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ENSEMBLE CLASSIFIER BASED MULTICLASS VEGETATION CLASSIFICATION SYSTEM

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Abstract

The applicability of remote sensing is improving hand in hand with time. Various research works focus on remote sensing technology, as it is one of the hottest research topics. This paper is all about satellite image crop classification. The crops being present in a particular location is differentiated by means of a classification algorithm. However, it is difficult to attain reasonable accuracy rates, as the images are captured from a greater altitude. This research article focuses to present a satellite image classification system for distinguishing between the crops being present in the agricultural area. To achieve the research goal, the entire work is broken down into satellite image pre-processing, feature extraction and classification. The satellite images are mostly affected by noise and poor contrast. These issues are addressed by employing bilateral filter and adaptive histogram equalization technique. The Gabor Local Vector Pattern (GLVP) based Scale Invariant Feature Transform (SIFT) features are extracted from the pre-processed images. The crops being present in a location are distinguished by means of ensemble classifier, which is a combination of k-Nearest Neighbour (k-NN), Support Vector Machine (SVM) and Extreme Learning Machine (ELM). The performance of the ensemble classifier is compared with the individual classifiers, and the ensemble classifier outperforms the other classifiers in terms of classification accuracy, sensitivity and specificity rates.

Keywords:

Extreme Learning Machine, SIFT, Ensemble Classifier, Classification System

1. INTRODUCTION

Remote sensing is one of the hottest research topics these days, owing to its wider range of applicability. The term 'remote sensing' indicates that the subjects of interest are sensed in a remote fashion. The subjects of interest vary from application to application. For instance, remote sensing is widely employed in crop classification, environment monitoring, traffic planning, vehicle tracking, irrigation planning and so on. Crops are the subject of interest when it comes to crop classification and similarly, vehicles and water bodies are the subjects of interest for vehicle tracking and irrigation planning. Though the remote sensing techniques are popularly employed, there are several challenges involved in remote sensing applications as presented below.

The remote sensing applications rely on satellites to acquire images through which the objective of the application is achieved. As the satellite images are taken from a greater altitude, the objects of the image are not clear enough to process. Hence, advanced image processing techniques are applied to process the satellite images. Remote sensing systems contribute more in the area of agricultural applications such as crop classification, estimating the crop yield, managing, tracking the crops and so on. Though there are enormous applications in the existing literature, there is a consistent demand for accurate crop classification approaches.

This article aims to classify between the vegetation in a specific location by employing advanced image processing techniques. The entire functionality of the work is decomposed into three significant phases such as satellite image pre-processing, SIFT feature extraction and classification. The satellite images are needed to pre-process such that the details of the images can be perceived clearly. The pre-processing phase of this work attempts to remove the noise and to enhance the contrast of the satellite images by employing bilateral filter and adaptive histogram equalization technique. The next phase attempts to extract GLVP based SIFT features from the pre-processed images. The classifier is trained with the feature vector being framed during the previous phase.

During the classification phase, the classifier is equipped with knowledge such that it can differentiate between different classes of vegetation. Some of the noteworthy points of this work are as follows.

- The image pre-processing activity processes the image to remove noise and to enhance the contrast of the images by means of bilateral filter and adaptive histogram equalization techniques.
- The GLVP based SIFT features are extracted from the pre-processed images, as they withstand the curse of rotation, scaling, illumination and so on.
- Ensemble classifier is employed to classify between the different classes of vegetation such as pine, yard, codar tree and grass.
- The performance of the proposed approach is evaluated in terms of accuracy, sensitivity and specificity and the proposed approach prove its efficacy.

The remainder of this paper is organised as follows. Section 2 presents the review of literature with respect to crop classification. The proposed crop classification approach is elaborated in section 3. The performance of the proposed approach is evaluated in section 4 and the concluding points of this work are summed up in section 5.

2. REVIEW OF LITERATURE

This section aims to review the related literature with regards to crop classification.

In the work proposed in [1], the crops are mapped by means of pixel based approaches and the effectiveness of Google Earth Engine (GEE) is proven. This study has been done in Ukraine and the classification is done by ensemble of neural networks and claims that this work is efficient than classifiers such as Support Vector Machine (SVM), decision tree and random forest. In [2], the crop species are classified by means of phenology based approach. In order to meet the objective, this work extracts the vegetation index from Landsat 8 and the profile of phenology has been created. From this profile, the classifier is made to detect the agricultural areas and to distinguish between various crops. The geographical area being considered for this work is Nakuru district of Kenya.

