www.ijarp.com ISSN 2456-9992 Page: 01-12

International Journal Advanced Research Publications

Review Article

Volume: 02
Issue: 06

FRUIT DISEASE DETECTION AND QUALITY GRADING USING CNN AND SSDAE-SVM

[*]Ashwini Nehe, Sakshi Bhusal, Abha Bhujbal, Rahmi Hiray, Poonam Jamdhade

Department of Computer Engineering Amrutvahini College of Engineering Sangamner, India.

Article Received: 4 May 2026, Article Revised: 24 May 2026, Published on: 14 June 2026

***Corresponding Author: Ashwini Nehe**

Department of Computer Engineering Amrutvahini College of Engineering Sangamner, India.

Doi: https://doi-doi.org/101555/ijarp.8482

ABSTRACT

For modern agriculture to preserve fruit quality and minimize losses, effective postharvest management is necessary. Conventional manual inspection technique sarelaborious,erratic, and subjective. With an emphasis on pomegranates, this study offer sahybridmethod for automated fruit disease diagnosis andgradingusingpicturedatathatcombinesdeeplearning and machine learning. Using deeper layers, residual connections, and batch normalization, an improved Convolutional Neural Network (CNN) reduces overfitting and increases accuracy by extractingkeycharacteristicsfromhigh-resolutionimages.Innext step these features are enhanced by SSDAE.SSDAE removes useless information and focuses on the important details.This makes system more reliable for real world farming.

INDEX TERMS: Agricultural Quality Control, Enhanced Con-volutional Neural Network (CNN), Stacked Sparse Denoising Autoencoder (SSDAE), Support Vector Machine (SVM)

I. INTRODUCTION

The global economy depends heavily on agriculture, par-ticularly in nations like India where fruit production greatly boostsfarmers'incomesandtheexpansionofagricultureas a whole [10], [12]. For fruits to maintain their market value and guarantee food safety, their quality must be maintained duringthepost-harvestphase[2],[5].However,avariety of illnesses frequently harm fruits, lowering their quality,shelf life, and market value [7], [11]. Fruit disease diagnosis and quality grading have traditionally been carried out by experts through manual examination [15]. It takes a lot of time, effort, and domain expertise to complete this process.

Furthermore,humansubjectivity,weariness,andinconsistency frequently affect manual inspection, which might produce incorrect results [12].
As a result, there is a growing demand for sophisticatedand automated systems that can effectively assess fruit quality andidentifyfruitdiseases.Recentdevelopmentsindeeplearn-ing (DL), machine learning (ML), and artificial intelligence (AI) have made it possible to create automated systems that canhandlechallengingvisualanalysistasks[7],[10],[12].
Convolutional Neural Networks (CNNs) have shown to bethe most effective of these technologies in tasks including objectdetection,patternrecognition,andpicturecategorization [7],[9],[11].FromunprocesseddataCNNmodelextracts the elements like color,texture,spots. [3], [17].Due to these extractedfeaturesCNNishighlyusedforprocessingaggrecul-tural image. [1], [3], [8].

In these system, machine learning techniques are employed for precise categorization and decision-making, while deep learning is used for efficient feature extraction. For fruit disease diagnosis and quality grading, this work proposes a hybrid architecture based on Convolutional Neural Networks (CNN), Stacked Sparse Denoising Autoencoders (SSDAE), and Support Vector Machines (SVM) [13], [14], [16]. By spotting patterns associated with disease signs and quality attributes, the CNN model extracts significant features from fruitphotos.SSDAEisusedtofurtherimprovethesefea-tures, enhancing the most pertinent information in the feature representation and reducing noise [13]. Ultimately, an SVM classifier[14],[15]isusedtoclassifytheoptimizedfeatures.

Theclassifiernotonlydetectsillnessesbutalsoassessesthe fruit’s quality. The suggested system’s main goal is to offeran automated, precise, and effective fruit inspection solution for agricultural applications. By lowering reliance on human inspection, this method can assist farmers, wholesalers, and other stakeholders in evaluating fruit quality more rapidly and accurately[2],[8].Farmerscanreducepost-harvestlossesand crop damage by taking preventive action when illnesses are detected early [7], [16]. Additionally, computerized grading guaranteesthatfruitsfulfillmarketcriteriapriortodistribution andenhancesqualitycontrol[1],[4].Precisionagriculture issupportedbytheseintelligentsystems,whichalsohelp to improve the productivity, sustainability, and efficiency of farming methods [10], [12].

