Meta-Learning Based Continual Learning Methods for Fine-grained Fruit Quality Classification

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***Abstract*—The inefficiency in food supply chain leads to significant food wastage. Traditional machine learning and deep learning approaches for fruit quality monitoring require large amount of training data and assumptions of independent and identically distributed (IID) data. Furthermore, most of these models are fruit specific that cannot be easily adapted for other types of fruits. In this paper, we have utilized and compared the performance of various meta-learning inspired continual learning algorithms as well as pure continual learning algorithms for few-shot fine-grained classification of quality stages of 14 types of fruits under the assumption of dynamic data distribution (i.e. the data for several fruits becomes available at different time intervals). Our results show that meta-learning-based continual learning algorithms, specifically Sync-MAML and C-MAML, perform significantly better than pure continual learning methods. These methods effectively mitigate catastrophic forgetting and adapt to new fruits with minimal data.**

***Index Terms*—Meta-learning, Continual learning, Fine-grained classification, Food quality analysis**

I. Introduction

With nearly one-third of all food produced going to waste each year[1], effective quality monitoring of food items at various supply chain stages is crucial. This need is particularly urgent for perishables like fruits and vegetables, which have short shelf lives and require careful handling to minimize waste and associated economic loss [1].

Traditional methods for assessing food quality are divided into invasive and non-invasive approaches [2]. Invasive methods, which physically alter the food item, provide accurate results but are impractical for large-scale operations due to their destructive nature and the waste they generate [1]. Non-invasive methods, based on external characteristics like color, texture, and shape, are better suited for real-time monitoring but often lack the precision of invasive methods [1].

Machine learning (ML) and deep learning (DL) methods have been applied to improve non-invasive food quality assessment by analyzing visual and spectral data [3]. However, these models typically require large datasets for training, which are expensive and time-consuming to collect [4]. Existing studies provide models that are specific to certain fruit types [5] and do not generalize well across different categories [6], limiting their effectiveness. Some studies have focused on utilizing minimal training data for fruit quality prediction [3] but they assume the training data for all the fruits to be available beforehand (assumption that the data is IID). In reality, fine-grained quality data of various fruits is often non-IID, being temporally available due to seasonality, growing conditions [1], and challenges with data curation.

To address the limitations of scarce training data as well as the temporal nature of data availability, this paper proposes utilizing meta-learning based continual learning methods for fine-grained fruit quality classification. Meta-learning [7] allows models to quickly adapt to new unseen fruits with minimal data, while continual learning [8] enables them to retain knowledge across various fruits without forgetting previously learned information [9]. By utilizing these approaches, we aim to enhance adaptability, data efficiency, and generalization across various ripening stages of different fruits, offering a robust solution for fruit quality assessment in dynamic, real-world conditions.

II. Dataset

The dataset used in this research was compiled through a combination of web scraping and manual selection of images from publicly available online sources. The dataset captures various fine-grained aspects of fruit ripening and quality assessment. It consists of 14 different types of fruits, categorized into two groups: 7 climacteric fruits (which continue to ripen after harvest [10]), namely, Apple, Banana, Guava, Jackfruit, Mango, Papaya, Pear, and the remaining 7 types of fruits being non-climacteric (which do not significantly ripen post-harvest).

The dataset includes five fine-grained ripening stages: ‘Unripe’, where the fruit is not yet edible; ‘Early ripe’, when ripening begins but has not peaked; ‘Ripe’, the optimal stage

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[1]https://www.un.org/en/observances/end-food-waste-day

for consumption; ‘Overripe’, where quality starts to decline; and ‘Rotten’, when the fruit is spoiled and inedible. Each stage is treated as a separate class, with 10 images per class, resulting in a total of 50 images per fruit. All images are resized to 100x100 pixels for consistency. The dataset is evenly split into training and testing sets, with 5 images per class used for training and 5 for testing. The complete dataset encompassing all fruit types contains a total of 700 images.

