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Machinelearninginagriculturedomain:Astate-of-artsurvey VishalMeshrama,KailasPatila,∗,VidulaMeshrama,DineshHanchateb,S.D.Ramktekec a*DepartmentofComputerEngineering,VishwakarmaUniversity,Pune,India411048*   
b*DepartmentofComputerEngineering,Pratishthan’sKamalnayanBajajInstituteofEngineering&Technology,Baramati,Pune,Maharashtra,India* c*ICAR-NationalResearchCenterforGrapes,ManjriFarmP.O.,Pune-SolapurRoad,Pune,India412307*

|  |  |  |
| --- | --- | --- |
| article | info | abstract |
| *Keywords:*  Deeplearning  Harvesting  Machinelearning  Post-harvesting  Pre-harvesting  Precisionagriculture |  | Foodisconsideredasabasicneedofhumanbeingwhichcanbesatisfiedthroughfarming.Agriculturenotonly fulfillshumans’basicneeds,butalsoconsideredassourceofemploymentworldwide.Agricultureisconsideredas abackboneofeconomyandsourceofemploymentinthedevelopingcountrieslikeIndia.Agriculturecontributes 15.4%intheGDPofIndia.Agricultureactivitiesarebroadlycategorizedintothreemajorareas:pre-harvesting, harvestingandpostharvesting.Advancementinareaofmachinelearninghashelpedimprovinggainsinagricul-ture.Machinelearningisthecurrenttechnologywhichisbenefitingfarmerstominimizethelossesinthefarming byprovidingrichrecommendationsandinsightsaboutthecrops.Thispaperpresentsanextensivesurveyoflat-estmachinelearningapplicationinagriculturetoalleviatetheproblemsinthethreeareasofpre-harvesting, harvestingandpost-harvesting.Applicationofmachinelearninginagricultureallowsmoreefficientandprecise farmingwithlesshumanmanpowerwithhighqualityproduction. |

**1.Introduction**

Agricultureisconsideredanimportantpillaroftheworld’secon-omyandalsosatisfiesoneofthebasicneedofhumanbeingi.e.food. Inmostofthecountriesitisconsideredthemajorsourceofemploy-ment.ManycountrieslikeIndiastillusethetraditionalwayoffarming, farmersarereluctanttouseadvancedtechnologieswhilefarmingbe-causeofeitherthelackofknowledge,heavycostorbecausetheyare unawareabouttheadvantagesofthesetechnologies.Lackofknowl-edgeofsoiltypes,yields,crops,weather,andimproperuseofpesti-cides,problemsinirrigation,erroneousharvestingandlackofinforma-tionaboutmarkettrendledtothelossoffarmersoraddstoadditional cost.Lackofknowledgeineachstageofagricultureleadstonewprob-lemsorincreasestheoldproblemsandaddthecosttofarming.Growth inthepopulationdaybydayalsoincreasesthepressureontheagri-culturesector.Overalllossesintheagricultureprocessesstartingfrom cropselectiontosellingofproductsareveryhigh.Asperthefamous saying“InformationisthePower”,keepingtrackofinformationabout thecrops,environment,andmarket,mayhelpfarmerstotakebetter decisionsandalleviateproblemsrelatedtoagriculture.Technologies likeblockchain,IoT,machinelearning,deeplearning,cloudcomput-ing,edgecomputingcanbeusedtogetinformationandprocessit.Ap-plicationsofcomputervision,machinelearning,IoTwillhelptoraise theproduction,improvesthequality,andultimatelyincreasetheprof-itabilityofthefarmersandassociateddomains.ThePrecisionlearningin

thefieldofagricultureisveryimportanttoimprovetheoverallyieldof harvesting.

Blockchaintechnology,cloudcomputing,internetofthings(IoT), machinelearning(ML)anddeeplearning(DL)arethelatestemerging trendsinthecomputerfield.Ithasbeenalreadyusedindifferentdo-mainslikehealthcare,cybercrime,biochemistry,robotics,metrology, banking,medicine,foodetc.tosolvethecomplexproblemsbythere-searchers.Manyapplicationsofmachinelearning,IoTindifferentdo-mainsarepresented[1–5].Deeplearningalgorithmsaremakingma-chinelearningmorepowerfulandaccurate.Byusingautomatedma-chinelearning(AutoML)onecancutthedemandofMLexperts,auto-matetheMLpipelinewithmoreaccuracy.

Whileperformingagriculturetasksthestepsasbelowisgenerally followedbyfarmers.