In [3], crops are classified by means of morphological profiles which are obtained from SAR and electro-optical satellite data. This work operates over SAR and electro-optical data spatially by closing and opening operations to classify between nine classes. This work shows about 90% classification accuracy. Unmanned Aerial Vehicles (UAV) are utilized for crop and weed classification, so as to notify the farmers in the work proposed in [4]. This work identifies sugar beets and weeds by employing a camera on lightweight UAV. This work detects the vegetation, extracts the features and classifies the distribution of crops and weeds in the field. The work considers the agricultural field in Germany and Switzerland.

The crops are classified on the basis of feature band set construction and object oriented classification technique in [5]. In this work, a crop classification technique is proposed that is based on the formation and optimization of vegetation feature band set. The feature band set is formed by spectral, textural and spectral indices. The performance of this work is tested by the images that contain seven different crops. In [6], a deep learning based classification technique is proposed to classify between the land cover and types of crop. The unsupervised neural network is employed for image segmentation. This work is carried by MultiLayer Perceptron (MLP) and the experimental results are compared with Convolutional Neural Networks (CNN). This work distinguishes between five agricultural crops.

The work presented in [7] proposes an Artificial Neural Network (ANN) and the parameters are varied. This work utilized the satellite images of Linear Imaging Self Scanning (LISS) IV and Landsat 8 Operational Land Imager (OLI). This work classifies between more than five agricultural crops. In [8], the crops are classified by means of multitemporal hyperion images into three different classes. Hundred samples of each class are trained by SVM and k-Nearest Neighbour (k-NN). This work concluded that SVM outperforms k-NN in terms of classification accuracy. A crop sequence based ensemble classification technique is proposed in [9], which utilizes TerraSAR-X multitemporal image. The first order and higher order dynamic conditional random fields are extracted. The random fields produce image and expert based phenology during the process of classification. The performance of dynamic conditional random fields is better than Maximum Likelihood Classifier (MLC) and Conditional Random Fields (CRF).

In [10], a classification approach is proposed to differentiate between crop and weed. The crop being considered by this work is maize. The maize crops are governed by means of camera and the images are collected. The texture, shape and colour features are extracted from the images and SVM classifier is exploited to differentiate between the maize and weed. In [11], an automatic pest identification system is proposed to detect the pest and thereby avoiding the disease earlier. Colour features are utilized to train the SVM classifier. A work to classify between the crop area and Vaijapur Tehsil over the IRS P6 LISS III sensor is presented in [12]. The satellite images are analysed by fuzzy convolutional technique and classified by MLC. It is concluded that the performance of MLC is better, when it comes to overall classification accuracy, however the fuzzy convolution technique provides reliable results.

In the work proposed in [13], the diseases detected in crops are classified by using texture analysis. This work focuses on sunflower crop and the input images are acquired by a high resolution camera and the k-NN clustering approach is applied to detect the affected portion of the leaf. The colour and texture features are extracted and the classifiers such as k-NN, multiclass SVM, Naïve Bayes and Multinomial Logistic Regression. The performance of all the classifiers is tested. In [14], the crop yield over a particular agricultural area is estimated and the crop with increased rate of harvest is found out. In order to achieve this, data mining approach is utilised to detect the good growing crop over that region through which the monetary benefits can be improved.

In [15], fruit tree crops are differentiated by exploiting the Landsat-8 time series data. This work classifies between six fruit tree crops by employing Linear Discriminant Analysis (LDA) over the areas of centra Chile. The spatial information of the time series is treated by LDA and the Normalized Difference Indices (NDI) are built from the time series data. In [19], the crop type classification issue is addressed by means of bat algorithm based clustering approach. The performance of this bio-inspired algorithm is compared with genetic algorithm and particle swarm optimization algorithm. Finally, it is concluded that the performance of bat algorithm is better than the compared algorithms.

A classification algorithm for paddy growth is proposed in [20], which relies on different regularizations such as Deep Neural Networks (DNN) and 1-D Convolutional Neural Network (CNN). The conclusion of this work is that the Multilayer Perceptron (MLP) shows the greatest accuracy rates. A crop classification technique that exploits airborne hyperspectral data is presented in [21]. This work compares the performance of supervised and unsupervised techniques. Finally, this work concludes that the performance of supervised techniques is better than unsupervised techniques in terms of accuracy rates.

Motivated by the aforementioned works, this work intends to present a GLVP based SIFT feature based multiclass vegetation classification system, which is reliable and promising. The results achieved by the ensemble classifier are efficient, when compared to individual classifiers such as k-NN, SVM and ELM classifiers in terms of accuracy, sensitivity and specificity rates. The proposed vegetation classification system is elaborated as follows.

3. PROPOSED MULTICLASS VEGETATION CLASSIFICATION SYSTEM

This section presents the proposed multiclass vegetation classification system in a detailed fashion, along with the overview of the proposed approach.

