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| **S.NO** | **Title** | **Author’s** | **Contribution** | **Drawbacks/Future Scope** | **Previous technique** | **Technique used** | **Device used** | **Applications** | **Advantages** | **Evaluation** |
| 1 | Improving remote sensing crop classification by argumentation-based conflict resolution in ensemble learning | Stefan Con¸t iu, Adrian Groza | 1) First approach that combines ensemble learning and argumentation in the agricultural domain.  2) Developed a hybrid system that merges machine learning and symbolic argumentation with the scope of improving the classification of four crop classes in remote sensing: corn, soya- bean, rice and cotton. | Authors apply classification only on four categories. Accuracy of classification can be increased if the category of crop will increased. | Voting-based method is used for  Classification | Classifiers: A decision tree, A neural network, and support vector machine algorithm. | NA | Crop classifica- tion in the agriculture domain. | 1.) Argument- based conflict resolutor proved to be more effective than voting- based resolutor in ensemble learning.  2) First approach that combines ensemble learning and argumentation in the agricultural domain.  3) The proposed solution improved both the accuracy of resolution of conflicting instances and the accuracy of the ensemble learner as a whole | 1)Ensemble Voting  Accuracy-95.5%  i) Corn :-  Precision – 99.5%  Recall- 99.8%  ii) Rice :-  Precision – 95.1%  Recall- 80.8%  ii) Cotton :-  Precision – 84.9%  Recall- 93.1%  ii) Soyabean :-  Precision – 89.1%  Recall- 77.4%  2)Ensemble DeLP  (Defeasible Logic Program)  Accuracy-98.4%  i) Corn :-  Precision – 99.8%  Recall- 99.9%  ii) Rice :-  Precision – 100%  Recall- 95.8%  ii) Cotton :-  Precision – 93.3%  Recall- 98.6%  ii) Soyabean :-  Precision – 98%  Recall- 90% |
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| **2** | Recognising weeds in a maize crop using a random  forest machine-learning algorithm and  near-infrared snapshot mosaic  hyperspectral imagery | Junfeng Gao a, David Nuyttens b, Peter Lootens c, Yong He d,\*,  Jan G. Pieters a | (1) To explore  the feasibility of near infrared (NIR) snapshot mosaic hyperspectral  camera in weed and maize classification;  (2) to  determine the relevant spectral wavelengths and important  features for classification;  (3) To provide optimal parameters  for building a Random Forest model.  . | The proposed  approach can be further supported through other snapshot  hyperspectral sensor applications like scouting early growth  stage field weeds using unmanned aerial vehicles or specialised  designed field | k-nearest neighbours (KNN) model. | Optimal random forest model | A snapshot mosaic hyperspectral imaging  sensor was applied to weed and maize classification. | Further applications  of this camera in the field for implementing SSWM.  (Site-Specific Weed Management) | Used in weed and maize classification | Crop (Z. mays) -94% recall -100%.  The precision  values for the three kinds of weeds,  C. arvensis -95.9%  Rumex -70.3%,  C.arvense -65.9%, |
| **S.NO** | **Title** | **Author’s** | **Contribution** | **Drawbacks/Future Scope** | **Previous technique** | **Technique used** | **Device used** | **Applications** | **Advantages** | **Evaluation** |
| 3. | Automated leaf disease detection in different crop species through image  features analysis and One Class Classifiers | X.E. Pantazi⁎, D. Moshou, A.A. Tamouridou  Nov- 2018 | 1) In the presented research a novel application of ascertaining the  presence of four different health conditions including healthy, downy  mildew, powdery mildew and black rot by using One Class  Classification is demonstrated.  2) The proposed methodology includes a training procedure with  target data regarding each one of the aforementioned diseases. A new  feature vector with unknown class is assessed by a group of one class  classifiers. which produce activations according their training data. | Limitations of One Class Classification- Extrinsic factors  such as image background and capture conditions and to intrinsic factors  including segmentation and different disorders with similar  symptoms. | NA | Presents the presence of four different health conditions including healthy,  downy mildew, powdery mildew and black rot in different leaf samples  by using One Class Classification.  1)Used Local Binary Patterns for feature extraction  2)Used One Class SVM for multi class problems  3)Nearest support vector strategy  4)GrabCut algorithm | NA | The presented  application is capable of identifying the afore mentioned health conditions  in plant species.  The presented scheme can further have expanded into detection  of crops condition in order to adapt best crop management  practices in the field of precision agriculture. | The novelty of  the current application is high generalization capability which was  proven through testing in various leaf samples belonging to different  plant species. | Success Rate - 95%  ( for total 46 plant condition combination tested) |
