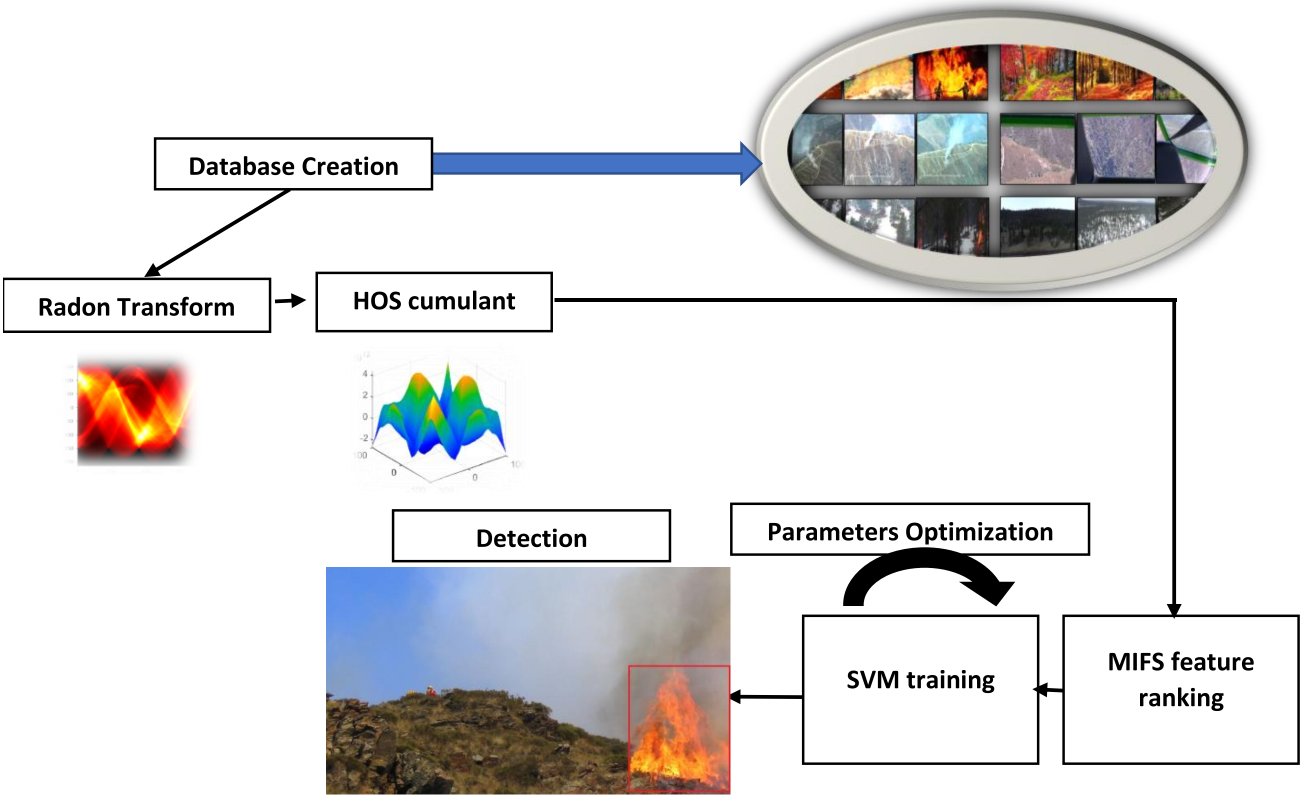

Figure 1- The proposed framework for fire classification adopting a handcrafted approach.

3. Material and methods

3.1. High order cumulants features

The present work, extract higher order statistical features from the pre-processed image. In specific, higher order cumulant features (Mendel 1991, Swami, Mendel et al. 1998) of order three is extracted from the image in an unbiased fashion. By removing the sample mean from the pre-processed image, radon transform (Stanley 1983) was performed to reduce the dimension of the image to a single dimension. Afterwards, cross-cumulant estimates were computed. The third order cumulant represent the normalized skewness and it can recover the cumulant information even in the presence of coloured Gaussian noise present in the image. For a random variable y the cumulant generating function can be expressed as $K(n)$,

$$K(n) = logE[e^{nY}] \qquad (1)$$

The higher order cumulants can further expressed as the central moments with polynomial functions as

$$K_1(\mathrm{Y}) = \mathrm{E(Y)} \qquad (2)$$

$$K_2(\mathrm{Y}) = \mathrm{var(Y)} = \mathrm{E}\left(\left(\mathrm{Y} - \mathrm{E(Y)}\right)^2\right) \qquad (3)$$

$$K_3(\mathrm{Y}) = \mathrm{var(Y)} = \mathrm{E}\left(\left(\mathrm{Y} - \mathrm{E(Y)}\right)^3\right) \qquad (4)$$

Where, equation 2,3,4 represents the mean (first order), variance (second order), and skewness (third order) respectively.