II. RELATEDWORK

Fruit disease identification and quality evaluation have receivedalotofattentionlatelybecauseoftheirsignificance in raising agricultural productivity. To improve accuracy and automate these procedures, researchers are increasingly using machine learning and deep learning approaches.

Deep learning models may successfully identify fruit cate-goriesandassessquality,asdemonstratedbyaproposedmulti-fruitclassificationandgradingsystemthatusesEfficientNetV2 andtransferlearning.Theprobleminthis,itusesonlya single Deep Learning model.So,its not reliable in real time application [1].

Anotherstudycontainsthedeepfeatureextractionofimage and ML for evaluating quality of fruit,extraction and clas-sification of quality.So,this mainly focuses on feature based learning,It doesn't do any improvement in features,So,it fails in noise or real world data [2].

Next study contains the evaluation of fruit quality that uses a DenseNet.It shows that deep CNN is able to find hidden visual patterns and makes high classification performance. Nevertheless,thisapproachsolelyreliesonCNN-basedfeature extractionandlackshybridapproachesforadditionaloptimiza-tion or better decision-making [3].

Thesestudiesshowthatthemajorityofcurrentmethodsrely oneithermachinelearningordeeplearningmodelsseparately. These approaches frequently lack hybrid learning algorithms and feature refinement, which can restrict their resilience and capacity for generalization.

A.Research Gap

Severalsignificantgapscanbefoundintheliterature:

- The majority of methods include machine learning tech-niques or single-model architectures like CNN. Feature improvement and noise reduction receive little attention.
- There is little research on hybrid frameworks that com-bine machine learning and deep learning. Few methods do both quality rating and disease detection at the same time.

III. CONTRIBUTIONOFTHEPROPOSEDWORK

Thedevelopmentofacombinedintelligentsystemaimedat identifying fruit diseases and evaluating quality is the primary contribution of this research [1], [2]. To increase robustness andclassificationeffectiveness,theproposedframeworkcom-bines deep learning and machine learning approaches [10], [12].Key visual features are obtained from images of fruits through an enhanced Convolutional Neural Network (CNN) [7], [9], [11]. To further process these features, a Stacked Sparse Denoising Autoencoder (SSDAE) is employed, which improves feature quality by removing noise and emphasizing significant patterns [13]. Finally SVM is used for grading quality of fruit [14], [15].This method gives farmer and aggri-culturalindustrythecompleteautomatedsolutionthatreduces the postharvest losses and improves the quality standard [4], [20].

IV. PROBLEMSTATEMENT

Accurately detecting fruit diseases while simultaneously ratingqualityisstilladifficulttask,despiteadvancements in deep learning methods for agricultural applications [12]. Conventional methods of inspection that are manual heavily depend on human expertise and often demand considerable labor,takingalotoftimeandbeingpronetomistakesbecause of personal bias and fatigue [15]. Many current automated methodsignorefruitqualitygradinginfavorofdiseaseidenti-fication.Additionally,theperformanceofclassificationmodels canbenegativelyimpactedbyenvironmentalfactorsincluding changesinlighting,backgroundnoise,andimagequality[11]. To increase the effectiveness and consistency of agricultural inspection procedures, an intelligent automated system that canaccuratelyidentifyfruitillnessesandgradefruitquality is therefore required.

V. OBJECTIVESOFTHEPROPOSEDSYSTEM

1. To implement techniques in image processing and ma-chine learning to develop an automated framework for evaluating fruit after harvest and identifying diseases.
2. To apply an improved Convolutional Neural Network (CNN) for effective extraction of features from high-resolution images of fruits.
3. ToimplementSVMforcorrectanddependablecategor-ical evaluation of fruit disease and quality grading.
4. Tochecktheeffectivenessofsystembycalculat-ing confusion matrix and performance measure like Accuracy,Precision,Recall,F1-score.

VI. PROPOSEDSYSTEM

This system is designed to automatic detection of diseasesinfruitandchecktheirqualityandgradethequality.Thedeep learning techniques are used so, it can work even if image is not perfect. This system generally uses the three parts: CNN, SSDAE and SVM. Every techniques works differently.

1) CNN: Extracts the important features from the image. Automatically understand the features. So, no need to tell it manually what to look for. At first it detect the simple things

like edges and texture. Then next it learns the complex things like shape, colour and disease signs. It helps to detect fruit is healthy or not.

2) SSDAE: It enhances the extracted details by CNN. It detect the noise i.e. unwanted information and removeit. It keeps only the useful and required parts Also it improve data simplicity and clarity. That helps in better decision making when the image is in bad quality.

