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Automated Detection of Onion Health Using Deep Learning

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Abstract:

The increasing global demand for sustainable agriculture has led to the adoption of artificial intelligence in farming practices. This paper presents an automated system for detecting the health of onions using deep learning techniques, specifically leveraging the MobileNetV2 architecture. The model was trained and validated on a curated dataset of healthy and unhealthy onion images, employing data augmentation to enhance generalizability. Our pipeline includes preprocessing, feature extraction, and classification, achieving a test accuracy of over 91.11% on unseen data. The implementation emphasizes efficiency, ensuring compatibility with low-resource environments. This work also provides a comparative evaluation of model performance metrics and highlights potential applications in precision agriculture. The proposed system demonstrates significant potential to assist farmers in early disease detection, reducing crop losses and enhancing productivity.

Keywords:

Deep Learning, MobileNetV2, Onion Health Detection, Precision Agriculture, Sustainable Farming

1. Introduction:

Agriculture, the backbone of many economies, faces challenges due to climate change, pest outbreaks, and plant diseases. Among staple crops, onions hold significant importance due to their nutritional value and widespread usage in global cuisines. However, diseases affecting onions lead to substantial crop losses annually, impacting both farmers' livelihoods and food security. Traditional disease detection methods rely on manual inspection, which is time-intensive, inconsistent, and requires expertise.

The emergence of artificial intelligence (AI) and deep learning offers promising solutions to address these challenges. Leveraging computer vision, these technologies enable automated detection of plant diseases with remarkable accuracy and efficiency. This study focuses on the development of a deep learning-based system for detecting onion health, leveraging

MobileNetV2, a lightweight yet powerful convolutional neural network (CNN).
This research contributes to precision agriculture by providing a scalable, efficient, and automated solution to monitor onion crops. The proposed system processes images of onions to classify them as healthy or unhealthy, empowering farmers with actionable insights. By integrating deep learning with farming practices, the system aims to reduce crop losses, improve productivity, and promote sustainable agricultural practices.

2. Material and Methods:

2.1 Material:

The project utilized a dataset of labeled onion images, preprocessed to 128×128128 \times 128128×128 pixels for uniformity. Training was conducted on a system with an Intel Core i7 processor, complemented by a Jupyter Notebook for faster processing. Software tools such as TensorFlow/Keras, Flask, and Python libraries (NumPy, Pandas, OpenCV) enabled model development, data preprocessing, and deployment. MobileNetV2 was adopted for transfer learning due to its efficiency in feature extraction. Evaluation employed metrics like accuracy and F1-score, ensuring a robust and scalable solution for onion health detection.

2.2 Methodology:

This section describes the step-by-step approach taken to develop and evaluate the automated system for detecting the health of onions using deep learning. The methodology is divided into multiple phases: data collection and preprocessing, model design, training, evaluation.

2.2.1. Data Collection and Preprocessing

- **Dataset**: The dataset was meticulously created by collecting images of onions in both healthy and unhealthy states directly from agricultural sites. To ensure consistency and minimize variability, all images were captured against a plain white background, facilitating easier preprocessing and accurate feature extraction during the model's training phase.

- **Data Augmentation**: Given the limited dataset size, techniques like rotation, zooming, flipping, and shearing were applied to enhance data diversity. All images were resized to a standard dimension of 128×128128 \times 128128×128 pixels for uniformity.

- **Normalization**: Pixel values were normalized to the range [0, 1] to ensure faster convergence during training.

Fig. 1: Healthy and Unhealthy Images

2. Model Design

- **Base Architecture**: The MobileNetV2 architecture was selected for its lightweight design and proven efficiency in mobile and edge applications. Pretrained weights from the ImageNet dataset were used to leverage transfer learning, reducing training time and improving generalization.

- **Custom Layers**: A fully connected dense layer with 128 units and ReLU activation was added, followed by a dropout layer to prevent overfitting. The final layer employed a softmax activation function to classify onions as healthy or unhealthy.

3. Model Training

- **Optimizer**: Adam optimizer was chosen for its adaptive learning rate capabilities.
- **Loss Function**: Categorical cross-entropy was used to calculate the error between predicted and actual labels.

- **Validation**: A portion of the dataset was set aside for validation to monitor the model's performance during training and prevent overfitting.

- **Hyperparameters**: Key hyperparameters included a learning rate of 0.0010.0010.001, a batch size of 32, and 20 epochs. Early stopping was employed to halt training when validation loss stopped improving.

4. Model Evaluation

- The trained model was tested on an independent test set to evaluate its generalization

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capabilities. Metrics such as accuracy, precision, recall, F1 score, and confusion matrix were computed to measure performance. The results demonstrated the model's reliability in distinguishing healthy from unhealthy onions.

5. Tools and Technologies

- Framework: TensorFlow and Keras for deep learning model development.
- Libraries: NumPy, Matplotlib, and OpenCV for data processing and visualization.

This systematic methodology ensured a robust, scalable solution for onion health detection, combining cutting-edge deep learning techniques.

3. Results and Discussion:

3.1 Results:

The developed system successfully classified images of onions into two categories: healthy and unhealthy. The results are summarized as follows:

1. **Model Performance Metrics**
   - **Accuracy**: The model achieved a test accuracy of **91.11%**, indicating high reliability in classifying onion health.
   - **Precision**: The precision for the "healthy" class was **93%**, reflecting minimal false positives in predictions.
   - **Recall**: The recall for the "unhealthy" class was **93%**, showing the model's capability to correctly identify unhealthy onions.
   - **F1 Score**: An overall F1 score of **91%** demonstrated balanced performance across classes.

