Potato Disease Detection Using Speckle Imaging and Deep Learning

Mohamed Abdallah Salem[1], Ahmed Harb Rabia[1, *]

[1]Department of Agricultural and Biosystems Engineering, North Dakota State University, Fargo, ND 58102, USA

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Abstract.

Potato disease detection is paramount for ensuring food safety and optimizing product quality in agriculture. However, traditional methods like manual inspection are labor-intensive and prone to errors. Addressing these challenges, this study presents an innovative, cost-effective approach utilizing speckle imaging and deep learning for automated potato quality evaluation. The critical issue tackled in this research is the necessity for a reliable, budget-friendly method to detect and classify potato defects, encompassing diseases and physical damage, to ensure consumer satisfaction and mitigate economic losses. The objective is to develop a machine learning-based solution capable of accurately classifying potato defects using speckle images captured with a red laser pointer and a lens-less USB camera. Our methodology involves creating a dataset of speckle images of both healthy and affected potatoes and training a convolutional neural network (CNN) using transfer learning with a pre-trained ResNet-50 model. With a dataset comprising 850 training images, 200 validation images, and 400 test images, the trained model is evaluated using accuracy, precision, recall, and F1-score metrics. Quantitative results demonstrate the effectiveness of the proposed method, with the model achieving an overall accuracy of 98% on the test set. Comparative analysis with existing methods, including traditional computer vision using RGB images, depth images, multispectral, and hyperspectral imaging, underscores superior performance in terms of defect classification accuracy. The significance of our findings lies in the potential of speckle imaging combined with deep learning to revolutionize potato quality evaluation in agriculture, particularly due to its affordability and cost-effectiveness compared to hyperspectral and multispectral imaging or depth camera approaches. By automating defect detection and classification, our approach offers benefits such as enhanced efficiency, reduced labor costs, and improved product quality assurance.

Keywords.
Potato quality evaluation, speckle imaging, deep learning, convolutional neural network, transfer learning, defect classification, food safety.

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Introduction

Potato quality is critical for consumer satisfaction and agricultural productivity. Traditional quality assessment methods, like manual inspection, are laborious and prone to errors. Integrating machine vision and artificial intelligence offers a promising solution. While RGB, hyperspectral, and multispectral imaging have been explored (Su, et al. 2017) (Zhang, Zhu,, et al. 2019), speckle imaging presents a novel approach. Coupled with deep learning, particularly CNNs, it shows potential for accurate defect classification. This study leverages speckle imaging and transfer learning with a pre-trained ResNet-50 model to classify potato defects efficiently. It presents a comprehensive methodology covering dataset collection, model training, and evaluation, alongside experimental results highlighting the effectiveness of the proposed approach compared to existing methods. This approach advances precision agriculture and lays the foundation for automated potato quality evaluation.

Methodology

The collected dataset consists of speckle images of both healthy and diseased potatoes. Speckle patterns were generated using a red laser pointer (650 nm, < 5 mW) and captured using a lens-less USB camera as shown in Figure (1). The dataset was divided into two sets: a training set of 850 images, and a validation set of 200 images. Another test set has been generated to assist the model performance in real-time imaging using 400 test samples. Since the scattered speckles from the surface are very random, it requires a deep learning model to extract the underlying patterns from the speckle images. Hence, A transfer learning model has been employed with the pre-trained ResNet-50 model for defect classification. Transfer learning allows us to leverage the knowledge learned by ResNet-50 on a large dataset (ImageNet) to improve the performance of our limited dataset. The pre-trained model was fine-tuned to the speckle image dataset to adapt it to the task of potato defect classification.

