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# A Method for Identifying Vegetation Under Distribution Power Lines by Remote Sensing

**Natália Yukari Kume Kinoshita[1] · Jean Schmith[1,3] · Eduardo Augusto Martins[1,2] · Rodrigo Marques de Figueiredo[1,3]**

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**Abstract**

One of the major causes of interruption in distribution power lines is the vegetation encroachment. The vegetation management is challenging and demands efforts in trimming trees planning. The literature presents many methods for encroachment over power lines detection that depends on local installation and manipulation of equipment, which may be unfeasible. Thus, the remote sensing raises as an valuable solution. Therefore, this work proposed a remote sensing based method for identification of probable vegetation encroachment over distribution power lines. Since the free satellite images have low resolution considering the size of treetops, and the high-resolution ones are expensive, our method used the Google Earth images. From that images, texture features and support vector machines were used to identify regions with and without vegetation. The accuracy of the method was of 95% and F1-score above 92% for testing and validation datasets. The method is suitable for real-time application in tree trimming planning, in addition to opening up new possibilities for innovation in vegetation management.

**Keywords** Vegetation identification · Vegetation encroachment · Faults by vegetation · Distribution power lines · Remote sensing

## 1 Introduction

The faults by vegetation encroachment over distribution power lines are common in urban areas and one of the largest causes of interruption in power energy supply (Carvalho et al., 2018; Louit et al., 2009; Sittithumwat et al., 2004; Ahmad et al., 2013). The higher trees tend to encroach over distribution power lines causing short circuit faults and instability in power grids. In the most extreme cases, trees can fall into distribution power lines breaking them and therefore safety is an important issue to consider, as well (Ma et al., 2020). Vegetation management in urban areas is not an easy task. The visual and manual inspection of trees touching the distribution power lines can be exhaustive, time-consuming and expensive for electric power distribution companies (Daily, 1999). These companies shall plan a route for trimming the trees, and thus accurate data from the trees over distribution power lines situation is important for an effective work.

Hence, many efforts to disentangle the problem of identifying vegetation around transmission power lines were published in the literature. The vegetation over transmission power lines was studied using monitoring cameras (Ahmad et al., 2015) and Faster Region Convolution Neural Networks (FRCNN) (Rong & He, 2020; Rong et al., 2020). The places that no monitoring camera is available, the inspection of transmission power lines is commonly done by helicopters, therefore an alternative was to detect vegetation encroach-

Natália Yukari Kume Kinoshita, Jean Schmith, Eduardo Augusto Martins and Rodrigo Marques de Figueiredo have contributed equally to this work.

✉ Jean Schmith
j.schmith@gmail.com

Natália Yukari Kume Kinoshita
nataliakume@gmail.com

Eduardo Augusto Martins
eamartins@unisinos.br

Rodrigo Marques de Figueiredo
marquesf@unisinos.br

1 Polytechnic School, Unisinos University, Av. Unisinos, 950, São Leopoldo 93022-750, RS, Brazil

2 ittFuse Institute, Unisinos University, Av. Unisinos, 950, São Leopoldo 93022-750, RS, Brazil

3 Technology in Automation and Electronics Laboratory - TECAE Lab, Unisinos University, Av. Unisinos, 950, São Leopoldo 93022-750, RS, Brazil

ment using Unmanned Aerial Vehicles (UAV) (Chen et al., 2022; Vemula & Frye, 2021; Fang et al., 2020) and LiDAR sensor (Munir et al., 2020). Another way to analyse the problem around transmission power lines was on studying the vegetation growth using the Wireless Sensor Network (WSN) (Carvalho et al., 2018; de Medeiros et al., 2018; Matikainen et al., 2016).

The use of satellite images was an important advance to support the identification and monitoring the vegetation growth around transmission power lines (Jardini et al., 2007; Ahmad et al., 2011a). An evolution was the use of satellite images with WSN sensors (Ahmad et al., 2011a, b) to identify vegetation over transmission power lines. The use of satellite images and texture analysis was presented as a good approach to determine the encroachment vegetation over transmission power lines, and the Support Vector Machines (SVM) also performed sufficiently for the related problem (Mahdi Elsiddig Haroun et al., 2021). One of the negative points of using satellite images highlighted by Jardini et al. (2007) was the low resolution of images and the impossibility of obtaining small details through them.

In a general way, the inspection methods for vegetation over transmission power lines identification include vehicles, helicopters, UAVs, monitoring cameras, satellite images, WSN and LiDAR scanning (Jenssen et al., 2018; Gazzea et al., 2021). Regarding the main machine learning method, the most used was the SVM with different choices of image texture features used as input (Sikorska-Łukasiewicz, 2020).