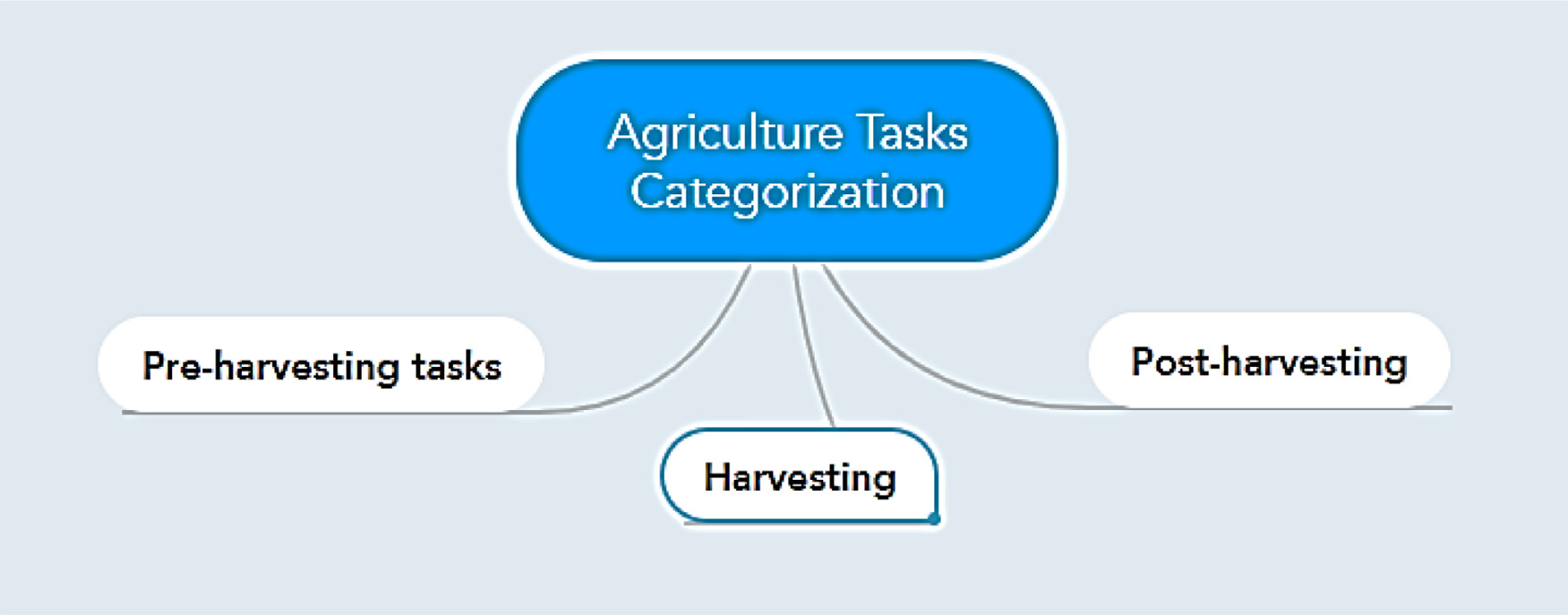
Step1:SelectionofCrop   
Step2:LandPreparation   
Step3:SeedSowing   
Step4:Irrigation&fertilizing   
Step5:CropMaintenance[useofpesticides,croppruningetc.] Step6:Harvesting   
Step7:Post-Harvestingactivities

Aspertheabovealgorithm,theagriculturerelatedtasksarecatego-rizedintheformajorsubareas.Fig.1showsthesefoursub-domainsof agriculturetasks.

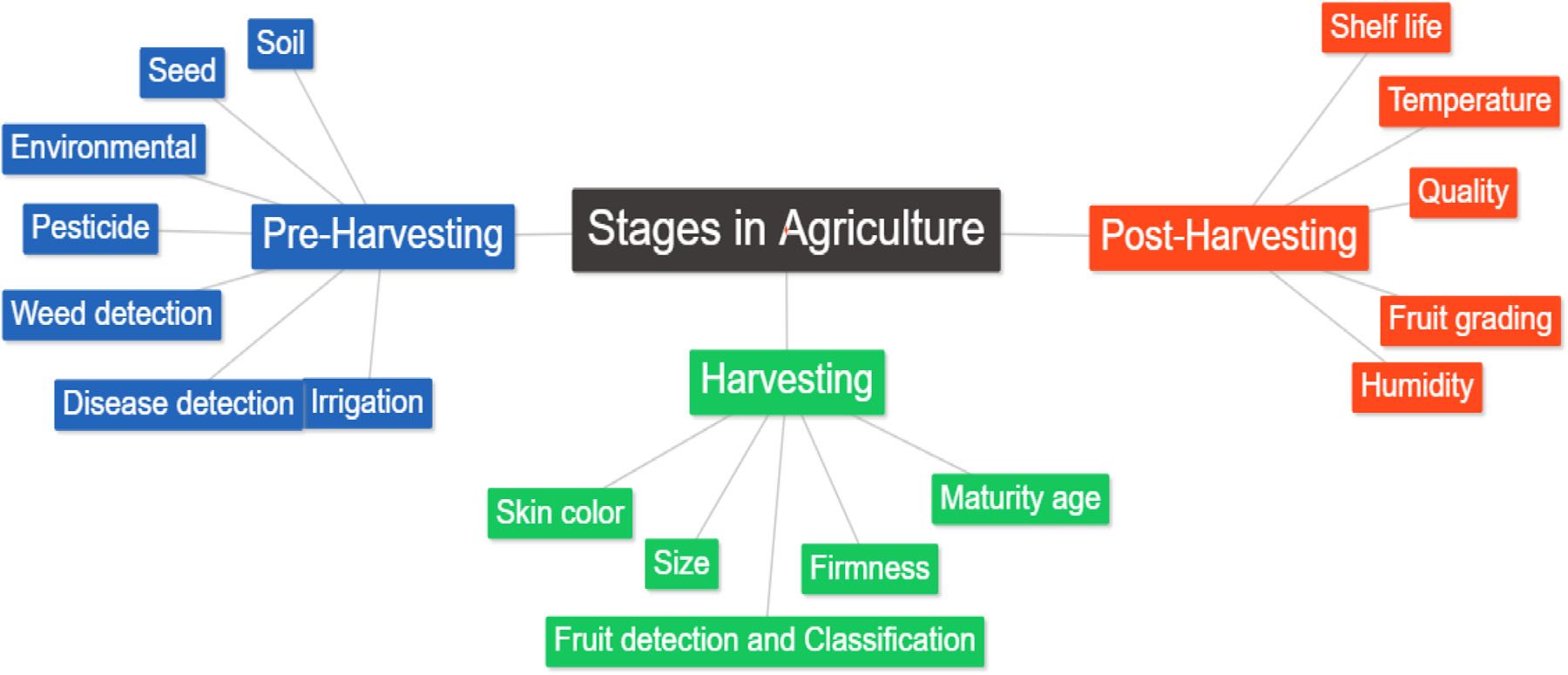
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Availableonline2October2021   
[2667-3185/© 2021TheAuthors.PublishedbyElsevi](http://creativecommons.org/licenses/by-nc-nd/4.0/)erB.V.ThisisanopenaccessarticleundertheCCBY-NC-NDlicense (<http://creativecommons.org/licenses/by-nc-nd/4.0/>)