3) SVM: This is the last step. It takes the enhance data and give the final decision. It differentiates the type of fruit disease by analysing the boundary between them.Also the main function of SVM is the quality grading.

By the combination of this three technique system becomes accurate and reliable.

A. SystemArchitectureDescription

Thecompletearchitectureofthesystemisdividedintothree main layers:

1) Datapreparationlayer
2) Hybridlayer
3) Deploymentlayer.

All these layers work together to make sure the process runs smoothly,startingfromtheinputimageandgoingtillthefinal output.

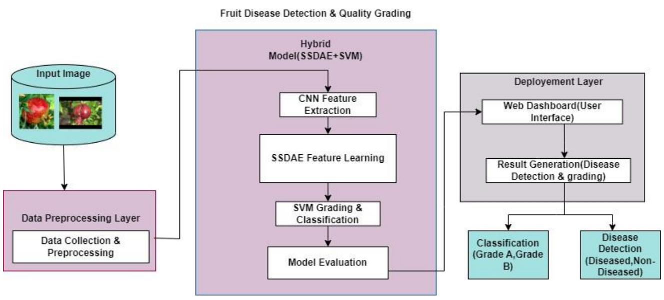

Fig. 1: System architecture of the proposed fruit disease detection and grading system.

1) *Data Preparation Layer:*This is the very first step, in this step we collect the fruit images. The dataset contains both healthy and diseased fruits, and they are labeled properly so thatthesystemcanlearncorrectly.Sincetheimagesmaydiffer in size, lighting, and overall quality, we need to preprocess them first. So we: noise from the images

- Resizeallimagestothesamesize(224×224)
- Normalizepixelvaluestomaintainconsistency
- Removenoisefromtheimages
- Applytechniqueslikerotationandflippingtoincrease the dataset

This step helps the system learn in a better way and also reduce errors during prediction.

2) *HybridLearningLayer:*Thisisthemainlayerofthe system where the actual learning and decision making happens.First,theimagesgoesintotheCNNmodel.CNNan-alyzestheimagesandextractsimportantfeatureslikepatterns, colors, and shapes. The convolution process can be computed as:

$$FeatureMap=(Input \times Filter)+Bias \quad (1)$$

Then, an activation function called ReLU is applied. It basicallykeepstheusefulvaluesandremovestheunnecessary ones. The equation of ReLU function is:

Thedecoderreconstructsthedataas:

$$x'=g(W'h+b') \quad (4)$$

Finally, this refined data is given to the SVM model. SVM makes the final decision by separating different categories using a proper boundary.

ThedecisionfunctionofSVMiscalculatedas:

$$f(x) = w \cdot x + b \quad (5)$$

At the end, the system tells:

- Whatdiseasethefruithas
- Whatqualitygradeitbelongsto

3) *Deployment Layer:*This is the final stage where model isreadytouseforrealworld.Inthisstagetrainedmodel is connected with user interface. User uploads fruit image through user interface and system automatically give result.

- Diseasedetection
- Qualitygrade(A,B,C)
- Howconfidentthepredictionis

As a result it helps users to understand the condition of fruitsquicklysothattheycantakerequiredactionsassoon as possible.

B. WorkingPrincipleoftheProposedSystem

Thesystemworksinstep-by-stepmanner:

1) Imagesoffruitsarecollectedfromdataset.
2) Toimprovequality,imagesoffruitsarepreprocessed.
3) UsingCNN,featuresfromimagesareextracted.
4) ThesefeaturesarethenenhancedusingSSDAE.
5) SVMclassifiestheimagesandassignsqualitygrades
6) Finalresultsaredisplayedtotheuser

C. DatasetPreparationandDivision

Totrainandevaluatethesystemeffectively,thedatasetis divided into three parts:

- TrainingSet(70%)forlearning
- ValidationSet(15%)fortuning
- TestingSet(15%)forevaluation

This ensures that the model performs well on new, unseen data.

D. PerformanceEvaluation

The performance of the system is measured using standard metrics:

Accuracy

$$Accuracy=\frac{TP+TN}{TP+TN+FP+FN} \tag{6}$$

Precision

$$Precision=\frac{TP}{TP+FP} \tag{7}$$

Recall

$$Recall=\frac{TP}{TP+FN} \tag{8}$$

F1Score

$$F1=2\times\frac{Precision\times Recall}{Precision+Recall} \tag{9}$$

Thesemetricshelpevaluatehowwellthemodelperforms in terms of accuracy and reliability.