The Normalised Difference Vegetation Index (NDVI) method is widely used for vegetation identification using satellite images (Jabal et al., 2022; Kadhim et al., 2022) and could contribute to encroachment of vegetation in distribution power lines. However, satellite images are expensive, and the free ones have the resolution problem related by Jardini et al. (2007). As an example, the Landsat-8 satellite has the minimum resolution of 15 m, considering the panchromatic band (Dibs et al., 2023). This resolution issue may be a point of concern specially in urban areas for treetops identification. On the other hand, UAVs depends on local inspection and an expert manipulation (Guan et al., 2021). The WSN, LiDAR and cameras depend on local installation and manipulation; moreover, it may not be available for all power grid, specially in distribution power lines. Furthermore, all cited works used the transmission power lines as main study issue, and no work using distribution power lines in urban areas was founded, for the best knowledge of the authors. Bearing in mind that the vegetation encroachment is also an urban problem, a method for identification of vegetation and distribution power lines intersection without local apparatus installation and manipulation has a lack in the literature. Remote sensing is a valuable solution to fill this gap using high-resolution images from Google Earth.

Therefore, this work proposes a method for identification of probable vegetation encroachment over distribution power lines in urban areas by remote sensing. The novelty is the use of Google Earth images, which is composed of a mosaic of images from different sources, and discrete wavelet transform to compute texture features as input for the SVM model. The texture features of the treetops indicate the vegetation areas and an interesting and novel tool for identification of it intersections with distribution power lines. The main advantage of this proposal is the no need of local inspection for potential vegetation encroachment over distribution power lines. Also, the proposed method is suitable for real-time applications of trimming trees routes planning and vegetation management, which demands more efficient methods (Jaramillo-Leon & Leite, 2022).

This work is divided in the following way. In Sect. 2 are presented the proposed methodology, how the dataset was computed, the description of the discrete wavelet transform computation, how the chosen features were extracted, the support vector machine model parameters, and the evaluation metrics. In Sect. 3, the results are presented and discussed in Sect. 4. Finally, Sect. 5 presents the conclusion.

## 2 Materials and Methods

The method for classification of regions with and without vegetation, which further identifies the intersections with distribution power lines, was based on images collected from Google Earth. Figure 1 presents the method scheme. First the images were collected in several regions of interest in the city of São Leopoldo, Brazil, next divided into sub-images of 20 × 20 pixels and by hand annotated as with or without vegetation. The sub-images were then processed using the Discrete Wavelet Transform (DWT) to extract 18 texture features. Finally, the sub-images were automatically classified between images with and without vegetation using the Support Vector Machines (SVM). The identification of potential intersection between vegetation and the distribution power lines was then possible. The following sections details all the steps of the method. The method was developed in Python programming, with OpenCV library (Bradski, 2000) for image processing, PyWavelets library (Lee et al., 2019) for discrete wavelet transform and scikit-learn library (Pedregosa et al., 2011) for the machine learning application.

### 2.1 Dataset

Remote sensing technologies (satellite images) were used in the works cited in the introduction for vegetation identification. Following the same direction, in this work the images from Google Earth were used. Google Earth has already been proved as an important tool for visualisation and dissemina-

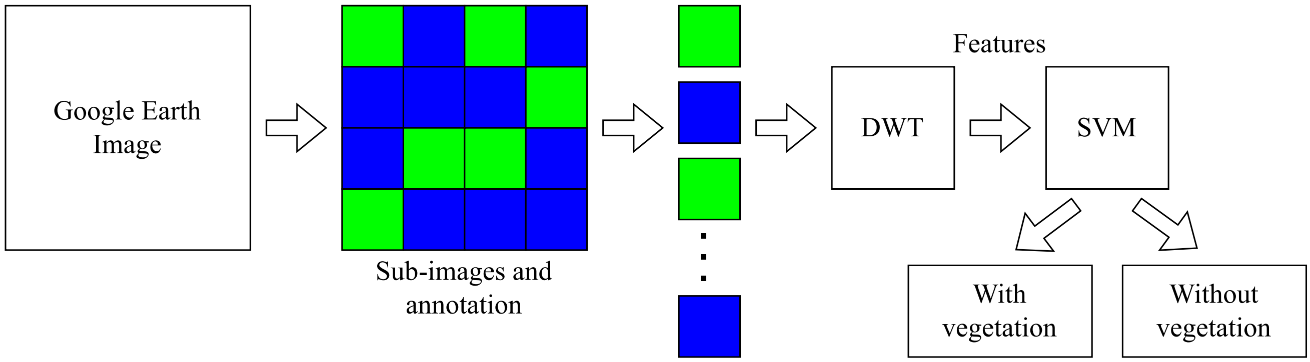


**Fig. 1** The method scheme for vegetation identification. The green marks indicate the presence, and the blue ones indicate the absence of vegetation