3.1 OVERVIEW OF THE PROPOSED APPROACH

The central theme of this paper is to present a multiclass vegetation classification system, which is of four classes. In order to achieve this goal, the complete work is segregated into four significant phases and they are image acquisition, satellite image pre-processing, SIFT feature extraction and ensemble classification. The satellite images are pre-processed, so as to enhance the contrast and remove the noise. The contrast of the satellite images is enhanced by means of adaptive histogram equalization and the images are denoised by bilateral filter. The adaptive histogram equalization technique is utilized to enhance the contrast of the satellite image and the reason behind the choice of adaptive histogram equalization is its working principle, which generates many histograms for different regions of an image. Hence, the contrast of the satellite images is uniformly updated. The satellite images are denoised by bilateral filter, which preserves the edges and other details of the satellite images.

As soon as the satellite images are pre-processed, the GLVP and SIFT features are extracted from the satellite images. The main motivation for the choice of SIFT features is that the features are invariant against several challenging issues such as pose, illumination, scaling and rotation. As these alterations are very common in satellite images, the GLVP based SIFT features are believed to work better. The GLVP based SIFT features are utilized to train the ensemble classifier. The overall flow of the proposed approach is presented in Fig.1.

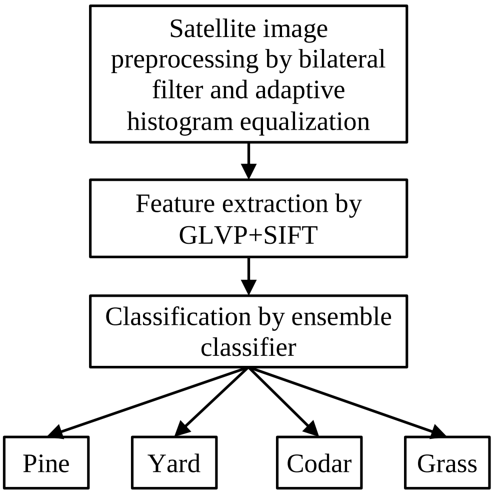

Fig.1. Overall flow of the proposed approach

During the testing phase, the ensemble classifier distinguishes between four different vegetation classes. The objective of the incorporation of ensemble classification is that the utilization of singe classifier may result in maximal false positives and negatives. The final decision of the ensemble classification does not rely on the outcome of the single classifier but a combination of three different classifiers. This idea paves way for better classification accuracy, sensitivity and specificity rates.

3.2 SATELLITE IMAGE ACQUISITION

The satellite image is acquired from Google earth and the total area being covered by this image is 696m. The satellite image processed by this work is observed in the locational coordinates of 11°00’52’N and 76°55’55’E. This locational coordinates is found in the botanical garden of the Tamil Nadu Agricultural University (TNAU). The overall algorithm of this work is presented as follows.

3.2.1 Proposed Crop Classification Algorithm:

// Training

Input: Satellite images

Output: Knowledge gaining

Begin

  Pre-process the images by bilateral filter and AHE;

  For all pre-processed images: do

    Extract GLVP and SIFT features;

    Construct fv(TD) and store it in the local database;

    Feed the knowledge to ensemble classifier;

  End;

End;

// Testing

Input: Satellite image

Output: Crop classification

Begin

  Pre-process the image by bilateral filter and AHE;

  For the test image: do

    Extract GLVP and SIFT features;

    Construct fv(TD);

    Apply Ensemble classifier to match the test and train samples;

    Collect the classification results of k-NN, SVM and ELM;

    Choose the dominant result as the final result;

    Analyse the performance;

  End;

End;

3.3 SATELLITE IMAGE DENOISING AND CONTRAST ENHANCEMENT

The intention of satellite image pre-processing is to remove noise from the satellite images and to enhance the contrast of the satellite images. The satellite images are denoised by means of bilateral filter and the contrast of the image is enhanced by adaptive histogram equalization technique. The adaptive histogram equalization technique calculates the several histograms by taking different regions of the satellite images. Hence, the histograms are computed separately by taking the regions into account, rather than the whole image. Besides this, as the contrast enhancement technique is adaptive, the values are distributed in an even fashion.

Consider a satellite image with $m \times m$ pixels. When the adaptive histogram equalization is applied, then this technique performs pixel based operations. Each and every pixel (pix_i) of the image is focused and the value of the pix_i is modified by taking the intensity of the neighbourhood pixels into account. Hence, the contrast of the satellite image is enhanced by performing region based operations rather than manipulating the whole image. As this contrast enhancement technique is adaptive, the value of pixel is modified by taking the intensity values of the region into account. The denoised and the contrast enhanced images are illustrated in Fig.2.

