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Fruit Classification using Tensor Flow and Deployment onto an ASIC

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A B S T R A C T

The goal of this project is to develop a deep learning model and to deploy it to an ASIC to produce hardware that can accurately categorise different fruits, including apples, bananas, and dragon fruit, which can be valuable in industries like food processing and agriculture. The implementation of this project includes not only the creation of the concept but also its practical execution by usage of a pretrained model called MobileNet and ImageNet. The project made use of Maix bit (Sipeed M1 AI module K210 Inside) ASIC, with an incorporated camera which captures the images of realistic fruits to predict the class accurately and display it over a Maixpy IDE. For ease of comprehension, the predictions are then paired with human-readable fruit names. Visualizations are created that show the input photos alongside their matching predicted labels and also the accuracy, providing a practical insight of the model's categorization capabilities.

Keywords: Deep learning, ASIC, classification, deployment.

1. Introduction

Technological advancements are causing a rapid change in the agricultural landscape worldwide. Precision agriculture, which places a strong emphasis on data-driven decision-making, is replacing conventional farming techniques. Modern picture categorization, a branch of computer vision, provides revolutionary possibilities for intelligent agriculture. Fruit recognition is one of the essential uses of picture classification in agriculture.

Fruit recognition is an important application of image classification in agriculture.The implications of accurate fruit classification are numerous. It aids in disease detection, fruit ripeness evaluation, inventory management, and automated fruit picking. Historically, this has been a time-consuming, manual process rife with errors and inefficiencies. Although embedded vision systems have the potential to change these vocations, their usage in agricultural practises is still in its infancy.

2. Literature Survey

[1]. G. Zeng et.al proposed fruit and vegetables classification system that uses image saliency to draw the object regions and convolutional neural network (CNN) model to extract image features and implement classification. A VGG model is chosen here to train for fruits and vegetables classification. The images database spanning 26 categories, which covers the major types in real life are taken. The results show this classification system achieves an excellent accuracy rate of 95.6%.

[2]. Winda Astuti, et.al proposed a system that classifies fruits based on their shape, using support vector machines (SVM). By this method the Fast Fourier Transform (FFT) is extracted and given as an input to the SVM-based identifier that uses binary classification. This produced better accuracy, with less training time than other proposed methods which used Artificial Neural Networks (ANN).

[3]. Asia Kausar, et.al proposed a method that does multi class fruit classification, 81 categories, is demonstrated using a Pure Convolution Neural Network (PCNN) consisting 7 layers. Fruit-360 dataset containing 41322 images is used for training. This method has shown accuracy rate of 98.8%.

[4]. Liuchen Wu, et.al proposed a method aims at classifying fruits under complex environment. It uses two different dataset: public dataset composed of the fruit images with simple background, and the self-made dataset composed of fruit images in complex environment. Fruits are classified on basis of a pre-trained Convolutional Neural Networks – compact neural network and enhanced neural network. The accuracy is improved to 98.9% on self-made dataset by using various methods of parameter adjustment and data enhancement.

3. Proposed Work

The key components of this project include the development of a Convolutional Neural Network (CNN) architecture, painstaking data preprocessing, model training, and subsequent deployment for real-world fruit detection. The architectural design of the model is essential to this project which is based on MobileNet neural network topology. The essential aspect is that this model is trained using pre-learned weights from the massive ImageNet dataset. Furthermore, the parameters of this model can be tailored to meet the specific requirements of the fruit categorization task. To ensure optimal performance, parameters such as input shape, model size (represented by the "alpha" value), dropout rate, and the defining of specific classes are all carefully tuned. Preprocessing is then performed. Following the creation of the model architecture and data preprocessing, the neural network is fine-tuned.