tion of scientific data (Butler, 2006; Compieta et al., 2007; Guralnick et al., 2007). Google Earth images are composed of aerial photographs, digital models and satellite images from different sources. The main advantage of using Google Earth images against free satellite images is the higher resolution, despite some area and position distortion. Sixteen Google Earth images were collected from different parts of São Leopoldo City (29°45′S, 51°08′W), Brazil. The location of the images was chosen based on known intersection of vegetation and distribution power lines. We confirmed the intersection using the Google Street View. From the collected images, 15 were used for training and testing the method and one was used for the validation.

All the images were collected with no angulation and the same scale of 1:100 m (viewpoint altitude: 800 m) resulting in images of 1024 × 768 pixels. Further, the images were cropped to 1020 × 700 pixels and then divided into 20 × 20 pixels sub-images forming a grid. Other sizes of sub-images were also tested; however, the 20 × 20 pixels achieved the best result. All the sub-images were manual marked as containing vegetation or not. Figure 2 presents an example of this processing, the green marks represents the presence, and the blue marks the absence of vegetation. Note that only trees were marked in green, other types of vegetation, like grass, were marked in blue. All sub-images were converted to grey scale. From the 15 images a total of 26775 sub-images were produced, 70% (18742 sub-images) were used for training and 30% (8033 sub-images) were used for testing the method. The test dataset resulted in 5398 without and 2635 with vegetation sub-images.

For the validation of the method, we used one image that passed through the same process of cropping, dividing into sub-images and manually annotation. This computation resulted in 1785 sub-images for validation. This validation data was not used for training the SVM algorithm.

## 2.2 Discrete Wavelet Transform

The Discrete Wavelet Transform (DWT) (Mallat, 1999, 1989a, b) is a widespread tool used for analysis of texture in images. The method divides the frequencies of an image into components keeping the spatial information according with the chosen Wavelet mother. Therefore, the decomposition results in approximated and detailed components of the original image. Figure 3 presents how the process works. The decomposition process uses low-pass filters and high-pass filters followed by down-sampling. The filters coefficients are determined with respect to the chosen Wavelet mother, and the down-sampling has a factor of two. Notice that for $A1$ computation the image passes through a low-pass filter, a down-sampling of two, a low-pass filter, and again a down-sampling of two. This process results in a filtered component with a quarter size of the original image. The same process occurs with the other components. For a level two decomposition, the process shall be applied to the $A1$ component to form the new components A2, V2, H2 e D2. An example of the DWT decomposition in two levels is presented in Fig. 4.

In this work, the second-order Daubechies (db2) (Daubechies, 1990, 1992, 1998) were used as Wavelet mother. The decomposition was computed in two levels for each sub-image. Therefore, each sub-image was decomposed into three detail components in each level, leading to a total of six detailed components: H1, H2, V1, V2, D1 and D2. The approximated components A1 and A2 were not used. The detailed components were used to compute the texture features.

## 2.3 Features

Upon the detailed components were determined, the main idea was to measure the texture characteristics of the sub-images with and without vegetation. All the sub-images were