E. AdvantagesoftheProposedSystem

- Reducestheneedformanualinspection
- Provideshighaccuracyusingahybridapproach
- Workswellunderdifferentenvironmentalconditions
- Canbeextendedtomultiplefruittypes
- Suitableforreal-timeapplications

VII. IMPLEMENTATIONDETAILS

A. SoftwareTools

The following software technologies are used to implement the proposed system:

- Pythonprogramminglanguage
- DeeplearningframeworkslikeTensorFlowandKeras
- ForImageprocessingOpenCV
- ToimplementMLalgorithmsScikit-learn
- BackendAPIdevelopmentbyusingFlaskframework

- FrontenduserinterfacedesignbyusingReact

B. HardwareRequirements

RequiredHardwaretoimplementthesystem:

- Windows10OS
- 8GBRAM
- IntelCorei5Processor

VIII.PERFORMANCEANALYSISANDRESULTS

By using test data from the splited dataset the model is evaluated.

Categorization results are shown by representing the con-fusion matrix in Fig. 2. The evaluation of the model is as follows:

- Accuracy:89.44%
- Precision:79.3%
- Recall:90.3%
- F1Score:84.5%

C. Fig. 3shows the comparison of some performance mea-sures.

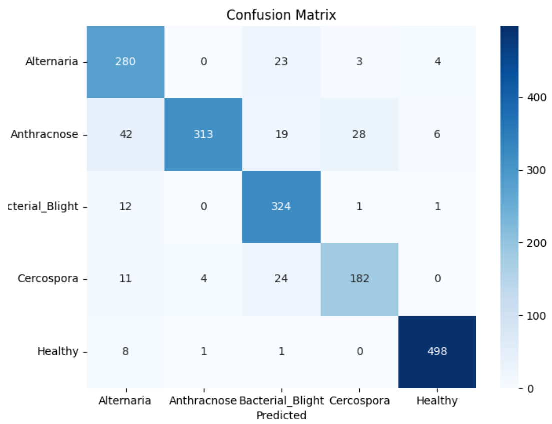

Fig.2:ConfusionMatrixoffruitdiseaseclassification.

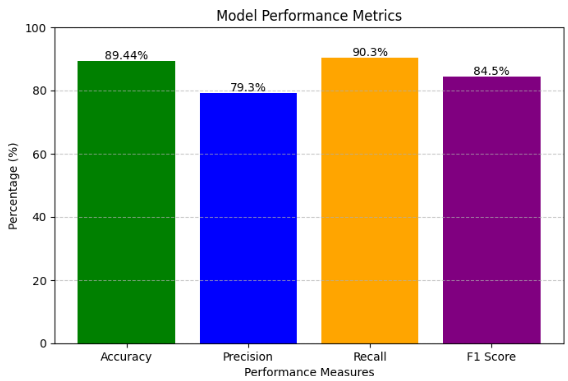

Fig.3:ComparisonofPerformancemeasures.

(a) Healthyfruit(Grade A, 0% severity)

(b) Cercosporadisease (moderate severity)

(c) Alternaria disease (Grade B)

(d) BacterialBlight(high severity, Grade C)

(e) Anthracnosedisease (moderate severity)

Fig.4:Sampleoutputsoftheproposedsystem(continued).

The results represents that the given hybrid system givesthe stable performance to all several disease type and better accuracy of classification.

IX. Conclusion

The CNN helps in extracting important features from the givenimage.TheSSDAEimprovestheextractedfeatured by removing noise and making the future more useful. Then the SVM is used for classification. It is used to classify the typeofdiseaseandqualitylevelofgivenfruitimage.As a result of this complete process we get more accurate and reliable result. We got an accuracy of 89.44%. This system will be useful in agriculture because it reduces human errors andhumanlabourbyautomatingtheprocess.Italsohelps in detecting fruit disease at an early stage, as a result in ithelps in improving quality of crop and reduce losses. Farmers and others can take quick actions based on these result, this willhelpeconomically.Wewilltrytoimproveoursystem in future. In future we will try to work on more diverse and largedatasetwithdifferenttypesoffruitsanddiseasestomake the model even better and more accurate. Overall, this hybrid approach of CNN,SSDAE and SVM helps in automatic the fruit disease detection and quality assessment process.

