Fruit Deformity Classification Through Single-Input and Multi-input Architectures Based on CNN Models Using Real and Synthetic Images

| Conference paper | First Online: 17 November 2024

| pp 46–62 | Cite this conference paper

Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications

(CIARP 2024)

Tommy D. Beltran, Raul J. Villao, Luis E. Chuquimarca, Boris X. Vintimilla & Sergio A. Velastin

Part of the book series: Lecture Notes in Computer Science ((LNCS,volume 15368))

Included in the following conference series:
Iberoamerican Congress on Pattern Recognition

Abstract

The present study focuses on detecting the degree of deformity in fruits such as apples, mangoes, and strawberries during the process of inspecting their external quality, employing Single-Input and Multi-Input architectures based on convolutional neural network (CNN) models using sets of real and synthetic images. The datasets are segmented using the Segment Anything Model (SAM), which provides the silhouette of the fruits. Regarding the single-input architecture, the evaluation of the CNN models is performed only with real images, but a methodology is proposed to improve these results using a pre-trained model with synthetic images. In the Multi-Input architecture, branches with RGB images and fruit silhouettes are implemented as inputs for evaluating CNN models such as VGG16, MobileNetV2, and CIDIS. However, the results revealed that the Multi-Input architecture with the MobileNetV2 model was the most effective in identifying deformities in the fruits, achieving accuracies of 90%, 94%, and 92% for apples, mangoes, and strawberries, respectively. In conclusion, the Multi-Input architecture with the MobileNetV2 model is the most accurate for classifying levels of deformity in fruits.

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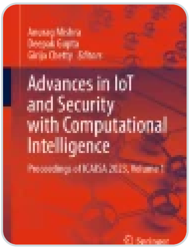

[Fresh and Rotten Fruit Detection Using Deep CNN and MobileNetV2]

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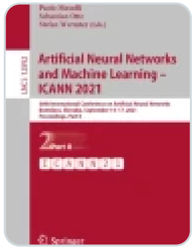

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Acknowledgment

This work has been partially supported by the ESPOL-CIDIS-11-2022 project.

Author information

Authors and Affiliations

ESPOL, CIDIS, ESPOL Polytechnic University, Guayaquil, Ecuador

Tommy D. Beltran, Raul J. Villao, Luis E. Chuquimarca & Boris X. Vintimilla

UPSE, FACSISTEL, UPSE Santa Elena Peninsula State University, La Libertad, Ecuador

Luis E. Chuquimarca

School of EECS, Queen Mary University of London, London, UK

Sergio A. Velastin

Department of Computer Science, University Carlos III, Madrid, Spain

Sergio A. Velastin

Corresponding author

Correspondence to Luis E. Chuquimarca .

Editor information

Editors and Affiliations

Universidad Católica del Maule, Talca, Chile

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Cite this paper

Beltran, T.D., Villao, R.J., Chuquimarca, L.E., Vintimilla, B.X., Velastin, S.A. (2025). Fruit Deformity Classification Through Single-Input and Multi-input Architectures Based on CNN Models Using Real and Synthetic Images. In: Hernández-García, R., Barrientos, R.J., Velastin, S.A. (eds) Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications. CIARP 2024. Lecture Notes in Computer Science, vol 15368. Springer, Cham. https://doi.org/10.1007/978-3-031-76607-7_4

.RIS .ENW .BIB

DOI
https://doi.org/10.1007/978-3-031-76607-7_4

Published
17 November 2024

Publisher Name
Springer, Cham

Print ISBN
978-3-031-76606-0

Online ISBN
978-3-031-76607-7

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