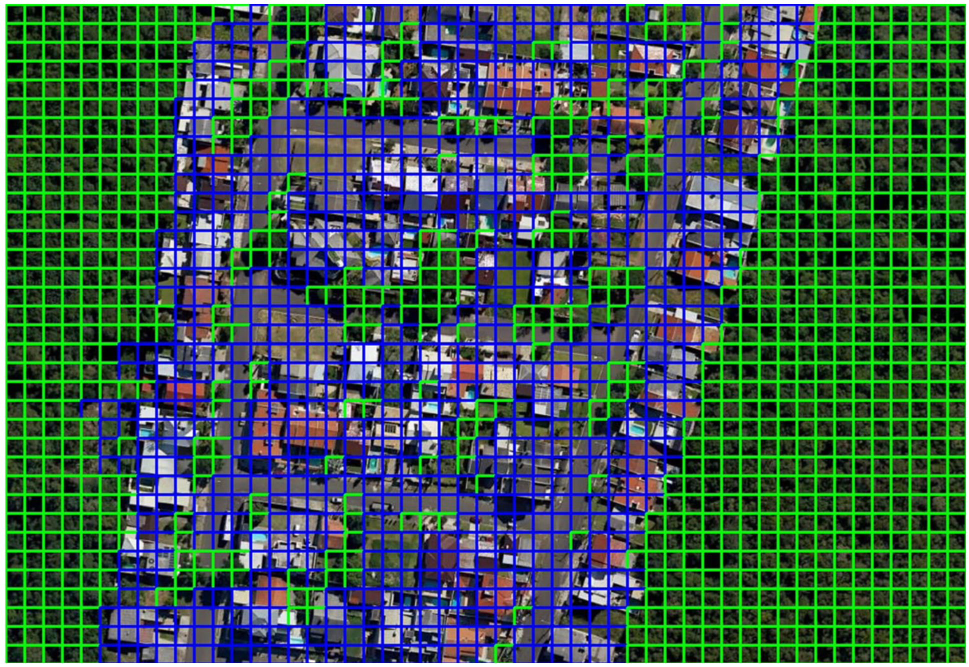

**Fig. 2** Example of manual annotation of the dataset. The green marks represent the presence, and the blue marks the absence of vegetation

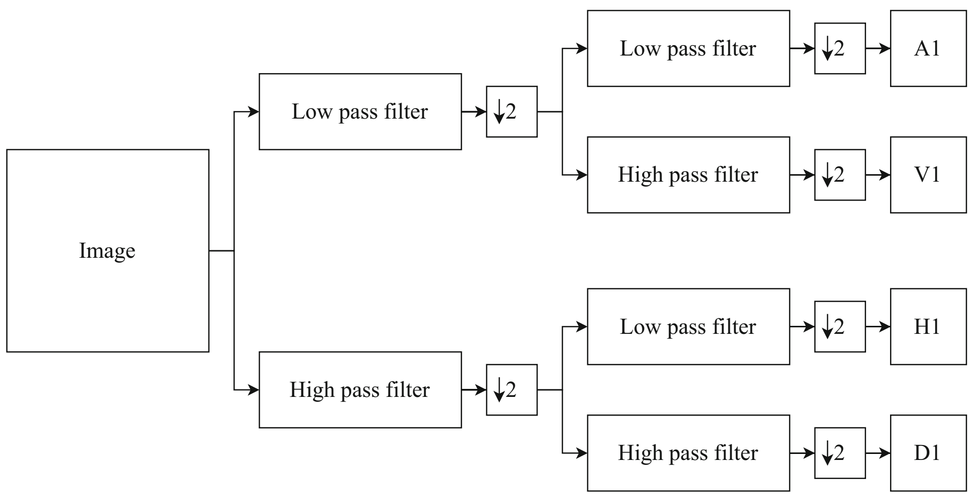


**Fig. 3** Decomposition process of discrete wavelet transform. The image passes through low-pass and high-pass filters followed by down-sampling with factor of two to form the components

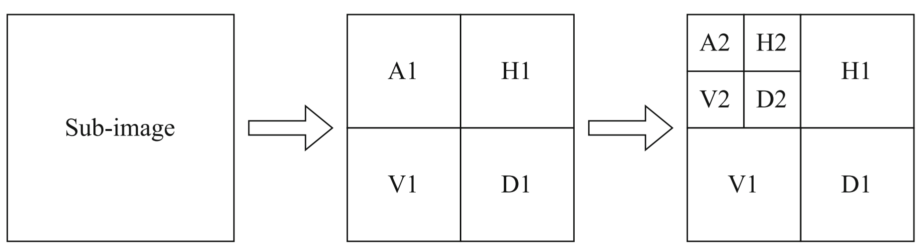


**Fig. 4** Example of a two level discrete wavelet transform decomposition using the process presented in Fig. 3. The components A1, H1, V1 and D1 denote the first level, and then the process is applied to A1 to form the components A2, H2, V2 and D2 in the second level

decomposed into two levels using the DWT. Therefore, for each decomposed sub-image six detailed and two approximated components were computed. The interest was in the texture information, and thus the higher frequencies variation has more interesting information. Then the detailed components were used, and the approximated were discarded. For each detailed component, the mean, Standard Deviation (SD), and entropy were computed resulting in 18 features for each sub-image. The list of the computed features for each DWT component are presented in Table 1.