The satellite images are denoised by means of bilateral filter, which preserves the pixel and the edge information of the satellite images. Bilateral filter is proposed by Tamosi and Manduchi in the year 1998 [16].

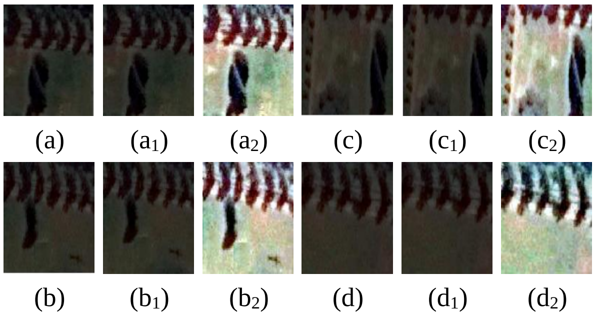

Fig.2. (a)-(d) Original images (a_1-d_1) Denoised images (a_2-d_2) Contrast enhanced images

The bilateral filter is a non-linear filter, which takes the weighted total of the pixels in a local neighbourhood window. The weight of the pixels is computed by taking the spatial and intensity distance. This way of operation conserves the edge information and the noise is eliminated by performing the mean operation. The bilateral filtering operation is carried out by the following equation.

$$BF\left(pix_i\right)=\frac{1}{c}\sum_{pix_j\in NH\left(pix_i\right)} e^{\frac{-\left\|pix_j-pix_i\right\|^2}{2\sigma_{sd}^2}} e^{\frac{-\left|\ln\left(pix_j\right)-\ln\left(pix_i\right)\right|^2}{2\sigma_{sr}^2}} \ln\left(pix_j\right) \quad (1)$$

In the Eq.(1), σ_{sd} and σ_{sr} are the control parameters in terms of spatial and intensity domains. $NH(pix_i)$ represents the spatial neighbourhood of pixel $BF(pix_i)$ and c is the constant represented by,

$$c=\sum_{pix_j\in NH\left(pix_i\right)} e^{\frac{-\left\|pix_j-pix_i\right\|^2}{2\sigma_{sd}^2}} e^{\frac{-\left|\ln\left(pix_j\right)-\ln\left(pix_i\right)\right|^2}{2\sigma_{sr}^2}} \quad (2)$$

By this way, the contrast of the satellite image is enhanced by adaptive histogram equalization and the noise being present in the satellite images is eliminated by means of bilateral filter.

3.4 GLVP BASED SIFT FEATURE EXTRACTION

The GLVP based feature extraction is the most important phase of this work, as the extracted features impart knowledge to the ensemble classifier. The GLVP works in two stages, Gabor filter application followed by LVP operation. To start with the feature extraction phase, the Gabor filter is applied over the satellite image with the window size 7×7. Gabor filter works efficiently for texture based feature extraction and detects the edges in a better way. In order to have better feature set, this work combines GLVP with SIFT features. The Gabor filter is created as follows.

$$Gabor=\frac{1}{2\pi\sigma_x\sigma_y}\exp\left[\frac{-1}{2}\left(\frac{x}{\sigma_x}\right)^2+\left(\frac{y}{\sigma_y}\right)^2\right] + k\beta\left(x\cos\theta+y\cos\theta\right) \quad (3)$$

where σ_x and σ_y are the spatial width of the pixels x and y, β is the frequency rate θ is the orientation. This is followed by the application of LVP. The LVP considers the orientations of 0, 45, 60 and 90 degrees. The entire image is splitted into the blocks of window size 7×7. Hence, the LVP considers a total of 25 pixels and then the feature vector is formed by considering the distance and orientation, which is represented as follows.

$$LVP_{o,dis}(pix_i) = \{LVP_{o,dis} \mid o=0°,45°,60°,90°\} \quad (4)$$

$$LVP_{o,dis}(pix_i) = \{ LVP_{o,dis} \mid dis=1,2,3\} \quad (5)$$

In the Eq.(4) and Eq.(5), o, dis are the orientation and distance between the pixels respectively. The GLVP is computed by

$$GLVP(pix_i) = Gabor(pix_i) \cup LVP_{o,dis}(pix_i) \quad (6)$$

By following this way, the GLVP features are extracted and the SIFT features are extracted as follows.