III. Methods

We implemented and evaluated several meta-learning-based continual learning algorithms, that take inspiration from the Model-Agnostic Meta-Learning (MAML) algorithm [11]. We explored extensions of MAML specifically designed for continual learning, including Continual-MAML (C-MAML), Synchronous-MAML (Sync-MAML), and Look-ahead MAML (La-MAML) [12].

MAML [11] facilitates quick adaptation to new fruits by learning an optimal parameter initialization by focusing on features common across different types of fruits. MAML is trained in two loops: an inner loop for fruit-specific updates and an outer loop for refining initial parameters across multiple fruits also known as meta-update. However, MAML assumes data of all fruits are available simultaneously, limiting its effectiveness in continual learning scenarios where tasks are sequential.

A. Meta-Learning Based Continual Learning Algorithms

Algorithm 1 Look-ahead MAML [12]

Require: Network weights θ, LRs α, inner objective ℓ, meta objective L, learning rate for $\alpha : \eta$, Fruits: $\mathcal{T}_1, \ldots, \mathcal{T}_n$

1: Randomly initialize network weights θ
2: $j \leftarrow 0, R \leftarrow \{\}$ ▷ Initialize Replay Buffer
3: **for** $t \leftarrow 1$ to T **do**
4: $\quad \mathcal{D}_t \leftarrow$ Images and labels for fruit $\mathcal{T}_t$
5: $\quad$ Split $\mathcal{D}_t$ into training set $\mathcal{D}_t^{\text{train}}$ and testing set $\mathcal{D}_t^{\text{test}}$
6: $\quad$ **for** batch b in $(X^t, Y^t) \sim \mathcal{D}_t^{\text{train}}$ **do**
7: $\quad\quad k \leftarrow \text{sizeof}(b)$
8: $\quad\quad b_m \leftarrow \text{Sample}(R) \cup b$
9: $\quad\quad$ **for** $k' \leftarrow 0$ to $k-1$ **do**
10: $\quad\quad\quad$ Push $b[k']$ to R with reservoir sampling
11: $\quad\quad\quad \theta^j_{k'+1} \leftarrow \theta^j_{k'} - \alpha^j \cdot \nabla_{\theta^j_{k'}} \ell$
12: $\quad\quad$ **end for**
13: $\quad\quad \alpha^{j+1} \leftarrow \alpha^j - \eta \nabla_{\alpha^j} L_t \left(\theta^j_k, b_m\right)$
14: $\quad\quad \theta^{j+1}_0 \leftarrow \theta^j_0 - \max\left(0, \alpha^{j+1}\right) \cdot \nabla_{\theta^j_0} L_t \left(\theta^j_k, b_m\right)$
15: $\quad\quad j \leftarrow j+1$
16: $\quad$ **end for**
17: $\quad$ Evaluate the model with weights θ on $\mathcal{D}_t^{\text{test}}$ and test dataset of previous fruits $(\mathcal{D}_1^{\text{test}}, \ldots, \mathcal{D}_{t-1}^{\text{test}})$ and compute the accuracy
18: **end for**

La-MAML [12] incorporates a look-ahead mechanism to enhance the model’s ability for continual learning. This mechanism introduces learnable per-parameter learning rates, which are adjusted based on the alignment of gradients from new and previous fruits. Specifically, La-MAML updates the learning rates and model parameters asynchronously, which allows the algorithm to be more adaptive and conservative in its updates, reducing the likelihood of catastrophic forgetting as shown in Algorithm 1.

C-MAML [12], a variation of La-MAML, employs two fixed learning rates for the task-specific and meta-updates. The task-specific learning rate is denoted as α, while the meta-update learning rate is referred to as β. This is achieved through a multi-step gradient-based approach, where updates are performed on fruit data to reduce interference between all the fruits seen till now. C-MAML focuses on finding parameter updates that minimize catastrophic forgetting by aligning the gradients across fruits while maintaining model performance.

