Towards bio-inspired fruit detection for agriculture

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***Abstract*—Automation presents a potential solution to agricultural challenges such as worker shortages, invasive pest species and decreasing profit margins. Many technical challenges remain including visual detection of soft fruits. State-of-the-art fruit detectors increasingly rely on deep learning models and standard imaging devices which achieve excellent performance but require significant effort to train and deploy, limiting their uptake. The fruit-fly species *Drosophila suzukii* successfully pinpoints a host of soft fruits visually presenting an excellent model system which can inspire a new class of fruit detector using sparse computational and training resource. Here we present an outline of the features of fruit fly vision that appear to underlie their fruit finding abilities and present a specification for a novel robot imaging system to verify hypotheses in real agricultural settings.**

***Index Terms*—Agriculture, Fruit Detection, Computer Vision, Bioinspired, Fruit Fly, Multi-Spectral Imaging, Novel Sensing**

I. INTRODUCTION

For essential agricultural tasks such as yield prediction, assessment of fruit health and ripeness and for harvesting to be automated, visual fruit detection systems must be: sufficiently robust to function in industrial settings with known challenges of lighting variance and occlusions; computationally efficient to be deployed on small, cheap robot platforms; perform in real-time, and ideally function for a variety of fruits (and their varieties).

A. Engineered approach

Deep neural networks (DNN) represent the state-of-the-art methodology in fruit detection, with models such as MangoYOLO [1], DeepFruits [2], and most recently L*a*b*Fruits [3] all achieving excellent detection scores when tested on realistic datasets while striving to reduce computational cost (see [1], [3] for discussion). Performance improvements can be traced to innovations in both imaging technologies (RGB [1], [3], 3D depth [4] and RGB + infrared [2] cameras) and network architectures moving from multi stage detectors with course feature maps [5] to single-stage detectors [6] and multi-scale feature maps [7], [8]. Most relevant to this work, L*a*b*Fruits [3], demonstrated the utility of looking to nature for inspiration by using a colour opponent process inspired by human visual perception to increase performance.

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Yet a concern for DNN models is the need for (re)training for each fruit type or variety not found in the original training dataset. This process often requires manual collection and annotation of images, and expert involvement in retraining models, presenting a potential barrier for fruit growers (see Fig. 1 Upper Panel for a typical DNN training pipeline).

B. Nature's approach

Our research has identified the fruit fly *Drosophila suzukii* (*DS*) as an ideal model for inspiring a new class of low computation, zero-retraining fruit detector. *DS* are an invasive pest species to Europe that can visually locate a variety of soft fruit types of a variety of colours (e.g. strawberries, raspberries, blueberries) despite possessing low-resolution eyes and a highly constrained nervous system [9].

Although *DS* uses a combination of olfactory and vision cues to find fruit, trapping studies demonstrate that bright colours alone actively attracting fruit flies [10]. Underpinning their colour detection abilities are eyes that detect light in spectra outside the range detected by imaging systems used by deep learning algorithms to date. Specifically, *DS* have two photo-receptors sensitive to ultraviolet (UV) light (at 335nm and 355nm), as well as green (530nm) and blue (460nm) light. UV light has already been demonstrated as a powerful cue for segmenting foreground objects from the solar background [11]. Moreover, a recent study has suggested that a similar colour opponent mechanism in this non-visible spectra provides fruit flies with their impressive fruit finding abilities [12]. The short life-span of *DS* would favour a hard-wired visual processing pipeline allowing fruits of various kind to be identified without a costly learning phase with associated benefits for artificial systems (see Fig. 1 Lower Panel for the proposed bioinspired pipeline).

II. DROSOPHILA EYE CAMERA SPECIFICATIONS

To verify whether non-visible light offers benefits for generic fruit detection we propose to construct a novel imaging system inspired by *DS* (See Table I for technical specification and comparison with state-of-the-art), and to collect data in real horticultural settings allowing bench-marking against state of the art models.