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**Fig.1.**Generalcategorizationofagriculturetasks.



**Fig.2.**Importantparametersconsideredineachstageoffarming.

**Table1**   
Importantfactorstobeconsideredineachstage.

|  |  |  |  |
| --- | --- | --- | --- |
| S.No. | Stage | Activities/Factors | References |
| 1 | Pre-harvesting | Soil,seedsquality,fertiliser/pesticideapplication,pruning,cultivarselection,geneticandenvironmentalconditions, irrigation,cropload,weeddetection,diseasedetection.  Fruit/cropsize,skincolor,firmness,taste,quality,maturitystage,marketwindow,fruitdetectionandclassification. Factorsaffectingthefruitshelf-lifesuchastemperature,humidity,gassesusedinfruitcontainers,usageofchemicalsin postharvestandfruithandlingprocessestoretainthequality,fruitgradingasperquality. | [6,7,9] |
| 2  3 | Harvesting  Post-harvesting | [7]  [7] |

Duringpre-harvestingtasksfarmersfocusesonselectionofcrops, landpreparation,seedsowing,irrigation,andcropmaintenancewhich includesusepesticides,pruningetc.Inyieldestimationthefarmersdo theactivitieslikeyieldmappingandcountingthenumberoffruitsso thattheycanpredicttheproductionandmakethenecessaryarrange-mentsrequiredatthetimeofharvestingorpost-harvesting.Whilehar-vestingfarmersarefocusedonmaturityofcropsorfruitsmarketneed quality.Whereasinpost-harvestingfarmersarefocusedonpost-harvest storageandprocessingsystems.Fig.2showstheimportantfactorsthat shouldbeconsideredineachstageoffarming.Table1summarizesfew worksineachstageofagriculturetasks.

ThemajorbranchesoftheagricultureareAgronomy,Horticulture, Forestry,Livestock,Fisheries,AgricultureEngineeringandEconomics. Thescopeofthepaperisconfinedtouseofmachinelearninginagri-culture,specificallyonfruits.

Inthefollowingsections,thereviewofthemostrecenttechniques ofmachinevisionsystemsusedforclassificationandobjectdetectionin

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**Table2**

Analysisofpre-harvestingparameter:Soil.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| S.No. | Property | Important features | Classesdefinedinthe work | Datasetused  (Public/Own) | Totalnumberof imagesusedfor training | Models/Method/ Algorithms  compared | Bestmodel/ method/  algorithm | Results | Reference |
| 1 | Soil | Villagewisesoil fertilityindices ofavailableSoil Reaction(pH), OrganicCarbon (OC)andBoron (B),Phosphorus (P),and  Potassium(K) | ForP,KandOCthree public(reports classes:Low,Medium, availableduring andHigh.ForBsix theyears  classes:VeryLow,Low, 2014to2017) Medium,Moderately  High,High,andvery  High.ForpHFour  classes:StronglyAcidic  (SA),HighlyAcidic  (HA),ModeratelyAcidic  (MA),andSlightlyAcidic  (SLA).  SOMandpHparametersOwn | | NA | ExtremeLearning  Machine(ELM)with differentactivation functionslike  sine-squared,  Gaussianradial  basis,triangular  basis,hyperbolic  tangent,andhard  limit | ELMswith  Gaussianradial basisfunction | 80%ofaccuracy[10] | |
| 2 | SoilOrganic  matter(SOM) andpH  parameter | 523soilsamplesfourMachine   Learningmodels   Cubistregression model(Cubist),   extremelearning   machines(ELM),   leastsquares-support vectormachines   (LS-SVM),and   partialleastsquares regression(PLSR) 140set Cubist,partialleast squaresregression (PLSR),leastsquares supportvector   machines(LS-SVM), andprincipal   component   regression(PCR)  NA OneNeuro-Fuzzy model(ANFIS)and twoartificialneural networks(a   Multi-Layer   Perceptron(MLP) andaRadialBasis Function(RBF)).  Multiplelinear  regression(MLR)  modelswithtwoand sixindependent  variables | | ELM | R2=0.81 | [11] |
| 3 | Moisture  content(MC), organiccarbon (OC),and  nitrogen(TN) | Estimatingmoisture content(MC),organic carbon(OC),and  nitrogen(TN) | Own | LS-SVMisbest forMCandOC andTNisbest bytheCubist | MC- RMSEP:0.457%, RPD:2.24TN- RMSEP:0.071  andRPD:1.96 | [12] , |
| 4 | soilmoisture | Auto-regressiveerror function(AREF)  combinedwith  computationalmodels  soiltemperature(ST)at 6differentdepthsof5, 10,20,30,50and  100cm | OwnThesoil  moistureand  densitywere  determinedby  volumetric  ringswith  100cm3  collectedin  eightpositions  alongtheplots, at  depthsfrom  25mmto  75mm  Public(For  BandarAbbas,  10years  measureddata  setsforthe  period  of1996–2005  andforKerman, 7years  measureddata  setsfor  theperiodof  1998–2004) | NeuralNetwork withAREF | RMSEbetween 1.27%and  1.30%,R2  around0.80,  andAPE  between3.77% and3.75% | [13] |
| 5 | Soil  Temperature | NA | ELM,SaE-ELM,  genetic  programming(GP) andartificialneural network(ANN) | SaE-ELM | MABE- 0.8660–1.5338 CR- 0.9084–0.9893 | [14] |