Sync-MAML [12], also a variation of La-MAML, distinguishes itself by performing synchronous updates in the meta-update stage on the network weights θ. It utilizes a continuously updating learning rate α for the task-specific loop and a fixed learning rate β for the meta-update step. Sync-MAML offers less flexibility in adapting to new fruits as compared to the asynchronous approach of La-MAML.

Lines 11, 13, and 14 are the only difference, between C-MAML, La-MAML and Sync-MAML in Algorithm 1. C-MAML uses a fixed scalar learning rate α for the task-specific update to $\theta^j_{k'+1}$ inplace of α^{j+1} while Sync-MAML performs inner update same as La-MAML. During meta-update, both C-MAML and Sync-MAML use a fixed scalar learning rate β for the meta-update to θ^{j+1}_0 instead of α^{j+1}.

B. Baseline Continual Learning Algorithms

Averaged Gradient Episodic Memory (AGEM) [13] prevents catastrophic forgetting by projecting new gradient of the fruit to avoid interference with gradients of previous fruits. It stores a subset of past examples and adjusts the gradient direction of current fruit if it conflicts with gradients from previous seen fruits, requiring extensive memory or computation.

Elastic Weight Consolidation (EWC) [14] selectively protects important weights from previous seen fruits by adding a regularization term to the loss function, based on the Fisher Information Matrix. This penalizes changes to critical parameters, preserving knowledge while learning about new fruits.

Learning Without Forgetting (LwF) [15] uses knowledge distillation to retain previously seen fruits knowledge. By combining the model’s predictions on previous seen fruits with the ground truth labels of the new fruit, LwF balances new learning with retention, enabling incremental learning without needing old data.

IV. Experimental Details

Training and testing of the models using algorithms mentioned in section III involves several steps. Initially, we have a sequence of dynamically available datasets, $\mathcal{T}_1, \mathcal{T}_2, \ldots, \mathcal{T}_n$, each corresponding to a different fruit, and a model $\mathcal{M}$. The model parameters, denoted as θ, are initialized before training begins. For each fruit $\mathcal{T}_i$ in the sequence, the dataset is split into a training set $\mathcal{T}_i^{train}$ and a testing set $\mathcal{T}_i^{test}$. The model $\mathcal{M}$ is then trained on the training set $\mathcal{T}_i^{train}$ using various algorithms discussed in section IV, and its parameters θ are updated. After training, the model is evaluated not only on the current testing set $\mathcal{T}_i^{test}$ but also on the testing datasets from all previous fruits $\mathcal{T}_1, \ldots, \mathcal{T}_{i-1}$. The model employed in this study is identical to that used by Gupta et al. [16].

We perform several experiments to prove the hypothesis that a meta-learning based continual learning approach outperforms a generic continual learning approach (H_0). Building upon this, we also aim to prove that the a meta-learning based continual learning model trained specifically on fruits that share common degrading properties (climacteric fruits) will outperform a more general meta-learning based continual learning approach that is trained on all types of fruits (H_1). In essence, H_1 refines H_0 by introducing the idea that training on a subset of data with shared characteristics may lead to even better performance.

The primary metric used to evaluate the performance of the models is "till-task accuracy". It measures the accuracy of a model trained on the i^{th} fruit by evaluating it on the test dataset comprising the current fruit and all previous fruits the model has been trained on. It effectively quantifies the extent of catastrophic forgetting by demonstrating how well the model retains knowledge from earlier fruits while learning new ones. Till-task accuracy for the i^{th} fruit is given by:

$$\text{Till-task Accuracy}_i = \frac{1}{i} \sum_{j=1}^{i} A(T_j) \tag{1}$$

where $A(T_j)$ is the accuracy of the model on the test dataset of fruit T_j, and i represents the current fruit index.

The hyper-parameters for various models were set differently in the two cases to prove H_0 and H_0. Across both scenarios, the models shared several common settings: Sync-MAML, C-MAML, and La-MAML had a learning rate of 0.001, an optimizer weight of 0.1, and an alpha initialization (alph_init) of 0.01. For the models aimed at proving H_0, Sync-MAML used 10 glances and 100 memories with an optimizer learning rate (opt_lr) of 0.4. C-MAML used 20 glances and 100 memories with an opt_lr of 0.01, while La-MAML had 20 glances and 50 memories with an opt_lr of 0.01. AGEM used 20 glances, a lr of 0.4 and a memory strength of 0.5. EWC had a lambda value of 1.0, and LWF had an alpha of 0.001.