III. OUTLOOK

DS offer an excellent inspiration to developing highly reliant, but computationally cheap fruit detection systems. The

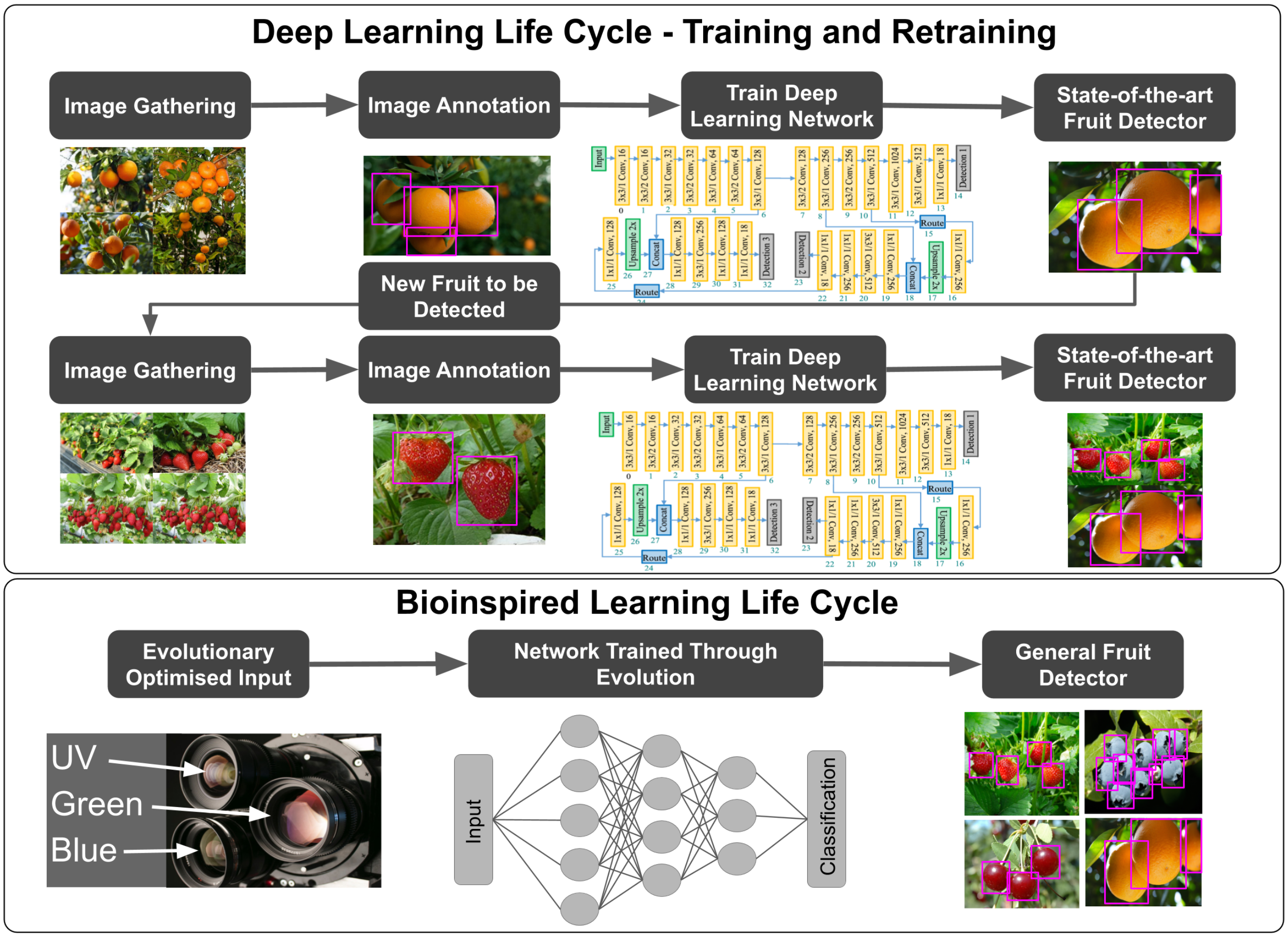

Fig. 1. Deep learning life cycle: Training and retraining - Steps of deep learning, 1) Gather images, 2) Annotate images, 3) Train neural network (Network architecture from [1], 4) High accuracy fruit detector. For additional fruits to be detected not found in the original dataset, repeat steps one, two and three. Bioinspired learning life cycle - 1) Evolutionary optimised input sensitives to UV (335nm and 355nm), green (530nm) and blue (460nm). 2) The network is trained through evolution to find fruits using a small brain requiring no training. 3) General fruit detector able to detect all fruits.

TABLE I
COMPARISON BETWEEN NATURE AND ENGINEERED APPROACHES.

Points of comparison	Detectors			
	DS	[1]	[3]	[2]
Input pixel count	700	4.1MP	0.9MP	2MP
Input type	UVGB	RGB	RGB	RGB + IR
FPS	100 [13]	14	26	5
Retraining for new fruit	No	Yes	Yes	Yes

custom camera detailed above and currently under development will play a crucial role in understanding how the humble fruit fly achieves such impressive feats which we will directly apply to solve real agricultural problems. Field data collection scheduled for Spring/Summer 2020.

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