The SIFT features are extracted in four steps. Initially, the significant keypoints are detected by means of Difference of Gaussians (DoG). The DoGs are computed in different scales by considering the neighbourhood pixels. The identified keypoints are positioned by computing the extrema of the DoG in terms of both scale and space. The unstable keypoints with low illumination are excluded from the process. For each stable keypoint, degree of orientation is computed. Finally, the best distinguishing descriptor is computed for each point. For each and every point, orientation of histograms are formed which considers 4×4 pixels in eight bins. Instead of computing the histograms, this work considers the GLVP features for normalizing the gradients. The feature vector is formed by combining the horizontal and vertical gradients, such that the memory consumption is lesser when compared to the traditional SIFT feature detector. Hence, the feature vector is formed and the classifier is trained with the computed feature vector.

3.5 MULTICLASS VEGETATION CLASSIFICATION BY ENSEMBLE CLASSIFIER

This section attempts to classify between four different classes of vegetation by employing ensemble classifier. The classifiers being utilized to build the ensemble classifier are k-NN, SVM and ELM. The classification decision is not made by a single classifier, but three different classifiers. This improves the classification accuracy and reliability of the classification system. Short notes on all the classifiers are presented as follows.

3.5.1 k-NN Classifier:

The k-NN is the simplest classifier, which classifies the vegetation by means of computing the Euclidean distance as given in the following equation.

$$Euc_D=\sum_{i=1}^{N}\sqrt{x_i^2-y_i^2} \quad (7)$$

The effectiveness of k-NN classifier is based on the value of 'k'. When the value of k is not optimal, then it impacts over the classification accuracy of the classifier. Besides this, the better value of k can be fixed, only when the prior knowledge about the dataset is rendered. This is a major drawback and this overcomes this shortcoming by introducing k fold cross validation. This technique chooses the value of k by itself. During the process of finding the value of k, the training samples are divided into k different samples. Each and every sample is considered as the test sample, while the rest of the samples are considered as train samples. This process continues until all the samples are considered as test samples. Finally, the mean of the *k* results is calculated and is treated as the value of *k*. By this way, this classifier omits the need for manual fixation of the value *k*.

3.5.2 SVM:

SVM is the supervised classification algorithm that intends to classify between the objects by setting a boundary. However, binary SVM is not feasible for the works with multiple categories. In this case, multiclass SVM is employed. In this work, multiclass SVM is employed as the work considers four different vegetation classes such as pine, yard, codar tree and grass. This work differentiates between the vegetation classes by incorporating $n(n-1)/2$ classifiers and the final decision of all these classifiers are taken into account. Finally, the regions are classified by max-voting policy [17]. Thus, all the different classes are processed simultaneously by solving the below given equation.

$$\min_{nh,b,sv} \frac{1}{2}\sum_{y=1}^{q} nh_y^p nh_y + c\sum_{i=1}^{r}\sum_{y\neq s_i} sv_{i,y} \tag{8}$$

Here, *nh* seems to be normal to the hyperplane, *b* is the bias, *sv* is the slack variable, i=1,2,…,r are training samples and *y* is the count of classes. The conclusive decision is done by the following equation.

$$decn = \max_y \left(w_y^p \beta\left(x_i\right) + b_y \right) \tag{9}$$

In this approach, all the classifiers are applied on every single pair of classes. Consider an object *obj* that has to be differentiated to one of three different classes (say *x*, *y*, *z*). This process is accomplished by applying all the classifiers over an image. Whenever a classifier differentiates the object to be in class *x*, then the value of class *x* is incremented by 1. The final classification decision is taken on the basis of the maximum votes for the class. This way of classification ends up with accurate decision in a reasonable span of time.

3.5.3 ELM:

ELM is employed for the purpose of classification, as it is proven to be the swiftly and reliable classifier [18]. During the training process, the ELM is trained with the knowledge gained from the feature extraction phase through the feature vectors. This prior knowledge helps in classifying between different categories.

Let *X* be the training samples represented as (a_i,b_i); here $a_i = [a_{i1},a_{i2},\ldots,a_{is}]^q \in Im^s$; where *n* is the dimension of the training representatives. $b_i = [b_{i1}, b_{i2},\ldots,b_{it}]^q \in Im^t$ indicates the i^{th} class label of dimension *t*. Here, *t* is the number of classes, which is four in our case. A Single hidden Layer Feed-Forward Neural Network (SLFN) is built by an activation function *act*(*x*) and *R* neurons, which is denoted as follows.

$$\sum_{i=1}^{R} \beta_i act\left(wt_i \cdot a_j + e_i\right) = b_i; i = 1,2,...,n \tag{10}$$

In the Eq.(10), wt_i is the weight of the feature vector, e_i is the bias of the i^{th} hidden neuron.