| **S.NO** | **Title** | **Author’s** | **Contribution** | **Drawbacks/Future Scope** | **Previous technique** | **Technique used** | **Device used** | **Applications** | **Advantages** | **Evaluation** |
| 4. | Automated robust crop-row detection in maize fields based on position  clustering algorithm and shortest path method, | Xiya Zhang, Xiaona Li, Baohua Zhang⁎, Jun Zhou, Guangzhao Tian, Yingjun Xiong, Baoxing Gu  September 2018 | 1) In this paper, a novel automatic  and robust crop row detection method is proposed for maize fields based on images acquired from a vision  system.  2) The designed automation method comprises three main  modules: image segmentation, feature point extraction, and crop row  detection. | Optimization  of processing time. | Hough Transform | 1) The procedure of crop row detection, the position clustering algorithm and shortest path  method were applied successively to confirm the final clustered feature point set.  2) Vegetation index and double  thresholding combining the Otsu method,  swarm optimization  (PSO) method for good segmentation result,  the vertical projection method is applied to divided  horizontal strips in order to extract the feature points that indicate the  crop row centers. | NA | Accurate Crop-row  Detection in maize fields. |  | deviation angle of the algorithm is less than  0.5° |
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| 5 | Classification and Identification of Primitive Kharif Crops usingSupervised Deep Convolutional Networks | Aditya Khampariaa, Aman Singha, Ashish Kr. Luhachb, Babita Pandeyc,Devendra K. Pandeyd | (i) obtained results shows improvement in the feasibility and performance of CNN over other machine learning models.  (ii) Highperformance shows the immediate crop disease identification ability of deep learning techniques overthe different feature extraction models. | Future work focuses on the involvement of deep stack and belief networks which uses tensor driven training algorithms in different areas like medical diagnosis, remote sensing, and automobile exhaust emission driven systems. | Support vector machine, k-nearest neighbor, genetic algorithm, and Artificial neural networks. | i) Convolutional Neural Networks (CNN) using visual computingand deep learning networks  ii) The collected images are processed and analyzed using PythonLibrary called Keras and Adam Optimizer with support of TensorFlow in back end. | NA | NA | The proposed model achieves betterrecognition accuracy, faster generalization, convergence ability andperformance in the comparison to other machine learning and fea-ture extraction models. | Accuracy - 93.7% |
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| 6 | Wheat yellow rust monitoring by learning from multispectral UAV aerial  imagery | Jinya Sua,⁎, Cunjia Liua, Matthew Coombesa, Xiaoping Hub,⁎, Conghao Wangb, Xiangming Xuc,  Qingdong Lid, Lei Guod, Wen-Hua Chena  october  2018 | Detection of plant stress caused by yellow rust disease in winter wheat for  sustainable  agriculture  Objectives of this  study are: (i) determining whether or not healthy and yellow rust infected  wheat plants can be discriminated by applying machine learning  algorithms to multispectral UAV imagery; (ii) selecting spectral band  and SVI that best differentiate healthy and yellow rust infected wheat  plants from available five bands and widely used SVIs; (iii) developing a  low-cost and easily-deployed UAV remote sensing system for yellow  rust monitoring at farmland scales. | (i) Identify the best band and SVI combination to build a better (in  terms of simplicity, accuracy, etc.) classification model by using  advanced dimension reduction approaches (Roffo et al., 2017);  (ii) Design more levels of yellow rust infection or combining the data of  different disease developmental stages so that regression analysis  can be performed between SVIs and disease severity in a quantitative  manner (Liu et al., 2018). | NA | Rust detection system is learned by random forest classifier  random forest is adopted as the  classifier, where its hyperparameters are fine tuned to guarantee satisfying  performance by using Bayesian optimization | Five-band multispectral camera | Developing a  low-cost and easily-deployed UAV remote sensing system for yellow  rust monitoring at farmland scales. | An automated yellow rust  monitoring system is developed by learning from labelled UAV aerial  multispectral image, which is user-friendly, low-cost and suitable for  use at farmland scales. | Average Precision -89.2%  Recall – 89.4%  Accuracy - 89.3% |
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| 7 | Wheat leaf rust detection at canopy scale under different LAI levels using  machine learning techniques | Mohsen Azadbakhta,⁎, Davoud Ashourlooa, Hossein Aghighia, Soheil Radiomb,  Abbas Alimohammadic  Nov-2018 | Accurate diagnosis of wheat leaf rust is of high interest for precision farming. | i) Leaf area index (LAI) can be further increase or decrease.  ii) Further modeling work will also have to be  conducted in order to determine the performance of different SVIs in  estimation of wheat leaf rust severity at different LAI conditions. | NA | **Estimate disease severity (DS) :-**  i)ν-support vector regression (ν-SVR),  ii)boosted regression trees (BRT),  iii) random forests regression  (RFR)  iv)Gaussian process regression (GPR)  feature selection  conducted by Boosted regression trees(BRT) | ASD Spectrometer | NA | Wheat leaf rust detection at canopy scale | *LOW LAI(Leaf Area Index)*  *a)T-test*  *BRT -1.00*  *SVR -0.00*  *RFR-0.00*  *b)Tuckey’s HSD*  *BRT -0.99*  *SVR -0.00*  *RFR-0.00*  *Medium LAI*  *a)T-test*  *BRT -0.00*  *SVR -0.00*  *RFR-0.00*  *b)Tuckey’s HSD*  *BRT -0.00*  *SVR -0.00*  *RFR-0.00*  *HIGH LAI*  *a)T-test*  *BRT -1.00*  *SVR -0.00*  *RFR-0.00*  *b)Tuckey’s HSD*  *BRT -0.99*  *SVR -0.00*  *RFR-0.00* |