For models trained on only climacteric fruits to prove H_1, Sync-MAML and C-MAML both had 20 glances, 100 memories, and an opt_lr of 0.4. La-MAML had 10 glances, 50 memories, and an opt_lr of 0.4. AGEM maintained 20 glances but used a lr of 0.01 and a memory strength of 0.6. EWC kept a lambda of 1.0, and LWF had an alpha of 0.01.

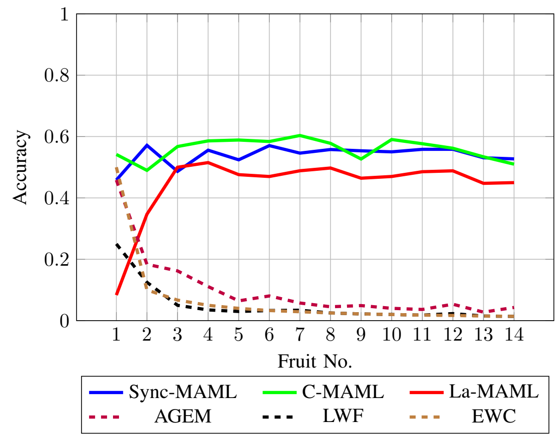

Fig. 1. Till-task accuracy for the models sequentially trained and tested on the dataset containing images of all fruits.

TABLE I
TILL-TASK ACCURACY OF THE MODELS SEQUENTIALLY TRAINED AND TESTED ON THE DATASET CONTAINING IMAGES OF ALL FRUITS

No.	Fruits	Sync-MAML	C-MAML	La-MAML	AGEM	LWF	EWC
1	Apple	45.83	54.17	8.33	45.83	25.00	50.00
2	Banana	57.14	48.98	34.69	18.37	12.50	10.00
3	Dragonfruit	48.65	56.76	50.00	16.22	5.00	6.70
4	Guava	55.56	58.59	51.52	11.11	3.50	5.00
5	Jackfruit	52.42	58.87	47.58	6.45	3.00	4.00
6	Lemon	57.05	58.39	46.98	8.05	3.30	3.30
7	Lychee	54.60	60.34	48.85	5.75	3.40	2.90
8	Mango	55.78	57.79	49.75	4.52	2.50	2.50
9	Orange	55.36	52.68	46.43	4.91	2.20	2.20
10	Papaya	55.02	59.04	46.99	4.02	2.00	2.00
11	Pear	55.84	57.66	48.54	3.65	1.80	1.80
12	Pineapple	55.85	56.19	48.83	5.35	2.30	1.70
13	Pomegranate	53.09	53.40	44.75	2.78	1.50	1.50
14	Strawberry	52.72	51.00	44.99	4.30	1.40	1.40
	Final	**52.72**	51.00	44.99	4.30	1.40	1.40

V. RESULTS

We performed various experiments as described in section IV using methods described in section III and discuss the obtained results in this section.

Table I and Figure 1 show the test accuracy obtained when different models are trained on all 14 fruits. It can be observed that Sync-MAML and C-MAML perform the best with final accuracy of 52.72% and 51.00%, respectively. La-MAML's performance is moderate, achieving a final accuracy of 44.99%. All pure continual learning based models AGEM, LWF, and EWC show poor performance, with final accuracy as low as 4.30%, 1.40%, and 1.40%. These results validate the hypothesis H_0 by showing the superiority of meta-learning based continual learning algorithms for few-shot learning in the dynamic data distribution setting.