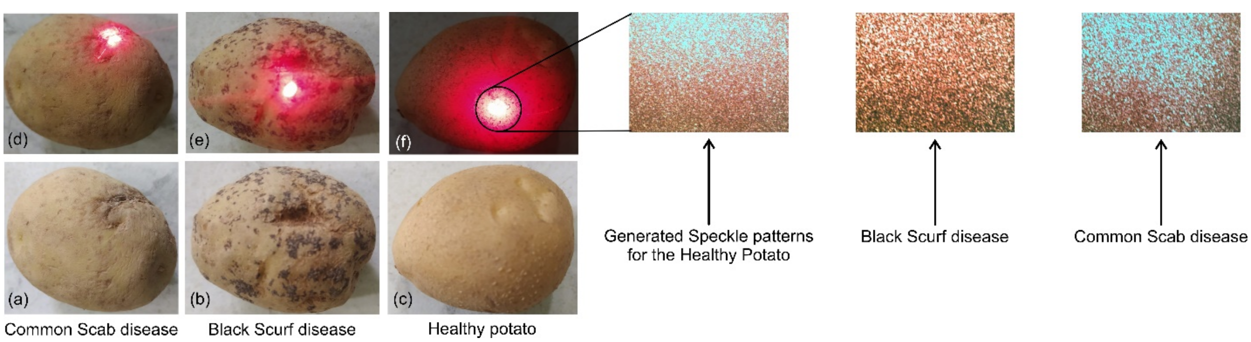
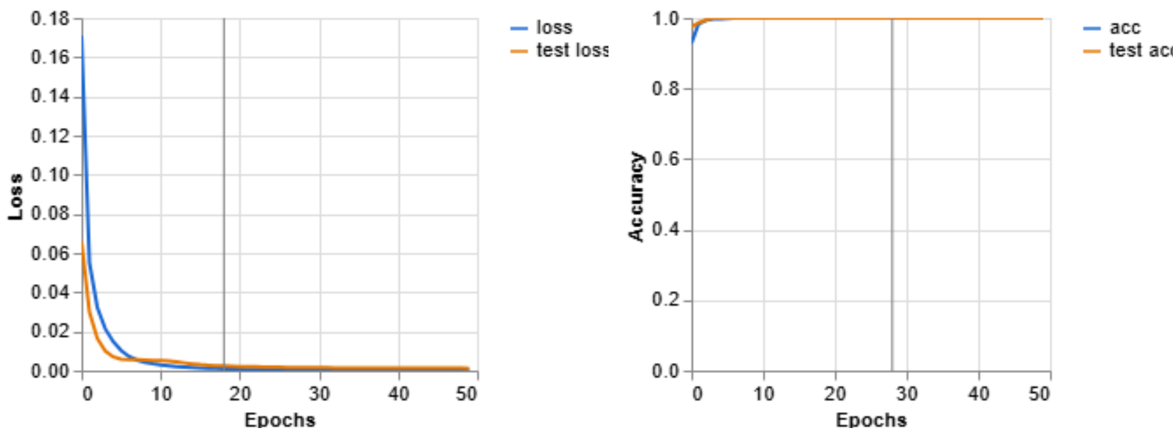


Figure 1. Samples of potatoes used for data generation and system evaluation, along with their corresponding speckle pattern images for each disease type. (a) An RGB image for a potato with Common Scab disease, (b) an RGB image for a potato with Black Scurf, and (c) an RGB image of a healthy potato. Images (d), (e), and (f) are the speckle pattern images generated by a red laser beam incident on the surface of the respective samples shown in (a), (b), and (c). The rightmost images in each row display the corresponding speckle pattern images for each disease type.

As the speckle patterns are generated using a coherent laser source, the ambient lighting environment was rigorously controlled during the data acquisition phase to enhance the model's generalizability to diverse illumination conditions encountered in real-world applications. Therefore, the potato quality and disease detection model was evaluated under two distinct illumination scenarios (ambient lighting/daylight, and Controlled ambient light). Additionally, image augmentation techniques, including horizontal and vertical flips, were applied to the generated dataset to further improve generalization. The images were preprocessed by rescaling to a resolution of 224x224 and a batch size of 16 was used during training. The fine-tuning process involved updating the weights of the pre-trained ResNet-50 model using backpropagation with the speckle images dataset. The Adam optimizer has been utilized with a learning rate of 0.001 and binary cross-entropy loss function for model training. The training process was conducted on the P100 GPU on the Kaggle platform to accelerate the computation.

Figure (2) illustrates the model's performance. Notably, both training and validation accuracy achieve 100% in early epochs. This suggests the model effectively learned the training data. However, for robust evaluation, it is crucial to assess generalization performance on unseen data. While the training and validation loss curves in Figure (2 - a) indicate reliable performance on the training and validation sets during initial epochs. Therefore, further analysis is needed to confirm the model's ability to be generalized to unseen data.



(a) (b)

Figure 2. The proposed CNN model performance during the training process. (a) shows loss per epoch, (b) shows the model accuracy per each epoch.

Results

The performance of the trained model was evaluated using standard classification metrics: accuracy, precision, recall, and F1-score as presented in Table (1). Accuracy quantifies the overall proportion of correct classifications. Precision and recall provide complementary insights into the model's ability to identify true positives (correctly classifying diseased potatoes) and avoid false positives (healthy potatoes classified as diseased). F1-score offers a balanced metric that considers both precision and recall. To assess the robustness of the proposed speckle imaging approach to varying lighting conditions, the potato quality and disease detection model was evaluated under two distinct illumination scenarios. Figure (3) shows the confusion matrixes for each scenario.