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| 8. | A review on weed detection using ground-based machine vision and image  processing techniques | Aichen Wanga,c,⁎, Wen Zhangb, Xinhua Weia,c | This review summarized the advances of weed detection using ground-based machine vision  and image processing techniques. | NA | ground-based machine vision and imaging processing techniques | ground-based machine vision | NA | NA | challenges and solutions provided by researchers for  weed detection in the field, including occlusion and overlap of leaves, varying lighting conditions and different  growth stages, were discussed. | NA |
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| 9. | Automated spectral feature extraction from hyperspectral images to  differentiate weedy rice and barnyard grass from a rice crop | Yanchao Zhanga,1, Junfeng Gaob,1, Haiyan Cena, Yongliang Luc,⁎, Xiaoyue Yuc, Yong Hea,d,⁎,  Jan G. Pietersb | Aimed to develop a classification  model with important spectral features to recognize Barnyard grass (*Echinochloa crusgalli*) and weedy rice (*Oryza sativa f. spontanea*) (weeds ) and rice based on hyperspectral  imaging techniques. | Discrimination only two kinds of weeds and rice | NA | Feature Selection - successive projection algorithm (SPA)  and random forests.  Classification- Random forest and Support Vector Machine  Wavelet algorithm was used to denoise  the raw spectral features. | NA | Weed detection from rice crop | Automatically extract  spectral features from line scan hyperspectral images for weedy rice,  barnyard grass, and rice recognition. | SPA-  barnyard grass, -100%  weedy rice – 100%  rice -92 % |
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| 10 | A low shot learning method for tea leaf’s disease identification | Hu Genshenga, Wu Haoyua, Zhang Yana,⁎, Wan Mingzhub | Proposes a low shot learning method for tea leaf’s disease identification. | The next step is  to find a better data generating method and a low shot learning method  with strong generalization performance, so as to improve the robustness  and accuracy of tea leaf's disease identification with few training  samples. | SVM, Decision Tree, Random Forest | Disease spot segmentation –SVM  Disease spot Identification –  a)Sample Augmentation- C-DCGAN(Generate Samples)  b) Image Idenification -  VGG16 deep  learning identification network | NA | NA | Augmented disease spot images can identify  tea leaf’s diseases accurately | i) Tea red leaf spot  a) SVM- 0.7  b) Decision Tree – 0.75  c) Random Forest – 0.65  d) C-DCGAN+VGG16 -0.7  ii) Tea leaf blight  a) SVM- 0.6  b) Decision Tree – 0.6  c) Random Forest – 0.8  d) C-DCGAN+VGG16 -1.0  i) Tea red scab  a) SVM- 0.8  b) Decision Tree – 0.8  c) Random Forest – 0.8  d) C-DCGAN+VGG16 -1.0 |
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| 11 | A comparative study of fine-tuning deep learning models for plant disease  identification | Edna Chebet Tooa,⁎, Li Yujiana, Sam Njukia, Liu Yingchunb  2017 | Deep learning model is implemented for detecting plant classification and disease detection | further research  needs to be done to improve on the computational time. | VGG 16,  Inception V4, ResNet with 50,101 and 152 layers | Deep  convolutional neural network with 152 layers for image-based plant disease classification  is performed | NA | image-based plant disease classification |  | DenseNets -99.75%  (30 epochs) |
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| 12 | Automatic plant disease diagnosis using mobile capture devices, applied  on a wheat use case | Alexander Johannes a,1, Artzai Picon b,1, Aitor Alvarez-Gila b,1, Jone Echazarra b,  Sergio Rodriguez-Vaamonde b, Ana Díez Navajas c, Amaia Ortiz-Barredo c | Candidate hot-spot detection algorithm  in combination with statistical inference methods is proposed to tackle disease identification in wild conditions. | i) Perform poorly under real field conditions |  | i) k-means clustering is used to extract infected spots.  ii ) Random Forest used to determine disease feasibility value. | 7 mobile devices with 3500 images(approx) used. |  | The presented technology is useful in detection of weeds and diseases in earlier stages | Disease, AuC ,Accuracy ,Sensitivity Specificity  i) Rust (Early) ,0.81 ,0.78, 0.80, 0.76  ii) Septoria (Early) ,0.81, 0.76 ,0.75 ,0.77  iii) Tan spot (Early) ,0.83, 0.73, 0.76, 0.70  iv) Rust (medium-late) ,0.83, 0.81, 0.80, 0.82  v)Septoria (medium-late), 0.82, 0.79, 0.80, 0.78  vi) Tan spot (medium-late), 0.81, 0.82, 0.96, 0.69 |
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