The features had variations in scale between each other. Scale variations introduce errors in SVM algorithm due to the fact that larger scales can produce less dense points regions and the separation from lower scales may be difficult. There-

**Table 1** Computed features for each DWT component

| DWT component | Features |
|---|---|
| H1 | Mean 0, SD 0 and Entropy 0 |
| V1 | Mean 1, SD 1 and Entropy 1 |
| D1 | Mean 2, SD 2 and Entropy 2 |
| H2 | Mean 3, SD 3 and Entropy 3 |
| V2 | Mean 4, SD 4 and Entropy 4 |
| D2 | Mean 5, SD 5 and Entropy 5 |

fore, we standardised all features using the Z-score method, given by

$$x_{\text{std}} = \frac{x - \mu}{\sigma} \tag{1}$$

where $\mu$ and $\sigma$ are the mean and standard deviation of the dataset. This process computes a new scale for all features with mean equal to zero and standard deviation equal to one. Upon the features standardisation were completed, they were used as input for the SVM algorithm.

The choice of features was made based on the distribution of each one. The box plots of Fig. 5 present the distribution of means computed for the detailed components of all sub-images. Notice that there was a good separation of sub-images with and without vegetation, with exception of Mean 2 and Mean 5.

The same analysis was done for the standard deviation features presented in Fig. 6. The worst cases were in SD 2 and SD 5 with an important intersection of data between with and without vegetation datasets.

Finally, the analysis was proceeded with the entropy data and it is presented in Fig. 7. In a general way, these features presented the worst separation between with and without vegetation classes. However, using together with mean and standard deviation features, it increased the accuracy of the SVM model. The best result was achieved using all 18 features.

### 2.4 Support Vector Machines

The Support Vector Machines (SVM) was first introduced by Cortes and Vapnik (1995), and it is a classification algorithm that seeks for a robust division between classes (Kerscher et al., 2022). It works very well in complicated domains as long as exists a clear margin of separation between classes. As previously mentioned, the proposed 18 features presented a good separation; therefore, the SVM was a suitable method for classification the classes with or without vegetation.

The SVM tries to set a line (or plan, or hyperplane) to divide two or more classes. Then the algorithm attempts to maximise the distance between the lines to points for each class establishing a margin. These separation lines are based on well-known functions.

The computed features for each sub-image were used as input to the SVM algorithm in order to classify into with or without vegetation. In this work, the best result was achieved using the Radial Basis nonlinear kernel function with the

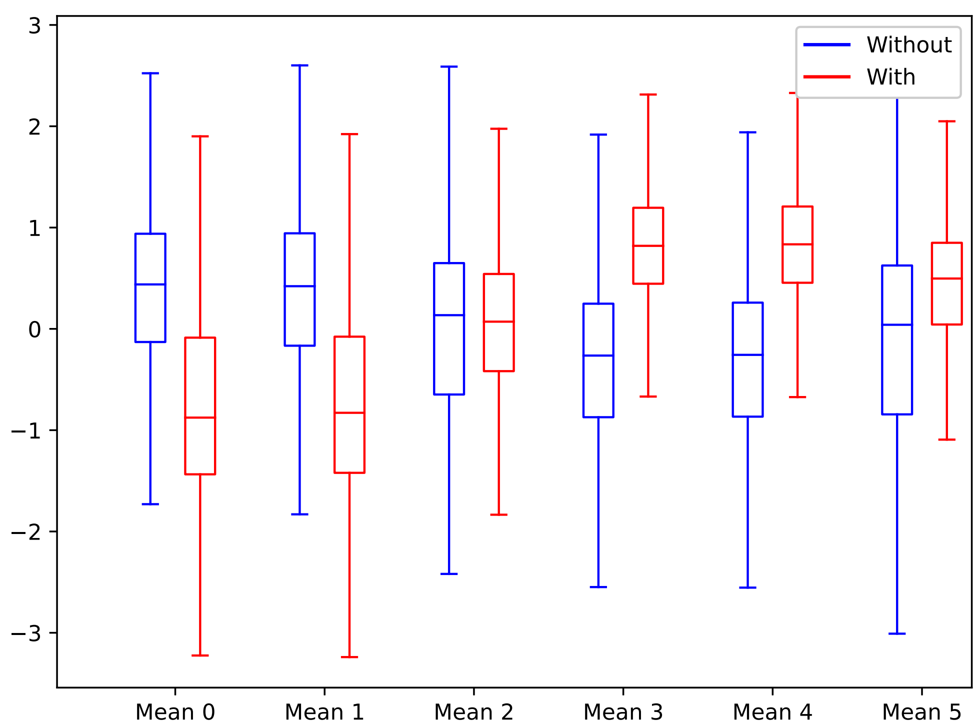


**Fig. 5** Box plot analysis of the Mean features for the entire dataset. In blue the data without and in red with vegetation