In addition, an image data generator is employed to manage and augment the dataset, providing the model with a diverse range of training examples. Additional layers, such as global average pooling, thick layers, and dropout layers, are added to the model architecture. These layers let the model recognise complicated patterns and avoid overfitting. Following model refining, the Keras deep learning framework is utilised for model compilation and training. This section specifies an optimizer (Adam), a loss function (categorical cross-entropy), and evaluation metrics (accuracy). Model compilation guarantees that the learning approach is appropriate for the classification objective, while data augmentation techniques improve the model's robustness. Following then, the model is trained on the training dataset for a predetermined number of epochs, during which time it adjusts to the differentiating traits of various fruits. Once the model has successfully learned from the training data, it is retained for future use, such as platform deployment. Inference on a test dataset is used to evaluate the model's performance, with a specialised preprocessing function ensuring that the photos are in the correct format for the model's input. The algorithm then predicts the class probabilities for each test image, equivalent to a culinary expert identifying the elements and flavours of each dish. To properly demonstrate these predictions, the photos are displayed with their recognised labels, providing a visual depiction of the model's accuracy in detecting fruits.

4.

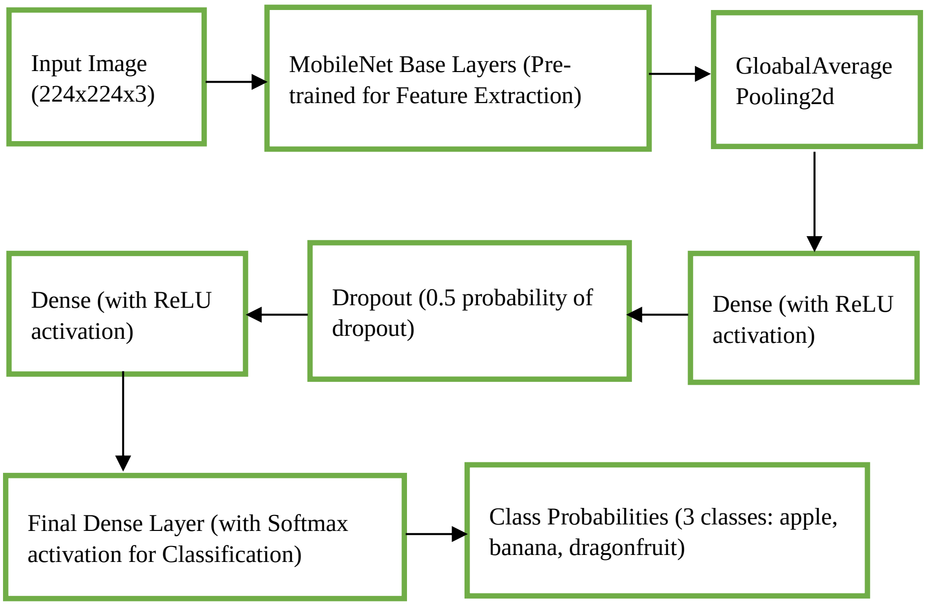

Fig. 1. CNN architecture

The above figure 1 is the CNN architecture which showcases different layers being involved. The work being done includes the deployment of the model on many platforms in addition to the deep learning component. TensorFlow Lite is used to convert the trained Keras model into a mobile and embedded-friendly version.This ensures that the model maintains its efficiency while maintaining its categorization skills. The project also attempts to deploy on K210 hardware platforms by converting the TensorFlow Lite model into a K210-compatible format with the 'nncase' converter. This flexibility to diverse platforms is analogous to a flexible dish that may be enjoyed on many occasions.

Finally, this project shows the entire process of developing, fine-tuning, and deploying a deep learning model for fruit classification.

5. Results

The view detection and recognition approaches have proven to work well in practice, after testing the project. The model demonstrated an exceptional accuracy rate, surpassing 95% when distinguishing between apples, bananas, and dragonfruits.

