Automated Fruit Classification Using Deep Convolutional Neural Network

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Introduction. Manual Fruit classification is the traditional way of classifying fruits. It is manual contact-labor that is time-consuming and often results in lesser productivity, inconsistency, and sometimes damaging the fruits (Prabha & Kumar, 2012). Thus, new technologies such as deep learning paved the way for a faster and more efficient method of fruit classification (Faridi & Aboonajmi, 2017). A deep convolutional neural network, or deep learning, is a machine learning algorithm that contains several layers of neural networks stacked together to create a more complex model capable of solving complex problems. The utilization of state-of-the-art pre-trained deep learning models such as AlexNet, GoogLeNet, and ResNet-50 was widely used. However, such models were not explicitly trained for fruit classification (Dyrmann, Karstoft, & Midtiby, 2016). The study aimed to create a new deep convolutional neural network and compared its performance to fine-tuned models based on accuracy, precision, sensitivity, and specificity.

Methods. An experimental-comparative study was used to create and determine the performance of a new deep learning architecture as a tool for fruit classification. The performance of the newly created deep learning architecture was compared to the performance of the pre-trained deep learning models. The basic structure of deep learning architecture was followed. A total of six deep learning architectures were created with varying numbers of convolutional layers. Three architectures were integrated with a dropout layer to resolve the issue of overfitting. The architectures were trained using the Fruits-360 dataset. Analysis of variance (ANOVA) with repeated measures determined that the architecture with five convolutional layers and a dropout layer outperformed the other architectures across all performance metrics. The architecture was later named Fruit114Net. AlexNet, GoogLeNet, and ResNet-50 were then fine-tuned using the Fruits-360 dataset. The pre-trained models' performance results, together with the Fruit114Net, were then compared and were subjected to a careful data analysis using the same statistical tool.

Results. The overall performance of the deep convolutional neural network was based on the following metrics: accuracy, precision, sensitivity, and specificity. Such metrics depicted how well the models' performance was in classifying fruits. The Fruit114Net was able to achieve a near-perfect rate across all performance metrics. The model was able to classify 114 classes of fruits found in the dataset. Despite having such high ratings, statistical analysis revealed that the accuracy rate of Fruit114Net was significantly lower compared to the three fine-tuned deep learning models. Moreover, the statistical results were also able to record lower rates in Fruit114Net's precision and sensitivity. In terms of specificity rate, the data revealed that Fruit114Net was significantly lower than GoogLeNet and ResNet-50. On the other hand, it was observed that there was no significant difference between the performance of Fruit114Net and AlexNet. To conclude, the overall performance of Fruit114Net was significantly lower compared to the fine-tuned models. Incidentally, Fruit114Net efficiently classified the fruit images in terms of computational power and memory. It can also be noted that Fruit114Net recorded the least time in training the network. Lastly, Fruit114Net also took the least storage capacity compared to the fine-tuned models.

Conclusion. The study affirmed the previous observations from different studies that deep convolutional neural network performs better as its depth and width increases. Fruit114Net was a new deep convolutional neural network that satisfactorily and efficiently classified the images found

in the Fruits-360 dataset. The new deep convolutional neural network model correctly classified the fruit images to their actual classes and reduced false-positive and false-negative results. The performance of Fruit114Net suggested that it can be used as an alternative model in classifying fruits despite having statistically lower results compared to AlexNet, GoogLeNet, and ResNet-50. In addition to this, the use of the fine-tuned models requires high computational power and longer time while being fine-tuned to a new set of data. Such observations were highly accorded with the complex architecture of the fine-tuned models, thereafter, making the Fruit114Net model more amenable in solving fruit classification problems.

Practical Value of the Paper. This study's findings provided additional baseline information that can help those who are designing deep learning architecture, specifically those involved in classifying different fruit varieties. The novel architecture's applicability may also be explored in other applications such as fruit recognition and fruit detection. Furthermore, automated fruit classification may also help different sectors, namely, the producers, consumers, and government agencies directly involved in fruit production.

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