Table 1. Model Performance under Varying Lighting.

	Precision	Recall	F1-Score	Test set
Natural Light Condition	0.9817	0.9800	0.9800	200 samples
Darkened Environment	0.9552	0.9545	0.9545	200 samples

Analyzing both confusion matrices reveal promising performance for the potato quality estimation and disease detection model. The model achieved high accuracy (98% and 95% for natural light conditions and darkened environment) in identifying healthy potatoes across both lighting conditions. However, a small number of false positives (diseased classified as healthy) were present in both tests. This suggests the model might be less certain under high lighting conditions encountered in the second test set. To improve robustness, future work should consider incorporating images with diverse lighting variations into the training data or applying data augmentation techniques to simulate different lighting scenarios. Overall, the model shows strong potential, and the next steps can be tailored based on the acceptable error rate for missed diseased potatoes in the specific application.

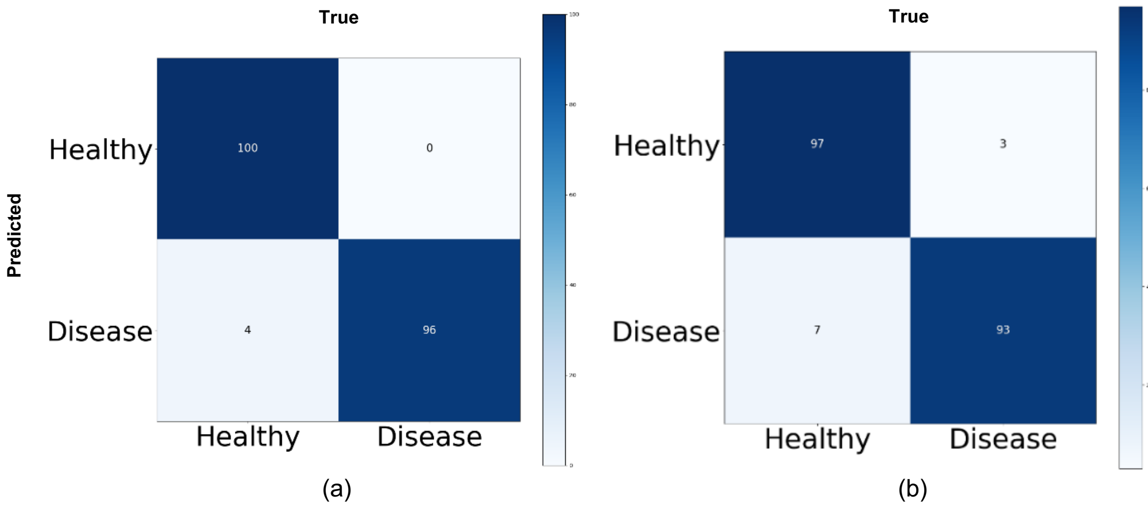


Figure 3. Confusion matrices under different lighting conditions. (a) natural light condition (ambient lighting/daylight), (b) darkened environment (controlled ambient light).

Comparing the performance of this method with other state-of-the-art techniques in potato quality evaluation (Arshaghi, Ashourian and Ghabeli 2023) (Zhang, Zhu, et al. 2019) (Du, et al. 2019), the proposed low-cost potato defect detection model demonstrated superior accuracy and efficiency, with accuracies reaching 98% as shown in Table (2).

Table 2. Comparison of Proposed Model with Existing Techniques for Potato Disease Detection and Quality Evaluation.

	Proposed model	Arshaghi, et al. 2023	Zhang, et al. 2019
Accuracy	0.98	0.98	0.90
Imaging technique	Speckle Imaging	RGB	Multispectral
Estimated Cost	Low-cost	Fair cost	Expensive

Conclusion

This study demonstrates the potential of speckle imaging combined with deep learning for automating potato quality evaluation. By leveraging transfer learning and pre-trained models, this method achieved a 98% accuracy in classifying potato defects, outperforming existing techniques. This approach offers a cost-effective and efficient solution for defect classification compared to methods using RGB, multispectral, or hyperspectral imaging. While a red laser pointer proved effective in this study, one limitation of this study is the dataset size, which may impact the model's generalizability. Future work will involve collecting a larger and more diverse data set encompassing a wider range of potato diseases. Additionally, investigating advanced deep learning architectures, incorporating other imaging modalities, and deploying the model in real-world agricultural settings are promising avenues for further exploration. Finally, ensuring scalability and robustness across different potato varieties and environmental conditions would be valuable for practical applications.

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