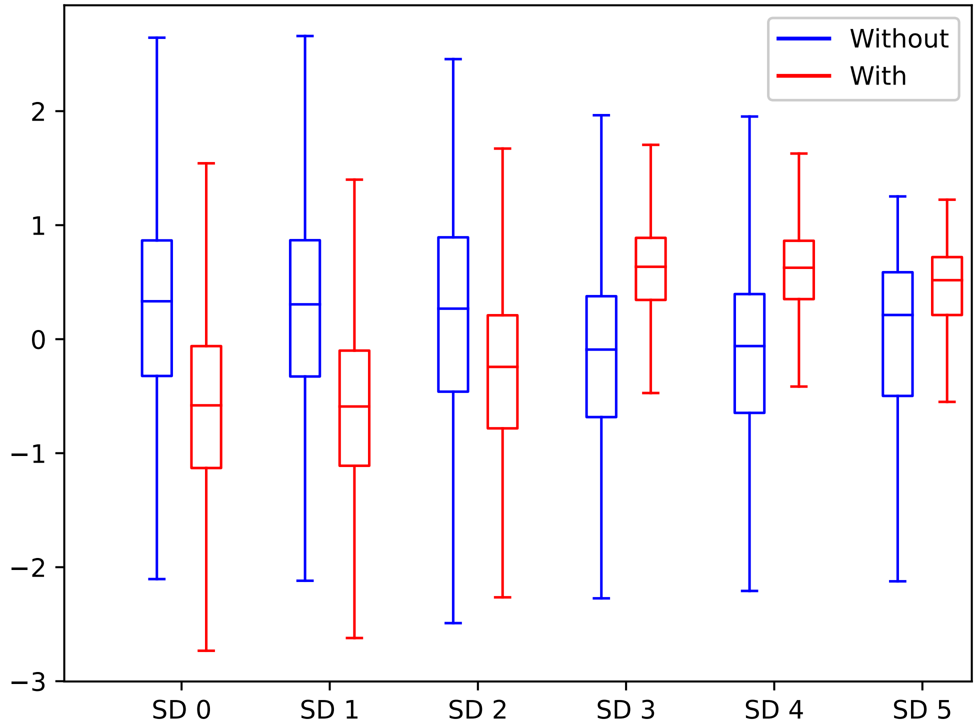


**Fig. 6** Box plot analysis of the Standard Deviation (SD) features for the entire dataset. In blue the data without and in red with vegetation

regularisation parameter $C = 56$ and kernel coefficient $\gamma = 0.44$.

### 2.5 Evaluation Metrics

The evaluation metrics used were the classical information from the confusion matrix, namely true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN) of the classification. From these information, we computed the accuracy, recall, precision and F1-score, respectively, described by

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{4}$$

$$\text{F1-score} = 2\frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} \tag{5}$$

## 3 Results

Once the dataset was computed, it was used as input in the SVM algorithm for classification in with or without vegetation sub-images. The accuracy for the test dataset was of 95%. The other evaluation metrics are presented in Table 2. Notice that all metrics presented good results, and the worst one was the recall for class 1 (with vegetation) of 91%. One might also notice the high F1-scores, which prove the good response of the classification algorithm.

Upon the SVM model was trained, an image that was not used in the train and test dataset was used as input to the algorithm. The same process of dividing into sub-images, hand annotation and features computation was applied to the validation image. Then the validation features were used as input to the already trained SVM model. The achieved accuracy for the validation image was 95%, and the other metrics are presented in Table 3. For the validation dataset the model presented good results as well, with the lowest score of 89% in Recall for the class 1 (with vegetation). Again, the F1-scores were above 90%.

With the good accuracy of the model in classifying as with or without vegetation to all sub-images, an example of an image with intersection between vegetation and distribution power lines is finally presented in Fig. 8. This image is the same one not used for training, only for validation of the SVM model. Notice that visually few errors may be detected. An easy to find error is the green mark at the roof top of a factory, in down left of the image pointed by the red arrow. However, this error had a weak impact to the region close to the distribution power line. On the other hand, the vegetation detection was correctly restricted to trees, notice that the grass areas were ignored as vegetation area by the classifier.