Consider Hd_l as the ELM's hidden layer output matrix, where the i^{th} column of Hd_l indicates that the i^{th} hidden neurons output vector by considering the inputs $a_{i1}, a_{i2},\ldots,a_{in}$.

$$Hd_l = \begin{bmatrix} act\left(wt_i \cdot a_1 + e_i\right) & \cdots & act\left(wt_v \cdot a_1 + e_G\right) \\ \vdots & \ddots & \vdots \\ act\left(wt_i \cdot a_n + e_i\right) & \cdots & act\left(wt_v \cdot a_n + e_G\right) \end{bmatrix} \tag{11}$$

$$\beta = \begin{bmatrix} \beta_1^q \\ \vdots \\ \beta_G^q \end{bmatrix} \tag{12}$$

$$B = \begin{bmatrix} b_1^T \\ \vdots \\ b_n^T \end{bmatrix} \tag{13}$$

The matrix form is represented as:

$$Hd_l \beta = B \tag{14}$$

The output samples are calculated by norm least-square solution, and the equation is given as follows.

$$\beta = Hd_l^{\dagger} \tag{15}$$

where, $HL^{\dagger}$ is the HL's Moore-Penrose generalized inverse. The ELM training phase is achieved by computing Eq.(16). During the testing phase, the output matrices are calculated and added together, in order to detect the greatest value against the row. The output matrix is calculated by,

$$b_{testing}\left(z\right) = Hd_{l_{testing}}\left(z\right) \times \beta_z \tag{16}$$

This work fixes the value of *z* as 12, as it generates the most feasible results. The performance of the proposed approach starts to degrade, when the value of *z* goes beyond 12.

When the classification results of all the classifiers are obtained, the maximum occurring result is declared as the final decision. For example, if two classifiers classify the test sample to be a part of class A and a classifier chooses class B for the same test sample, class A is declared as the final class for the test sample. By this way, the classes are determined by the ensemble classifier, which increases the classification accuracy, sensitivity and specificity rates. The following section analyses the performance of the proposed approach.

4. RESULTS AND DISCUSSION

The proposed work is simulated in Matlab environment in a standalone computer with 4GB RAM. This work utilizes 50 images for evaluating the performance of the proposed approach. Out of fifty images, thirty images are used for training and the remaining images are used for testing. This train-test ratio is followed for all the classifiers. The results of the proposed approach are discussed in this section. The proposed approach is justified by measuring the performance in terms of classification accuracy, sensitivity and specificity. The Fig.3 shows the classification results between the proposed and other methods.

Classification accuracy is the most important parameter for any classification algorithm. The efficiency of the classification depends on the effectiveness of the features being extracted. The accuracy of the classification algorithm is computed by the following equation.

$$ac_{rate} = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \tag{17}$$

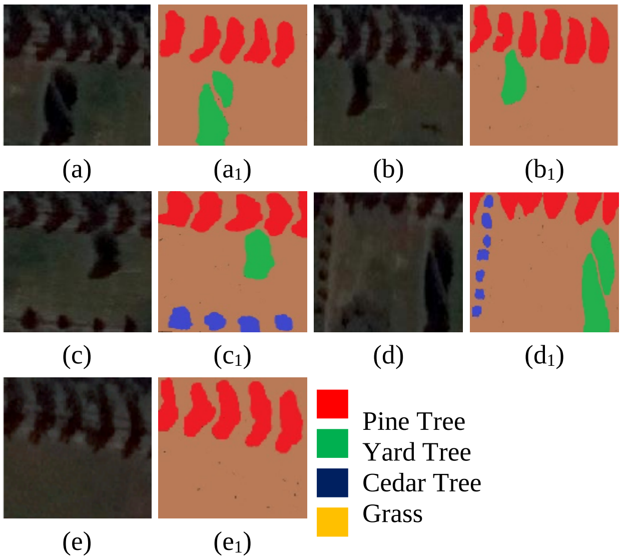

Fig.3. Sample classification results

Sensitivity and specificity are other important measures that could rate the performance of the classification algorithm. Sensitivity is the measure which is the rate of correctly classified images to the sum of images that are correctly classified as positive and wrongly classified as negative. Specificity is measured by the ratio of the sum of images that are correctly classified as negative to the sum of images that are incorrectly classified as positive and correctly classified as negative. The sensitivity and specificity are represented as follows.

$$sens_{rate} = \frac{TP}{TP+FN} \times 100 \tag{18}$$

$$spec_{rate} = \frac{TN}{FP+TN} \times 100 \tag{19}$$

where,

- *TP* is the count of images that are correctly classified with respect to the class and
- *TN* is the count of images that are correctly classified as these images do not belong to a particular class.
- *FP* is the count of images that are wrongly classified as these images belong to a particular class and
- *FN* are the count of images that are misclassified as the images do not belong to a specific class.