*2.1.Soil*

Liakos,etal.[8]andSharma,etal.[9]presentedasoilmanage-mentsurveywiththeapplicationofMLtechniquesforpredictionor identificationofsoilproperties(estimationofsoiltemperature,soildry-ing,andmoisturecontent).Thecategorizationandestimationofthe soilattributeshelpfarmersinminimizingextracostonfertilizers,cut thedemandofsoilanalysisexperts,increaseprofitability,andimprove healthofsoil,whereasSuchithraandPai[10]presentedpHvaluesand soilfertilityindicesclassificationandpredicationmodel.Yang,etal. [11]observedthatimportantindicatorsofsoilfertilityarepHvaluesand

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ofdailysoiltemperature(ST)at6differentdepthsof5,10,20,30,50 and100cm.Thedetailsummaryofworkdonebydifferentauthorson soliparameterismentionedinTable2.

*2.2.Seeds*

Seedgerminationisavitalfactorforqualityofseed,whichisan importantdeterminingfactorofyieldandqualityofproduction.Seed germinationratecalculationisstilldonemanuallywiththehelpof trainedpersonswhichisnotonlyatiresomeprocessbutalsoprone toerror.Thus,variousmachineleaningandimagerecognitiontech-niqueshavebeenproposedbydifferentauthorstoautomatetheprocess ofseedsortingandcalculation.Variouscomputervision,machinelearn-ingtechniques,ConvolutionNeuralNetwork(CNN)methodshavebeen presentedinD.Sivakumar,etal.[15],Huang,etal.[16],Zhu,etal. [17].Imagerecognitiontechniqueforseedsortingwithhighaccuracy isdevelopedbyYoung,etal.[18].Ke-ling,etal.[19]usedamulti-layerperceptronneuralnetworkmodelforimprovingtheaccuracyof theclassificationmethodtoseparatepepperseedsofhigh-qualityfrom low-quality.Uzal,etal.[20]andVeeramanietal.[21]usedthedeep neuralnetwork(DNN)modelusingCNNfortheassessmentofthequan-tityofseedsperpodinsoybeanandforsortingofhaploidseedsonbasis ofshape,phenotypicexpression,andtheembryopose.Nkemelu,etal. [22],builtamodelusingCNNforplantseedlingsclassificationinto12 species.Medeiros,etal.[23]assessedtheproficiencyofcomputervision asanalternativetoroutinevigorteststoexpeditetheprocessofaccurate evolutionofseedphysiologicalpotential.Amiryousefi,etal.[24]used imageanalysistechnique,principalcomponentanalysis(PCA),tosave timeandcostofplacingseedsindifferentclustersbyreducingthefea-turestobeconsideredforclustering.Vlasov,etal.[25],Kurtulmuş,etal. [26]usedmachinelearning(ML)techniquesforefficientseedclassifica-tion.Thedetailsummaryofworkdonebydifferentauthorsismentioned inTable3.

*2.3.Pesticidesanddiseasedetection*

In-timediseasedetectionisthemostimportanttasktosavecrops frommajorloss.Somefarmersregularlyanalyzeleaforbranchesof treewhilegrowingandidentifythediseasesormanytimestoavoid thediseases,theyapplythepesticidesonallthecropsequally.Boththe activitiesarebasedonhumanexperiencewhichispronetoerrorsand risky.Decisionofwhichpesticide,whentoapplyandwheretoapplyis totallydependentontypeofdisease,itsstageandaffectedarea.Appli-cationofunnecessarypesticideonallthecropsmayharmcropsaswell asfarmer’shealth.Precisionagriculturehelpsfarmersforapplicationof therightpesticideatrighttimeatrightplace.Manyworkscombined pesticidespredictionwiththedetectionofdiseaseonplants.Thissection discussesboutdiseasedetectionusingmachinelearning.

Alagumariappan,etal.[27],developedareal-timedecisionsupport systemintegratedwithacamerasensormoduleforplantdiseaseiden-tification.Inthisworkauthorsevaluatedtheperformanceofthreema-chinelearningalgorithmsnamely,ExtremeLearningMachine(ELM) andSupportVectorMachine(SVM)withlinearandpolynomialkernels andobservedthattheperformanceofELMisbetterwhencomparedto otheralgorithms.Savary,etal.[28]studiedhowdiseasescausethecrop lossesandtheirimplicationsforglobalfoodproductionlossesandfood security.Theobjectiveofthisworkistoshowthatcroplossresearchis vitalandshouldbeconsiderasfullbranchofplantscience.