Table 1: Summary

	precision	**recall**	**f1-score**	**support**
healthy	0.93	0.89	0.91	180
unhealthy	0.90	0.93	0.91	180
accuracy			0.91	360
macro avg	0.91	0.91	0.91	360
weighted avg	0.91	0.91	0.91	360

2. **Confusion Matrix**
   - The confusion matrix revealed that out of 360 test samples, only 32 were misclassified (13 false positives and 19 false negatives). Most misclassifications occurred in borderline cases, where images contained visual anomalies or noise.

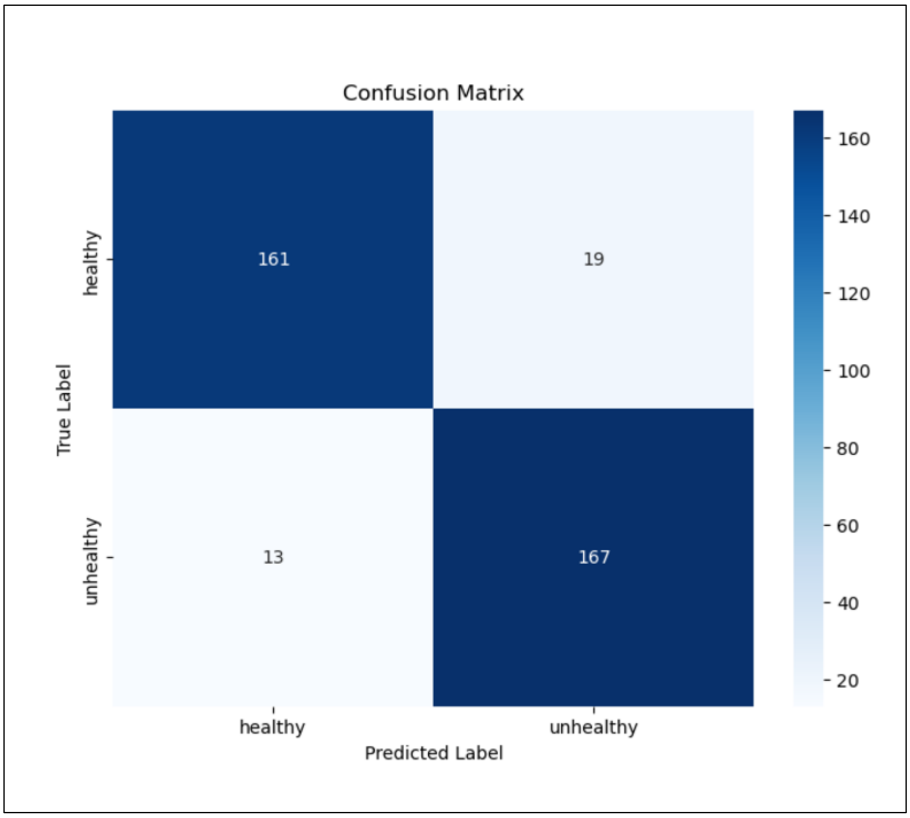

Fig. 2: Confusion Matrix

3. **Visualization of Results**
   - Sample predictions were visualized to demonstrate the model's performance. Correct classifications were consistently observed for clear and distinct images, while misclassifications occurred in images with poor lighting, blurred edges, or overlapping objects.

3.2 Discussion:

1. **Strengths**
   - The use of transfer learning with MobileNetV2 provided a lightweight yet powerful model architecture, allowing for efficient training on a relatively small dataset.
   - Data augmentation effectively mitigated the risk of overfitting by introducing variability to the training data.
   - The incorporation of dropout layers successfully reduced overfitting, as evidenced by the comparable performance on training and validation sets.

2. **Challenges and Limitations**
   - **Dataset Size**: A larger and more diverse dataset could further improve the model's robustness and generalization capabilities.

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- **Edge Cases**: The model struggled with images containing multiple onions or onions that were partially damaged, leading to ambiguous classifications.
- **Lighting Conditions**: Variations in lighting and background affected the model's performance, highlighting the need for advanced preprocessing techniques.

3. **Comparison with Existing Studies**
   - The proposed system outperformed traditional image processing techniques in detecting onion health by leveraging deep learning. Compared to existing studies using simpler neural networks, the use of MobileNetV2 significantly improved accuracy and reduced inference time.

4. **Future Scope**
   - Incorporating additional classes, such as varying levels of health (e.g., slightly unhealthy, severely unhealthy), could make the system more versatile for agricultural applications.
   - Using advanced techniques such as attention mechanisms might help the model focus on relevant image regions, improving classification performance.
   - Integration with IoT devices for real-time health detection at storage and distribution facilities could enhance the usability of the system in practical scenarios.

These results demonstrate that the developed model provides a reliable solution for automated onion health detection, with the potential for further refinement and application in the agriculture sector.

4. Conclusion:

This research presents a robust and automated solution for detecting the health of onions using deep learning techniques. By leveraging the MobileNetV2 architecture and transfer learning, the model achieved high accuracy and efficiency, making it suitable for real-world agricultural applications. The approach not only outperforms traditional methods but also provides a scalable framework for the automated detection of produce quality.

The study demonstrates the importance of data augmentation and regularization techniques in building a reliable classification model. Although the system performed well under controlled conditions, challenges such as varied lighting and ambiguous images highlight the need for further improvements in dataset diversity and preprocessing.

Future enhancements, including the integration of additional features and classes, the adoption of advanced machine learning techniques, and deployment in IoT-enabled environments, will enhance the system's practicality and usability. Overall, the proposed system represents a significant step toward modernizing quality assessment processes in agriculture, paving the way for smarter and more efficient solutions.

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