Table II and Figure 2 show the results obtained on the models trained and tested on the data of only climacteric fruits. Sync-MAML exhibits the highest performance, with final accuracy of 67.24%, followed by C-MAML with final accuracy of 60.92%. However, the pure continual learning models continue to perform poorly. Figure 2 also indicates that the magnitude of catastrophic forgetting is the lowest for Sync-MAML followed by La-MAML. The accuracy of Sync-

TABLE II
TILL-TASK ACCURACY OF MODELS SEQUENTIALLY TRAINED AND TESTED ON DATASETS CONTAINING IMAGES OF CLIMACTERIC FRUITS

No.	Fruits	Sync-MAML	C-MAML	La-MAML	AGEM	LWF	EWC
1	Apple	45.83	50.00	29.17	37.50	15.00	45.00
2	Banana	57.14	53.06	38.78	16.33	7.50	10.00
3	Guava	55.41	55.41	35.14	12.16	5.00	6.70
4	Jackfruit	59.60	55.56	37.37	8.08	5.00	5.00
5	Mango	59.68	54.03	37.10	5.65	5.60	4.00
6	Papaya	63.09	59.73	37.58	9.40	3.30	3.30
7	Pear	67.24	60.92	45.40	8.05	2.90	2.90
	Final	**67.24**	60.92	45.40	8.05	2.90	2.90

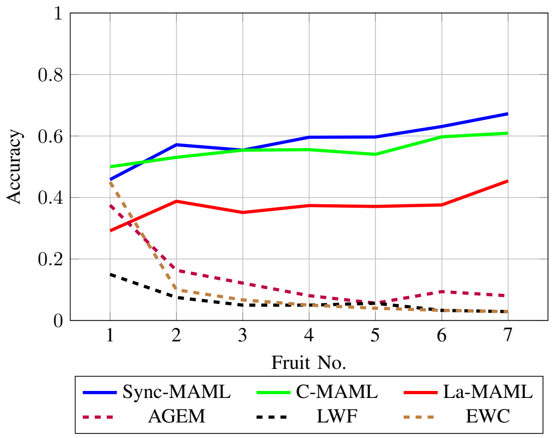

Fig. 2. Till-task accuracy graph for the model sequentially trained and tested on the dataset containing images of only climacteric fruits.

MAML is significantly better as compared to when trained on the dataset of all fruits (Table I). The better performance of the models in the case when only trained and tested on climacteric fruits suggests their strong adaptation capabilities and effective handling of the dynamic data in scenarios where the fruits show similar degradation properties. The accuracy drops observed in Figure 1 as compared to Figure 2 indicate that the increased variability and complexity when the model is trained on dataset comprising all fruits challenges the models' ability to generalize. Also, the clear delineation of ripening stages in climacteric fruits suggests that models can effectively recognize visual cues associated with these stages. These results validate the hypothesis H_1, which suggests that a meta-learning-based continual learning approach trained on fruits sharing common degrading properties performs better than one trained on all fruits.

VI. CONCLUSION

In this paper, we have utilized and compared the performance of various meta-learning inspired continual learning algorithms as well as pure continual learning algorithms for few-shot fine-grained classification of quality stages of various types of fruits under the assumption of dynamic data distribution (i.e. the data for several fruits becomes available at different time intervals). Our results show that meta-learning-based continual learning algorithms, specifically Sync-MAML and C-MAML, perform significantly better over pure continual learning methods. These methods effectively mitigate catastrophic forgetting and adapt to new fruits with minimal data. In future, we would like to expand this study using a larger dataset as well as exploring other advanced neural network architectures.

REFERENCES

[1] M. Rizzo, M. Marcuzzo, A. Zangari, A. Gasparetto, and A. Albarelli, "Fruit ripeness classification: a survey," 2023. [Online]. Available: https://arxiv.org/abs/2212.14441

[2] O. Chauhan, S. Lakshmi, A. Pandey, N. Ravi, N. Gopalan, and R. Sharma, "Non-destructive quality monitoring of fresh fruits and vegetables," *Defence Life Science Journal*, vol. 2, no. 2, pp. 103–110, May 2017. [Online]. Available: https://publications.drdo.gov.in/ojs/index.php/dlsj/article/view/11379