Sujatha,etal.[29],comparedtheMLalgorithms(SVM,RF,SGD) withDLalgorithms(Inception-v3,VGG-16,VGG-19)intermsofcitrus plantdiseasedetectionandobservedthatDLmethodsperformedmuch better.Karada˘g,etal.[30]studieddetectionofhealthyandfusarium diseasedpeppers(capsicumannuum)fromthereflectionsobtainedfrom thepepperleaveswiththehelpofspectroradiometer.ArtificialNeural Networks(ANN),NaiveBayes(NB)andK-nearestNeighbor(KNN)ma-chinelearningalgorithmswereusedforclassification.Authorsclaimed

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**Table3**

Analysisofpre-harvestingparameter:Seed.

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Sr.No.Property | | Important features | Classesdefined inthework | Datasetused  (Public/Own) | Totalnoof  imagesusedfor training | Models/  Method/  Algorithms compared | Bestmodel/ method/  algorithm | Results | Model  evaluation  technique | Reference |
| 1 | Seed | color,shape, andtexture | mazeseed | Own | 4000 | ensemble  learning,  K-nearest  neighbor(KNN), logistic  regression,  supportvector  machine(SVM), andSpeededUp RobustFeatures (SURF)  algorithmto  classifythe  extracted  features,  GoogLeNet,  VGG19  SVM,PLS-DA,  andLRmodels  basedondeep  features  extractedby  self-designCNN andResNet  models  multilayer  perceptron  (MLP);BLR  binarylogistic  regression,  singlefeature  models | GoogleNet | 95% | ConfusionTable, Trainingloss.  Testingloss.  Training  accuracy.  Testingaccuracy | [16] |
| 2 | Cotton Seed | 15features(ten colorfeatures:  R,G,B,L∗,a∗,  b∗,hue,  saturation,  brightness,and  Gray,three  geometric  features:width, length,and  projectedarea,  seedweightand density)  38tailored  features,  geometrical  characteristics  (area,  perimeter,major andminoraxis  length),shape  features  (density,  elongation,  ompactness,  rugosityandaxis ratio),first4  Humoments,  andfinallya25 binshistogram  oftheprofileof thepod  straightenmask addedalongthe shortaxis  texture,  morphology,  colorandshape | Jinxin5,Jinxi7, own,dataset  Shennongmian1, collectedfrom Xinjiangzaomian1, Shihezi,Xinjiang Xinluzao- Uyghur  mian29, Autonomous  Xinluzhong52 Region,China and  Xinluzhong42  germinatedseed Own  (1)and  un-germinated  seed(0) | | 13,160 | self-designCNN80% | | classification accuracy | [17] |
| 400seeds | multilayer  perceptronand binarylogistic regression | 90% | [19] |
| 3 | pepper seeds | classification accuracy |
| 4 | soybean pods | 2-SPP,3-SPP, and4-SPP | Own | 18,178 | tailoredfeatures extraction(FE) followedbya  SupportVector Machines  (SVM),CNN | CNN | 86.20% | accuracy | [20] |
| 5 | haploid maize  seeds | True-Diploid, True-Haploid | Own | 4021 | DeepSort,  SupportVector Machine(SVM), RandomForest (RF),and  Logistic  Regression(LR) | DeepSort | 0.961 | 5-fold  cross-validation | [21] |

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**Table4**

Analysisofpre-harvestingparameter:Pesticidesanddiseasedetection.

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Sr.No.Property | | Important features | Classesdefinedin thework | Datasetused (Public/  Own) | | Totalnoof  imagesused fortraining | Models/Method/  Algorithmscompared | Bestmodel/method /algorithm | Results | Model  evaluation technique | Reference |
| 1 | Disease  detection | color,shape, andtexture | 12differentspecies and42different  classes(bothhealthy anddiseased) | Own 79,265  (PlantDisease) | | | AlexNet,VGG19,  Inception,DenseNet,  ResNet,PlantDiseaseNet ObjectDetection:  Two-StageMethods- FasterR-CNN,Faster  R-CNNwithTDM,Faster R-CNNwithFPN,  One-StageMethods- YOLOv3,SSD513,  RetinaNet  GoogLeNetCNN | PlantDiseaseNet | 94% | TOP-1  Accuracy | [32] |
| 2 | Plant  disease | individual lesionsand spots | Healthy,  Mildlydiseased,  Moderatelydiseased, Severelydiseased  8classes:5disease (Coryneum  beijerinckii,Apricot monilialaxa,Peach monilialaxa,Cherry myzuscerasi,  Xanthomonas  arboricola);3pest  (Walnutleafmitega, Peach  sphaerolecanium  prunastri,Erwinia  amylovora)  4classes:Brown  spot,Rust,Mosaic,  andAlternarialeaf  spot | Own(Plant-Disease) | PDDB- 1575XDB-46,409 | | GoogLeNetCNN | 12%higherConfusion matrices | | [33] |
| 3 | Plant  diseaseand pest  detection | deep  features | Own | 1965 | | extremelearning  machine(ELM),support vectormachine(SVM), andK-nearestneighbor (KNN),VGG16,VGG19, andAlexNet | ResNet50modeland SVM  classifier | 98% | accuracy,  sensitivity, specificity, and  F1-score,  confusion  matrix | [35] |
| 4 | AppleLeaf Diseases | edge,  corner,  color,shape andobject, | Own | 13,689 | | AlexNetPrecursor,VGG 19,Inception,DenseNet, ResNet,PlantDiseaseNet, SVMBPAlexNet  GoogLeNetResNet-20  VggNet-16OurWork  FuzzyRule-Based  ApproachforDisease  Detection(FRADD) | AlexNetPrecursor | 97.62% | confusion matrix | [36] |
| 5 | AppleFruit Disease | background and  foreground pixels | 4classes:Poor, Average,Good, Excellent | Own(Two datasets) | NA | | FRADD | 91.66 | accuracy | [37] |