FUTURE SCOPE

There are still many ways to improve this system and make it more useful in real world situation

1. **Multiple fruit varieties:** In future we can train model onmorevarietiesanddifferenttypesoffruitsand mighteventrytoworkonvegetables.Asfarnowit is limited only to one fruit i.e. pomegranate, but we will try to make the system flexible and useful in different agricultural use.
2. **Real time mobile application:** A mobile app or web based platform can be developed so that farmers or vendors can easily use the system anytime. This will help them to quickly check fruit quality on the spot without needing any complex setup.
3. **Improved Deep Learning Models:** We can try more advancedmodelslikeResNetorEfficientNettoimprove the accuracy. These models help in better performance.
4. **Automated Sorting Mechanism:** We can connect the system with hardware like conveyor belts or robotic arms. This can help in automatic sorting and packaging of fruits based on their quality, reducing the manual work.
5. **DeploymentintheCloud:**Wecandeploythemodelon cloud platforms to make it more easier to access from anywhere. It can also support large scale operations and provide faster processing for bigger datasets.

REFERENCES

1. T. Mehra and V. Agarwal, “Multi-fruit classification and grading usingEfficientNetV2andtransferlearning,”*ProcediaComputerScience*,vol.218, pp. 1120–1131, 2024.
2. I. D. Apostolopoulos, M. Tzani, and S. I. Aznaouridis, “A machinelearning model for assessing fruit quality using deep image features,”*AI*, vol. 4, no. 4, pp. 812–830, 2023.
3. S. Morshed *et al.*, “Fruit quality assessment with densely connectedconvolutional neural

network," *arXiv preprint arXiv:2212.04255*, 2022.

4. "Online grading of fruits using deep learning models and computervision," in *Proc. ACM Int. Conf.*, 2023.
5. "Simplified deep learning for fruit quality assessment in resource-constrained environments," *Applied Sciences*, vol. 14, no. 18, 2024.
6. "Smart disease detection system for citrus fruits using CNN-LSTMtechniques," *Sustainability*, vol. 15, no. 5, pp. 4576, 2023.
7. S. P. Mohanty, D. P. Hughes, and M. Salathe´, "Using deep learning forimage-based plant disease detection," *Frontiers in Plant Science*, vol. 7, pp.1–10,2016.
8. K. P. Ferentinos, "Deep learning models for plant disease detection anddiagnosis,"*ComputersandElectronicsinAgriculture*,vol.145,pp.311–318, 2018.
9. E.Too,L.Yujian,S.Njuki,andL.Yingchun,"Acomparativestudyof fine-tuning deep learning models for plant disease identification,"*ComputersandElectronicsinAgriculture*, vol.161,pp.272–279,2019.
10. A. Kamilaris and F. X. Prenafeta-Boldu´, "Deep learning in agriculture: Asurvey,"*ComputersandElectronicsinAgriculture*,vol.147,pp.70–90,2018.
11. P. Jiang *et al.*, "Real-time detection of apple leaf diseases using deeplearning approach based on improved CNN," *IEEE Access*, vol. 7, pp.59069–59080, 2019.
12. L.Li,S.Zhang,andB.Wang,"Plantdiseasedetectionandclassificationby deep learning—A review," *IEEE Access*, vol. 9, pp. 56683–56698,2021.
13. J.Wang,Y.Chen,andH.He,"Plantdiseaserecognitionbasedonstackedautoencoder and deep neural networks," *IEEE Trans. Instrumentationand Measurement*, vol. 70, pp. 1–10, 2021.
14. H. Zhang *et al.*, "A hybrid CNN-SVM classifier for plant diseaserecognition," *IEEE Access*, vol. 8, pp. 160915–160926, 2020.
15. R. K. Singh, M. Jain, and S. Bhatia, "Plant disease detection usingsupport vector machine and image processing techniques," *ProcediaComputer Science*, vol. 167, pp. 2240–2249, 2020.
16. M. A. Rahman, M. Hasan, and M. A. Islam, "Hybrid deep learningapproachforplantdiseaseclassificationusingCNNandSVM,"in*Proc.IEEEInt.Conf. ArtificialIntelligenceinAgriculture*,2023,pp.145–150.
17. Y. Toda and F. Okura, "How convolutional neural networks diagnoseplant disease," *Plant Phenomics*, vol. 2019, Article ID 9237136, 2019.
18. A. Ouamane *et al.*, "Enhancing plant disease detection using CNN withtensor subspace

learning," *IEEE Access*, 2024.

19. U. Mishra *et al.*, "Deep learning-based disease detection in potato andmango leaves using CNN architectures," *Scientific Reports*, 2026.
20. S. Gupta and P. Sharma, "Automated fruit disease detection usingconvolutionalneuralnetworksandmachinelearningclassifiers,"in*Proc.IEEE Int. Conf. Smart Agriculture*, 2024, pp. 101–106.