[3] J. Dutta, M. Patwardhan, P. Deshpande, and B. Rai, "Transfer learning with pairwise comparison for fine-granular fruit shelf-life prediction," in *2nd AAAI Workshop on AI for Agriculture and Food Systems*, 2023. [Online]. Available: https://openreview.net/forum?id=d14vdxFbsSh

[4] H. S, J. Dutta, M. Patwardhan, P. Deshpande, S. Karande, and B. Rai, "A generic few-shot solution for food shelf-life prediction using meta-learning." in *AIxFood @ ACM Multimedia*, R. Guerrero, M. Spranger, S. Jiang, and C.-W. Ngo, Eds. ACM, 2021, pp. 13–17. [Online]. Available: http://dblp.uni-trier.de/db/conf/mm/aixfood2021.html#SDPDKR21

[5] N. E. A. Mimma, S. Ahmed, T. Rahman, and R. Khan, "Fruits classification and detection application using deep learning," *Scientific Programming*, vol. 2022, pp. 1–16, 11 2022.

[6] D. Li, Y. Yang, Y.-Z. Song, and T. M. Hospedales, "Learning to generalize: Meta-learning for domain generalization," 2017. [Online]. Available: https://arxiv.org/abs/1710.03463

[7] T. Hospedales, A. Antoniou, P. Micaelli, and A. Storkey, "Meta-learning in neural networks: A survey," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 44, no. 9, pp. 5149–5169, 2022.

[8] G. I. Parisi, R. Kemker, J. L. Part, C. Kanan, and S. Wermter, "Continual lifelong learning with neural networks: A review," *Neural networks*, vol. 113, pp. 54–71, 2019.

[9] J. Kirkpatrick, R. Pascanu, N. Rabinowitz, J. Veness, G. Desjardins, A. A. Rusu, K. Milan, J. Quan, T. Ramalho, A. Grabska-Barwinska, D. Hassabis, C. Clopath, D. Kumaran, and R. Hadsell, "Overcoming catastrophic forgetting in neural networks," *Proceedings of the National Academy of Sciences*, vol. 114, no. 13, pp. 3521–3526, 2017. [Online]. Available: https://www.pnas.org/doi/abs/10.1073/pnas.1611835114

[10] R. K. Rahul Kumar and A. K. Sharma, "Ethylene perception and signalling in ripening fruit." *CABI*, p. 193–201, 2014. [Online]. Available: https://doi.org/10.1079/9781845939625.0193

[11] C. Finn, P. Abbeel, and S. Levine, "Model-agnostic meta-learning for fast adaptation of deep networks," 2017. [Online]. Available: https://arxiv.org/abs/1703.03400

[12] G. Gupta, K. Yadav, and L. Paull, "La-maml: Look-ahead meta learning for continual learning," 2020. [Online]. Available: https://arxiv.org/abs/2007.13904

[13] G. Hu, W. Zhang, H. Ding, and W. Zhu, "Gradient episodic memory with a soft constraint for continual learning," 2020. [Online]. Available: https://arxiv.org/abs/2011.07801

[14] J. Kirkpatrick, R. Pascanu, N. Rabinowitz, J. Veness, G. Desjardins, A. A. Rusu, K. Milan, J. Quan, T. Ramalho, A. Grabska-Barwinska, D. Hassabis, C. Clopath, D. Kumaran, and R. Hadsell, "Overcoming catastrophic forgetting in neural networks," *Proceedings of the National Academy of Sciences*, vol. 114, no. 13, p. 3521–3526, Mar. 2017. [Online]. Available: http://dx.doi.org/10.1073/pnas.1611835114

[15] Z. Li and D. Hoiem, "Learning without forgetting," 2017. [Online]. Available: https://arxiv.org/abs/1606.09282

[16] G. Gupta, K. Yadav, and L. Paull, "Official code repository for la-maml: Look-ahead meta-learning for continual learning," 2020. [Online]. Available: https://github.com/montrealrobotics/La-MAML