fine-tunedmodeltoclassifythefruitsbyHossain,etal.[42].Thefirst modelwasbuiltwithsixlayerswhilethesecondwasfine-tunedvisual geometrygroup-16pre-trainedDLmodel.Twodatasetswereusedto evaluatetheperformanceoftheproposedmodels.Dataset-1ispublicly availableanditconsistsof2633colorimageswhereasdataset-2con-sistsoftotal5946images,distributedamong10classes.Itwasclaimed VGG-16fine-tunedmodelachievedexcellentaccuracyonbothdatasets. Kirk,etal.[43]studiedonimprovingnetworkperformanceonunseen datathroughastructuredapproachandanalysisofthenetworkinput. Insteadofmodifyingnetworkarchitectureandincreasingdepthofneu-ralnetwork,thefusionoffeatureswaschosen.Resultshowsthatthe modelcomplexityformoreaccuracyandgeneralizationcapabilitiescan beavoidedbyusingbio-inspiredfeatures.Itisclaimedthatforthecolor centricdataclassesthisapproachshowsmorepromisingresultswiththe robustDLmodelinrealworld.Forthistheworkauthorcreateddataset consistsof6189imagesover2months,AugustandSeptember2018, andmanuallyannotated150ofthem.Altaheri,etal.[44]proposeda machinevisionsystemtocategorizedatefruitimagesaccordingtheir maturitystageswhichhelpinharvestingdecision.Adatasetof8072 imageswerecreatedconsistingoffivedatetypes:NabootSaif,Kha-las,Barhi,Meneifi,andSullajwithdifferentpre-maturityandmaturity stages.Theimageswerecapturedinvariousangles,scales,illumination conditions,andtherewerefewoccludedimages.Transferlearningfrom twofamousCNNmodelsAlexNetandVGGNetwereusedtobuildthe threeclassificationmodelstoclassifydatefruitaccordingtotheirmatu-ritystage,type,andwhethertheyareharvestableornot.Resultshows thatVGG-16modeloutperformedwiththeaccuracyof99.01%in20.6

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**Table5**

Analysisofharvestingtechniques.

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Sr.No.** | **Property** | **Important features** | **Classesdefined inthework** | **Dataset**  **used**  **(Public/ Own)** | **Totalnoof images**  **usedfor**  **training** | **Models/Method/**  **Algorithmscompared** | **Bestmodel /Method**  **/Algorithm** | **Results** | **Model**  **evaluation technique** | **Reference** |
| 1 | Real-Time Fruit  Detection  withintree | fruit  shapes,  colorand/or other  attributes  NA | apple  andpearfruits | own | 5000 | Single-ShotConvolution Neural  Network(YOLO) | YOLO | 90% | confusion matrix. | [41] |
| 2 | fruitclassifi-cation | 1stdataset:15  classes,2nd  dataset:10  classes  3classes:Ripe  Strawberry,  Unripe  Strawberry,  BothClasses  fivedatetypes  indifferent  pre-maturity  andmaturity  stages:Naboot  Saif,Khalas,  Barhi,Menei,  andSullaj  applesDetected, Undetected | 1stdataset: Public,2nd Dataset:  own  own  (DeepFruit) | 1stdataset:  2633,2nd  dataset:5946 | 2deeplearningModels: 1)lightmodelofsixCNN layersand2)VGG-16  basedarchitecture  FeaturePyramid  Networks,Residual  NeuralNetworks  andRetinaNet | VGG-16  based  architecture | 99.75% | Confusion matrix | [42] |
| 3 | Outdoor  Fruit  Detection | Bio-Inspired Features,  fusionof  features | 4219 | L∗a∗b∗Fruits system | performance increaseof  6.6times | F1score,the harmonic  meanof  precision  andrecall  Confusion  matrix. | [43] |
| 4 | DateFruit Classifica-tion | localand  spatial  featuresand patterns | own | 8000 | VGG-16,AlexNet | VGG-16 | 99.01% | [44] |
| 5 | fruit  harvesting robot | NA | public | 169 | SingleShotMultiBox Detector(YOLO) | YOLO | 0.9 | precision, recall | [47] |

canbeconsiderinthisstageareshelf-lifeoffruitsandvegetables,post-harvestgradingandexport.Everycountryhastheirownstandardrules andregulationsforgradingthefruits[49–51].

In[52],aninformationmanualwithdirectionsfor“Post-harvest managementofmangoforqualityandsafetyassurance” waspresented. Thisisveryinsightfulforallthestakeholdersofhorticulturalsupply chain.Studyshowedthatwrongpost-harvesthandlingmethodscanaf-fectthequalityandquantityoffruitswhichincreasestheoveralllosses. 31%losseswhichareidentifiedatretaillevelwerecausedbydecay only.Theotherpracticeswhichaddlossesarepoorharvesting,careless handling,andimproperpackagingandcarriageconditions.