3.2. Mutual information ranking technique

MIFS (Battiti 1994), a greedy feature selection method, guarantees the selection of highly informative features using mutual information as a metric. This selection paradigm uses a regularisation parameter, β, to identify the non-linear relationship between selected features and output class. This value β reduces the level of uncertainty among the optimal feature subsets by eliminating duplicate features. Finally, for classification, the ideal feature subset with pre-defined feature information will be fed into machine learning classifier.

MIFS has an advantage over other linear transformation-dependent approaches in that it considers the non-linear relationship between features and the output class labels. As a result, MIFS delivers strong generalisation for training while also reducing computing time.

The MIFS algorithm uses the following approach to ensure that every feature chosen is informative (Battiti 1994):

1. Feature set (empty) $\hat{S}$ initialized with initial features, as $\hat{S} \leftarrow f_0 \ldots, f_n$ features.
2. Mutual information among the feature variables, f to be computed between the feature variables and the class labels (output: O), as I (O: f) in the extracted feature set $\hat{S}_f$
3. Select the features that are highly mutually informative with the output, O and add them to the empty feature set based on the increasing order mutual information as, $\hat{S} \leftarrow \hat{S} \backslash \{f\}$ and $\hat{S} \leftarrow \{f\}$
4. Implement a "greedy" selection of features for a set of pre-determined numbers such as 30, 50 and 80
   a. For every set of feature pair in the set $\widehat{S}$, calculate $I(f, \hat{s})$, $\hat{s} \in \hat{S}$, if not calculated already.
   b. The features that are highly related to each other are chosen to satisfy the criteria of mutual information as,

$$I(O : f) - \beta \sum_{\hat{s} \in \hat{S}} I(f, \hat{s})$$

5. Finally, the set $\hat{S}$ is treated as an ideal feature subset as it contains highly informative features.

4. Results and discussion

The experiments were conducted over a dataset of 8036 pictures, where 4016 represent fire and 4020 are non-fire images. One hundred and twenty-five sun pictures are injected on the database to simulate high intensity pictures that could be misleading to the classifier. The exact contribution of every set of data (Corsican, FLAME and Firefront_Gestosa) into the final dataset is given in table 1. The final dataset was partitioned to training, validation, and test sets with the following ratio: 60%, 20% and 20% respectively. The SVM model, with gaussian kernel, was trained in a loop with varied parameters configurations to find the optimal Gamma and cost parameters.

Table 1- The corresponding parameters of the conducted experiments

Dataset	Corsican Dataset	FLAME Dataset	Firefront_Gestosa Dataset	Sun Pictures
Fire	1775	2003	238	**0**
Non-Fire	0	2782	1113	**125**

Table 3. represent the experimental results by varying the selected features as 30, 50 and 80 from the total set of extracted feature vector. The MIFS paradigm performs the feature selection with regularisation parameter β set to three different values as 0.1, 0.5 and 0.8. The parameters of the conducted experiments are given in table 2., while the corresponding results are given in table 3. The model's performance was measured with overall accuracy, sensitivity, specificity, precision, recall, f-measure and g-mean metrics. The results observed to be better with increasing number of features irrespective of β. Overall performance reported high with set of 80 selected cumulant features with no significant difference in the reported values with β.

Table 2- The corresponding parameters of the conducted experiments

Experiment Nº	***Number of Features***	***Other Parameters***
Experiment 1	30	The regularization parameter β = 0.8
Experiment 2	50	
Experiment 3	80	
Experiment 4	30	The regularization parameter β = 0.5
Experiment 5	50	
Experiment 6	80	
Experiment 7	30	The regularization parameter β = 0.1
Experiment 8	50	
Experiment 9	80	

Table 3- The given results of every experiment

Experiment Nº	***Overall accuracy***	***sensitivity***	***specificity***	***precision***	***recall***	***f-measure***	***g-mean***
Experiment 1	95,78	93,40	98,16	98,07	93,40	95,68	95,75
Experiment 2	96,02	94,05	97,99	97,90	94,05	95,94	96,00
Experiment 3	96,093	**94,15%**	**98,04%**	**97,95%**	**94,15%**	**96,01%**	**96,07%**
Experiment 4	95,981	93,88	98,09	98,00	93,88	95,89	95,96
Experiment 5	96,068	94,12	98,01	97,93	94,12	95,99	96,05
Experiment 6	96,105	**94,17**	**98,04**	**97,95**	**94,17**	**96,03**	**96,09**
Experiment 7	95,856	93,83	97,89	97,79	93,83	95,77	95,83
Experiment 8	96,03	94,12	97,94	97,85	94,12	95,95	96,01
Experiment 9	96,068	**94,07**	**98,06**	**97,98**	**94,07**	**95,99**	**96,05**

5. Conclusions and outlooks

Fire detection is a task that require high precision to localize the exact position of flames. Hence, an accurate and well-trained model need to be developed to make the intervention of the firefighters faster. The current paper divulgates the results of an SVM model trained with 3rd high order cumulant feature set reduced with a mutual information algorithm. The given results are very promising. However, more experiments need to be run using other feature ranking techniques to observes the fluctuation of different parameters and the performance of the classification technique.

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