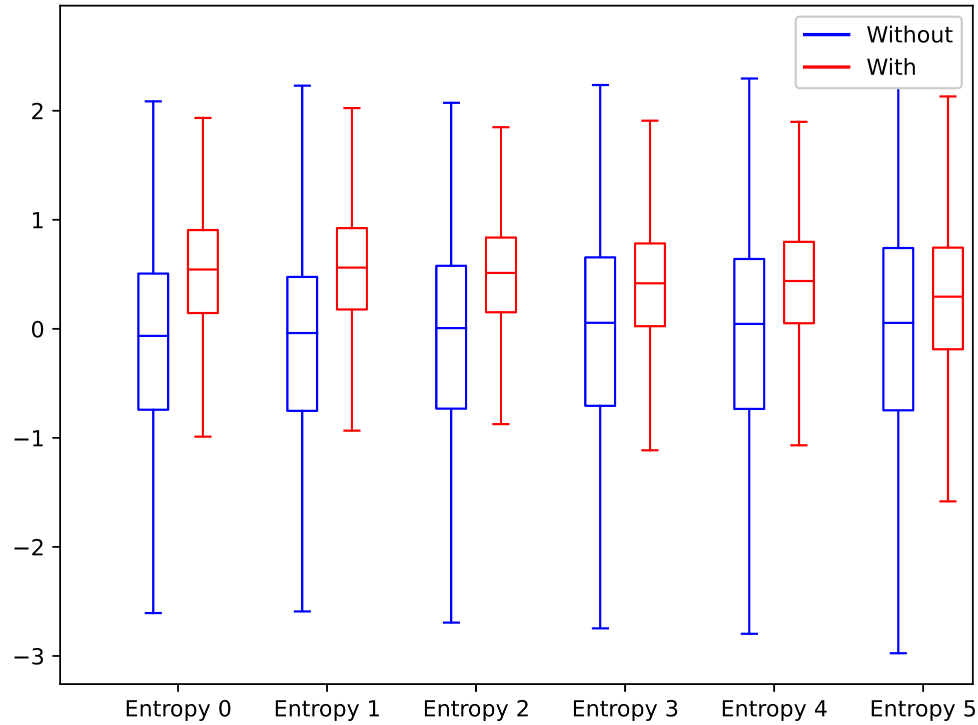


**Fig. 7** Box plot analysis of the Entropy features for the entire dataset. In blue the data without and in red with vegetation

**Table 2** SVM model results for testing dataset

| Class | Precision | Recall | F1-score |
|---|---|---|---|
| 0 | 96% | 97% | 97% |
| 1 | 94% | 91% | 93% |

The class 0 and 1 represents the without and with vegetation sub-images, respectively

**Table 3** SVM model results for validation dataset

| Class | Precision | Recall | F1-score |
|---|---|---|---|
| 0 | 95% | 98% | 97% |
| 1 | 95% | 89% | 92% |

The classes 0 and 1 represent the without and with vegetation sub-images, respectively

In Fig. 8, the distribution power line is presented in red, and the blue marks represent the vegetation detected by the algorithm close to the distribution power line. The distribution power line had the points marked using the Google Street View. Naturally, as the distribution power line has a known position, the region around it is user configurable in a resolution of 20 pixels and all vegetation detected by the algorithm inside this region was marked as blue. In Fig. 8, the chosen region was of 1020x80 pixels.

## 4 Discussion

It was reported in the literature several studies to detect vegetation encroachment, specially in transmission power lines. Complex systems using cameras and Convolution Neural Networks (CNN) presented low error in vegetation detection (Rong & He, 2020; Rong et al., 2020). Good results were also achieved using Unmanned Aerial Vehicles (UAV) (Chen et al., 2022; Vemula & Frye, 2021; Fang et al., 2020) and LiDAR sensor (Munir et al., 2020). However, the application of those methods demands local equipment installation, inspection and expert manipulation (Guan et al., 2021). In addition, training CNNs demands a lot of computer capacity, large datasets and memory consuming (Ponti et al., 2021). Thus, the use of SVM algorithm is a viable option (Sikorska-Łukasiewicz, 2020; Mahdi Elsiddig Haroun et al., 2021).

Herein, the SVM model presented good results in classification of sub-images with or without vegetation. This behaviour points the good choice in features selection. The example of Fig. 8 presented that the method had success to identify the vegetation under distribution power lines. Moreover, the proposed method is suitable for real-time applications.