Thewrongdiseasemanagementduringproductioncausesthede-cayathigh-levelofpre-harvestinfections.Thedecaysintheformof anthracnoseandstemendrotareverycommonlyobserved.Atrain-ingmanualfor“handlingfreshfruits,vegetablesandrootcrops” for Grenadawaspresentedin[53],asapartofthe“AgriculturalMarket-ingImprovement” ProjectTCP/GRN/2901whichwasimplementedby GrenadaGovernmentandFAO.Thegoalofthisprojectwastoincrease theprofitsforhorticultureproductsandrootcropgrowersthrougha well-organizedagriculturalmarketingsystem.Thisdocumentprovides indetailstudyaboutallpost-harveststageswithhowtominimizethe lossesineverystage.Ucat,etal.[54]exploredtheuseofimagepro-cessingwithdeepleaningalgorithmtoclassifyCavendishbananaas pertheirgrades.Python,OpenCVandTensorflowwereusedtobuild themodeltoclassifythebananasintodifferentcategoriessuchasClass Abig-handorsmall-hand,ClassBbig-handorsmall-handandCluster class(partofhand).Resultshowsthatthemodelachievedmorethan 90%classificationaccuracy.Ireri,etal.[55]proposedamachinevision systemforpost-harvesttomatograding.ThesystemworksonRGBim-agesgivenasaninputtothesystem.Datasetwascreatedbymanually labelingthetomatoimagesintofourcategoriesaccordingtotheirde-fect,healthyandripenessparameters.Fourdifferentmodelswerebuilt toclassifyimageintooneofthecategoryaccordingtothematchingfea-tures,total15featureswereconsideredwhiletakingthedecisionResult showsthatRBF-SVMperformedwellascomparedtoothersforcate-gory1i.e.healthyordefectedwith0.9709detectionaccuracy.Piedad, etal.[56]developedasystemforbanana(MusaacuminataAAGroup

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**Table6**

Analysisofpost-harvestingworks.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Sr.No. | Property | Classes  definedin thework | Datasetused (Public/  Own) | Totalnoof  imagesused fortraining | Models/  Method/  Algorithms compared | Results | Model  evaluation technique | Reference |
| 1 | POSTHARVEST GRADING  CLASSIFI- CATIONOF  CAVENDISH  BANANA  Defectdis- crimination  andgrading  intomatoes | 4classes | own | 1116 | Python  OpenCVand Tensorflow | 0.9 | accuracy | [54] |
| 2 | 4classes:  category1, 2,3,and4.  depends  upondefect, healthy,and ripeness  (redcolor  intensity) | own | 8000 | linear-SVM, quadratic- SVM,  cubic-SVM,  andradial  basis  function  (RBF-SVM), ANN,  decision  tree,and  random  forest  artificial  neural  network,  support  vector  machines  andrandom forest  K-means,  C4.5  decisiontree | 0.9709 | Confusion  matrix | [55] |
| 3 | Postharvest classifica- tionof  banana  (Musa  acuminata) | extraclass, classI,class IIandreject class | own | 1164 | 0.942 | Classification Accuracy,  F-Score,  Confusion  matrix | [56] |
| 4 | Automatic  apple  sorting  system | small,  normal,  large,light anddark,  defective  andnon- defective  3classes:  grades1,2 and3 | own | 183 | 0.79 | statistical  test | [58] |
| 5 | Datefruit  grading | own | 1860 | back  propagation neural  network  (BPNN) | 0.8 | Confusion  matrix | [59] |

sixclasses.Table6,presentedthedetailsummaryofpost-harvesting works.