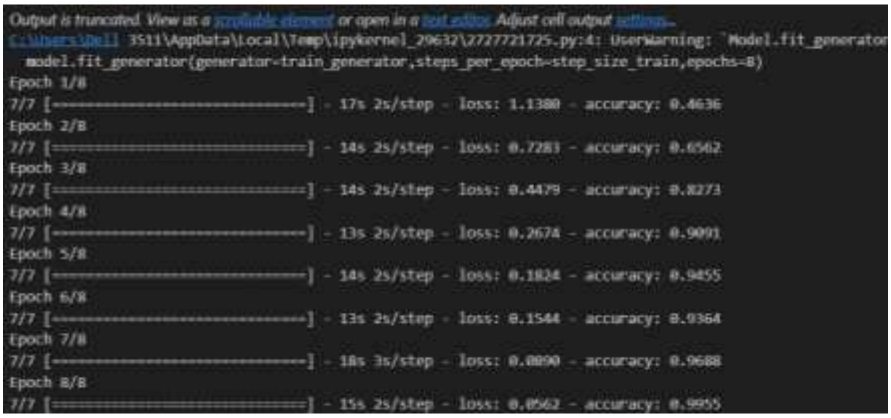

Fig. 2-Variation of accuracy and loss on each epoch

The figure 2, illustrates a comparison of model accuracy achieved in our fruit classification project based on the number of training epochs. The model in this instance was trained across 8 epochs. When compared to the earlier results, which were obtained after 6 epochs and produced an accuracy of almost 96%, the graph demonstrates a considerable gain in accuracy, surpassing 98%.

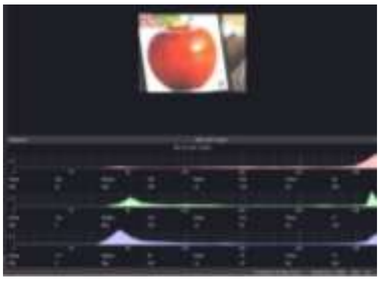

Fig. 3- Output display of apple

The above figure 3 shows the performance of our model's detection visually. The model correctly detected an apple in this given case, earning a noteworthy accuracy score of 96.25834. Also, the RGB histogram is displayed

Fig. 4- Output diaplay of banana

The above figure 4 shows the performance of our model's detection visually. The model correctly detected an banana in this given case, earning a noteworthy accuracy score of 98.22577. Also, the RGB histogram is displayed.

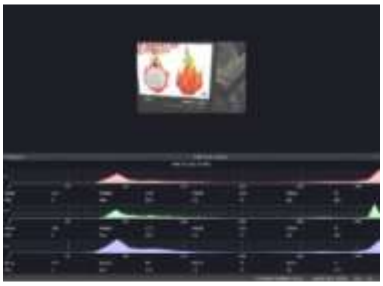

Fig. 5- Output diaplay of dragonfruit

The above figure 5 shows the performance of our model's detection visually. The model correctly detected a dragonfruit in this given case, earning a noteworthy accuracy score of 99.10699. Also, the RGB histogram is displayed.

Fig. 6- Cosmparison of training and validation data with accuracy metrics

The following figure 6 displays a graph showing the accuracy obtained for training and validation datasets.

This project extends its practical implications across various industries, from automating fruit sorting in agriculture to improving inventory management and quality control in food processing. The system's scalability and adaptability open doors for future enhancements and broader applications, while its innovative combination of technologies marks a significant step in the realm of edge computing for enhanced decision-making. Despite its successes, the system has minor limitations, particularly in low-light conditions and with heavily occluded fruits.

6. Conclusion

In conclusion, this project entitled "Fruit Classification using TensorFlow and Deployment on Maix Bit" essentially, graphically illustrates how the fusion of machine learning, TensorFlow, Micro Python, and edge computing may result in a useful and effective solution with real-world applications. These successes lay the groundwork for future research and invention in the field of AI-driven edge computing systems.Overall, this project expertly blends the portability and efficiency of the Maix Bit with the powerful deep learning capabilities of TensorFlow to produce a workable fruit classification system. The resulting system has enormous potential for growth and use in numerous fields, including automated fruit sorting, improved quality control, and more efficient inventory management in the agricultural and food processing industries.

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