The accuracy, sensitivity and specificity are measured by varying the feature extraction techniques and classifiers (SVM, ELM, Ensemble classifier). The sample visual results are shown in Fig.3. The experimental results of the proposed approach are presented in the following Fig.4 and Fig.5.

Initially, the accuracy rates of the proposed classification approach is presented by varying the feature extraction techniques such as GLVP, SIFT, GLVP+SIFT and the classifiers such as SVM, ELM and ensemble classifier. Initially, the features are varied and the proposed ensemble classification is utilized for checking the efficiency of the features.

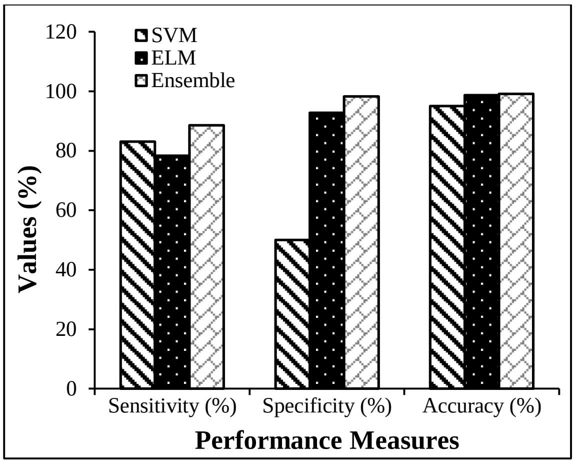

Fig.4. Performance analysis w.r.t feature extraction techniques

From the Fig.4, it is evident that the combination of GLVP and SIFT works better, when compared to the GLVP and SIFT features. The GLVP features are rich in texture and the SIFT features stand stable against variations of scale, rotation, illumination and so on. Combining these features together improvises the accuracy, sensitivity and specificity rates. The maximum accuracy rate is achieved by GLVP + SIFT with the value of 99.1%. Similarly, the least accuracy rate is shown by GLVP features, which is 91.6%. The highest sensitivity and specificity rates are 98.7% and 98.3% respectively, which is proven by the combination of GLVP and SIFT features. Hence, the potential of the combination of GLVP and SIFT is justified. In the second round of performance analysis, accuracy, sensitivity and specificity rates are computed by varying the classification techniques. The performance of the classification technique is analysed by incorporating the combined features of GLVP and SIFT and the experimental results are presented below.

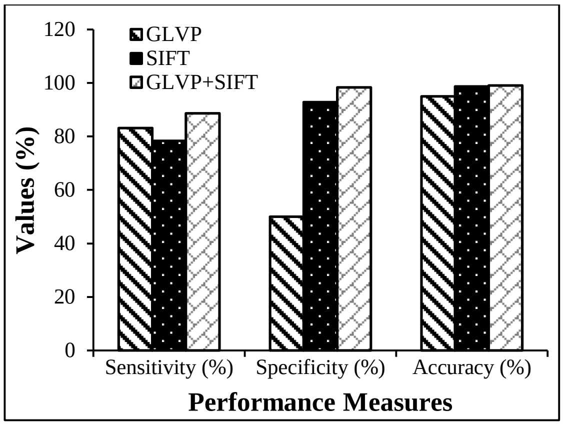

Fig.5. Comparative analysis by varying classifiers

Hence, the performance of ensemble classification is proven with greater accuracy, sensitivity and specificity rates. Instead of employing a single classifier for making decision over the class, ensemble classifier takes the classification decision of three different classifiers and the final decision is made. The maximum accuracy rate is 99.1%, which is shown by ensemble classifier. Similarly, the greatest sensitivity and specificity rates are shown by ensemble classifier with the value of 98.6% and 98.3%, respectively. Thus, the capability of ensemble classifier is proven.

Hence, the performance of the proposed approach is justified with the greatest accuracy, sensitivity and specificity rates.

The following part presents the performance evaluation of the proposed approach by comparing it with the state-of-the-art techniques such as Object Oriented Classification (OOC) [5], deep learning based classification [6] and SVM classification [10]. The performance of the proposed vegetation classification system is evaluated and the experimental results are presented as follows.