Most of the cited works here had the main issue focused on transmission power lines in right-a-way corridors, not rarely installed among dense vegetation areas. Also, the 3D analysis is commonly used (Matikainen et al., 2016; Gazzea et al., 2021). As previously discussed, those analysis may depend on expensive installed apparatus. Naturally, although

**Fig. 8** Validation image used in the trained SVM model. The green marks indicate vegetation. The blue marks point the vegetation close to the distribution power line. The distribution power line was marked in red. The region to be considered close to the distribution power line was user defined with the resolution of 20 pixels; in this image the chosen region was of 1020 × 80 pixels

no work on specific distribution power lines in urban areas was founded for the best knowledge of the authors, those methods could be applied to that situation. However, the high cost of those technologies may turn it usage impracticable specially if all power grid should be monitored. Therefore, the method proposed here has an extremely lower cost in comparison with the cited works, but with the lack of information regarding the high of the trees since all Google Earth images collected were in a 2D fashion. Despite that, the presented method has the capacity of providing a good information of the vegetation and power lines intersection.

Hence, the proposed methodology allows a better planning in vegetation management without the need of in local visual inspections since potential intersections between vegetation and distribution power lines could be previously identified. As previously mentioned, the height of the trees is not available; therefore, a good practice is to arrange the vegetation management plan taking into consideration the previous trimming of the trees in that region. Furthermore, the approach of biology data of growth rates from the managed trees may increase the accuracy in choosing routes for vegetation management. One concern is dependency on Google Earth updates which is much slower than a commercial satellite. However, considering the vegetation management, this update time should be considered when planning trimming trees causing no further implication due to the fact that the growth rates of the trees are usually in a lower step. Therefore, this methodology can contribute to already reported methods for planning trimming trees (Jaramillo-Leon & Leite, 2022).

Taking a holistic point of view, the main issue is to identify vegetation, specially treetops, in urban areas. Regarding this observation, the method presented good results since it could even distinguish treetops from grass and shadows, as an example. The most classical method for detecting vegetation is the Normalised Difference Vegetation Index (NDVI) computed from satellite images (Gazzea et al., 2021). However, the free satellite images have low resolution (Jardini et al., 2007) making unfeasible treetops identification near distribution power lines. In addition commercial Satellite images are expensive. Thus, the Google Earth images are a good choice regarding cost and resolution.

As presented in Fig. 8, the region determined around the distribution power line was previously known; therefore, any predetermined region could be evaluated to detect treetops (recreation parks, as example). Hence, although the main motivation in this work was to identify treetops near distribution power lines, the method can be used in other applications. Important to say that the method has the capacity of identifying treetops in urban areas and in areas with more dense vegetation it could have some miss classifications. Thus, since transmission power lines are usually placed among dense vegetation areas, the method proposed here may not be a good choice.

In a general way, the proposed method is a low cost, simple to implement and suitable for real-time applications. The novelty here is to use the Google Earth images together with DWT texture features and SVM classification to determine regions with vegetation using sub-images. As aforementioned, several sizes for the sub-images were tested and best results were achieved with 20 × 20 pixels. For higher sizes, the sub-images had the problem to delimit treetops since other structures were also included in it and taking to a difficulty in classification, even manually (treetops plus roof top buildings, as example). The process of DWT decomposition results in filtered components with a quarter size of the original image (for a size of 20 × 20 results in 5 × 5 pixels components), and thus smaller sizes for sub-images led to a limitation in calculation of components. The chosen size comprehend that more than half of the sub-image shall be covered by a tree top; otherwise, this sub-image was considered as not containing vegetation. Naturally these observations are valid for scale and viewpoint configured in Google Earth explained in Dataset section. For a different configuration in collected images, a new choice of sub-images size should be done, always taking into consideration that at least half of the sub-image should contain treetops to be considered as a with vegetation class. Therefore, a good agreement between treetops size and sub-images size should be observed. Naturally, we considered only images of good quality with no noise, blur or clouds. The expectation is that noise, blur and clouds may contribute to the texture features in a manner that no clear division between with or without vegetation could be possible.

## 5 Conclusion

This work proposed a method for identification the intersection of distribution power lines and vegetation using the Google Earth images. The method presented good results with 95% of accuracy in identification of regions with and without vegetation. The F1-scores were above 92% for test and validation datasets. The high accuracy in vegetation identification allows analysing the intersection with known distribution power lines. The proposed remote sensing method was effective in vegetation identification, and it is suitable for real-time applications. This method opens a possibility of innovation in vegetation management and a more accurate planning for trimming trees since the remote sensing technologies tend to produce even more accurate satellite images. Future works are focused on analysing the vegetation species and add the growth time variable for more efficient routes for trimming the trees.

### Declarations

**Conflict of interest** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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