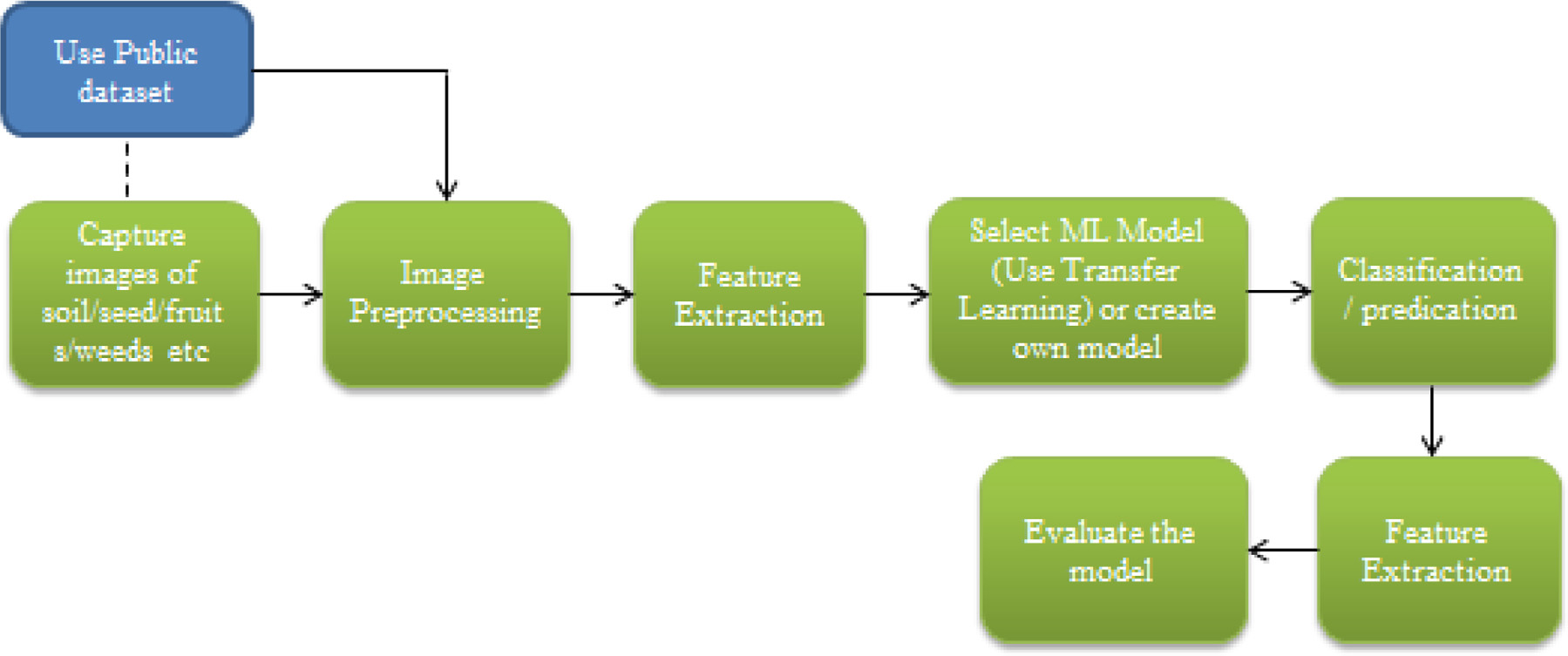
**5.Discussion**

Thispaperhasextensivelyreviewedtheavailableliteratureonappli-cationofmachinelearninganddeeplearninginagriculture.Different state-of-the-artmachinelearninganddeeplearningmodelsindiffer-entstagesofagriculture,includingpre-harvesting,harvestingandpost-harvestingindifferentdomainswerereviewed.Deeplearningtechnol-ogyisbecomingmatureday-by-day.ThissurveyshowsthatuseofCNN inagricultureishugeanditisalsogettingremarkableresults.Byex-ploitingdepth,otherstructureandhardwaresupport,thelearningca-pacityandaccuracyoftheCNNissignificantlyimproved.Stillthere arechallengeslikedatasetcreation,timerequiredfortrainingandtest-ing,hardwaresupport,deploymentofbigmodelsonsmalldeviceslike boardsorandroidphones,userawarenessetc.

Apopulartechniquecalled“TransferLearning” isoftenusedtomiti-gatetheproblemsofsmalldataset,timerequiredfortrainingandtoim-provetheaccuracyofthemodel.InternetofThings(IoT)systemscom-binedwithmachinelearningprovidesabeneficialsolutiontoimprove farminggains.RealtimeparametersofthefarmsaregatheredusingIoT, andthecollecteddataisusedbymachinelearningalgorithmseitherto predictorforrecommendationstofarmersforimprovementsinfarm-ing.FromthesurveyitisalsoobservedthatSingle-ShotConvolution

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**Fig.3.**StepsofMachineLearningusedinliterature.

Thebenefitsofmachinelearninginagriculturedomainareenor-mous.However,thebenefitscomewithitschallenges.Fewsuchchal-lengeswhileimplementingmachinelearningalgorithmsinagriculture domainarelistedasfollows:

1)*Data:*Dataisthemostfundamentalrequirementtobuildthemachine learningmodels.Manyresearchersfacedthechallengesregarding datalikelackofdata,unavailabilityofdatainrequiredformat,poor qualityofdata,datamaycontainextraneousfeaturesetc.Fromthis surveyitisobservedthat,manyresearchersusedatasourcesiteslike Kaggel,Meandly,IEEEDataportetc.togetthedatatobuildmodels. Iftherequireddataisnotavailablethenresearchersneedtobuild theirowndataset[70–75].

2)*Pre-processingofthedata:*Astherearelotofproblemsassociated withdata,onehastoapplythedifferentpre-processingtechniques tomakethedatasuitablefortraining,testing,andvalidationtesting themodel.Thismightbetimeconsumingprocess.

3)*Selectionofmachinelearningalgorithms:*Widelistofmachinelearn-ingalgorithmisavailablewhichmakeitdifficulttofindoutmore suitablealgorithmtobuildthecustomizemachinelearningmodel. Manytimes,itisrequiredtodorandomselectionoraftercompar-ingresultsofmultiplealgorithmsonecancometoconclusionfor bestsuitablealgorithm.Thistrial-anderrortechniquemaydelaythe modeldeploymentprocess.

4)*Trainingandtestingofthemachinelearningmodel:*Buildingtheaccu-ratemodelneedshugedatafortraining.Testingandvalidationare alsoimportanttochecktheaccuracyofthemodelbeforeitsdeploy-ment.Buildingamodelfromscratchforbestdesiredandpossible outcomesneedslongtrainingandmultipletimetestingwhichare verytime-consumingtasks.Itneedshighconfigurationhardwarere-sources;domainknowledgeprogrammers,testingtoolsetc.Overfit-tingandunderfittingarethecommonchallengesfacedwhilebuild-ingthemodels.

5)*Deploymentofmodels:*Thisisthemostchallengingphasetobringthe modelsintheproductionasthereisabsenceofdeploymentskills, thirdpartylibrarydependencies,sizeofmodels,complexreal-world scenarios,deploymentplatformhardwarelimitations,(likeandroid phones,embeddedboards)etc.

Somemorechallengesareimportanttomakeanoteof:

1)Understandingthebusinessneedandidentificationofproblem.

2)Understandinguserandtheirinteractionwithtechnology 3)Userfriendlyapplicationdesign.

4)Performanceofmodelsinthereal-wordscenarios.

5)Powerconsumptionbymodelandbatterylimitationstorunthe modelonthedevices.

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**DeclarationofCompetingInterest**

Theauthorsdeclarethatthereisnoconflictofinterestsregarding thepublicationofthispaper.

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