Table.1. Comparative results w.r.t state-of-the-art classification techniques

Metrics / Techniques	Accuracy (%)	Sensitivity (%)	Specificity (%)	Time (ms)
[5]	93.6	86.4	82.3	1893
[6]	96.3	89.7	97.3	2683
[10]	88.6	83.1	78.4	1832
Proposed	99.1	98.7	98.3	2489

On analysis, it is observed that the proposed vegetation classification system outperforms the state-of-the-art classification techniques in terms of classification accuracy, sensitivity and specificity rates. The proposed classification approach proves 99.1% as accuracy and the least accuracy rate is shown by the SVM classifier. Similarly, the greater sensitivity and specificity rates are shown by the proposed approach, when compared to the analogous approaches. Greater performance rates are shown by the proposed approach at the cost of greater time consumption. The time consumption of all the techniques is measured in milliseconds. The least time consumption is shown by the SVM based classification approach, which is 1832 milliseconds. However, the time consumption is tolerable and acceptable.

5. CONCLUSION

In this paper, a multiclass vegetation classification system is proposed which classifies between different trees such as pine, yard, codar tree and grass. The objective is attained by segregating the work into three important phases like pre-processing, feature extraction and classification. The pre-processing phase denoises and enhances the contrast of the satellite image by employing bilateral filter and adaptive histogram equalization technique. In the next step, the GLVP and SIFT features are extracted from the satellite images. Finally, the ensemble classifier is utilised for classifying between four different vegetation classes. The performance of the proposed approach is analysed by varying the feature extraction and the classification techniques. The proposed approach outperforms other approaches in terms of accuracy, sensitivity and specificity. In future, this work is planned to be extended with many vegetation classes.

REFERENCES

[1] Andrii Shelestov, Mykola Lavreniuk, Nataliia Kussul, Alexei Novikov and Sergii Skakun, "Large Scale Crop Classification using Google Earth Engine Platform", *Proceedings of IEEE International Symposium on Geoscience and Remote Sensing*, pp. 23-28, 2017.

[2] R. Luciani, G. Laneve, M. Jahjah and M. Collins, "Crop Species Classification: A Phenology based Approach", *Proceedings of IEEE International Symposium on Geoscience and Remote Sensing*, pp. 178-185, 2017.

[3] Caner Demirpolat and Mustafa Teke, "Crop Classification with Morphological Profiles Derived from SAR and Electro-Optical Satellite Data", *Proceedings of International Conference on Recent Advances in Space Technologies*, pp. 19-24, 2017.

[4] Philipp Lottes, Raghav Khanna, Johannes Pfeifer, Roland Siegwart and Cyrill Stachniss, "UAV-based Crop and Weed Classification for Smart Farming", *Proceedings of IEEE International Conference on Robotics and Automation*, pp. 29-37, 2017.

[5] Xia Zhang, Yanli Sun, Kun Shang, Lifu Zhang and Shudong Wang, "Crop Classification Based on Feature Band Set Construction and Object-Oriented Approach Using Hyperspectral Images", *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, Vol. 9, No. 9, pp. 4117-4128, 2016.

[6] Nataliia Kussul, Mykola Lavreniuk, Sergii Skakun and Andrii Shelestov, "Deep Learning Classification of Land Cover and Crop Types Using Remote Sensing Data", *IEEE Geoscience and Remote Sensing Letters*, Vol. 14, No. 5, pp. 778-782, 2017.

[7] Pradeep Kumar, Rajendra Prasad, Varun Narayan Mishra, Dileep Kumar Gupta Arti Choudhary and Prashant K. Srivastava, "Artificial Neural Network with Different Learning Parameters for Crop Classification using Multispectral Datasets", *Proceedings of International Conference on Microwave, Optical and Communication Engineering*, pp. 18-20, 2015.

[8] Mustafa Teke and Yasemin Yardimci, "Classification of Crops using Multitemporal Hyperion Images", *Proceedings of 4th International Conference on Agro-Geoinformatics*, pp. 20-24, 2015.

[9] Benson Kipkemboi Kenduiywo, Damian Bargiel and Uwe Soergel, "Higher Order Dynamic Conditional Random Fields Ensemble for Crop Type Classification in Radar Images", *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 55, No. 8, pp. 4638-4654, 2017.

[10] Suhas S. Athani and C.H. Tejeshwar, "Support Vector Machine-Based Classification Scheme of Maize Crop", *Proceedings of IEEE 7th International Conference on Advance Computing*, pp. 1-7, 2017.

[11] Preetha Rajan, B. Radhakrishnan and L. Padma Suresh, "Detection and Classification of Pests from Crop Images using Support Vector Machine", *Proceedings of International Conference on Emerging Technological Trends*, pp. 21-27, 2016.

[12] Rajesh K. Dhumal, Amol D. Vibhute, Ajay D. Nagne, Yogesh D. Rajendra, Karbhari V. Kale and Suresh C. Mehrotra, "Fuzzy Convolution Tactic for Classification of Spatial Pattern and Crop Area", *Proceedings of International Conference on Intelligent Systems and Control*, pp. 341-348, 2017.