# Adaptability of deep learning: datasets and strategies in fruit classification

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[2]'HSDUWPHQW RI %LRV\VWHP (QJLQHHULQJ 1L÷GH gPHU +DOLVGHPLU 8QLYHUV
[3]'HSDUWPHQW RI &RPSXWHU 6FLHQFH DQG (QJLQHHULQJ 6KUL 9HQNDWHVKZDUD 8QLYHUVLW\ *DMUDXOD
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**Abstract.** 7KLV UHYLHZ DLPV WR XQFRYHU WKH PXOWLIDFHWHG ODQGVFD UHVHDUFKHUV IRU DFFXUDWH IUXLW FODVVLILFDWLRQ 7KH H[SORUDWLR each tailored to address the nuanced challenges presented by IUXLW FODVVLILFDWLRQ WDVNV )URP I QHXUDO QHWZRUNV &11V WR UHFXUUHQW QHXUDO QHWZRUNV 511V the spectrum of approaches underscores the innovative strategies harnessed to achieve precision in fruit FDWHJRUL]DWLRQ $ VLJQLILFDQW IDFHW RI WKLV UHYLHZ OLHV LQ WK UHVHDUFKHUV IRU IUXLW FODVVLILFDWLRQ 'LIIHUHQW GDWDVHWV SUH shaping the design and effectiYHQHVV RI WKH PRGHOV )URP ZLGHO\ UHFRJQL]HG GD VSHFLDOL]HG FROOHFWLRQV WKH UHYLHZ QDYLJDWHV WKURXJK D SO GDWDVHWV FRQWULEXWH WR WKH GLYHUVLW\ It highlights the variety in fruit W\SHV DQG DWWULEXWHV EXW DOVR HPSKDVL]HV WKH DGDSWDELOLW\ R variations. By amalgamating findings from diverse articles, this study offers an enriched understanding of the evoOYLQJ WUHQGV DQG DGYDQFHPHQWV ZLWKLQ WKH GRPDLQ RI IUXL synthesis of methodologies and dataset variations serves to inform future research pursuits, aiding in the refinement of accurate and robust fruit classificatioQ PHWKRGV $V WKH ILHOG SURJUHVVHV WK D YDOXDEOH FRPSDVV JXLGLQJ UHVHDUFKHUV WRZDUG LPSDFWIXO FR applicability of fruit classification models.

## 1 Introduction

Fruits, nature's vibrant and diverse gifts, hold a profound significance in our day-to-day lives that transcends their GHOLFLRXV IODYRUV DQG FRORUIXO UHPDUNDEOH ERWDQLFDO ZRQGHUV KXPDQ QXWULWLRQ DQG FXOWXUH navigate the hustle and bustle of modern life, it is easy to RYHUORRN WKH LPPHQVH LPSRUWDQFH VRXUFH RI HVVHQWLDO QXWULHQWV culinary versatility.

Fruits are rich in essential vitamins and minerals such DV YLWDPLQ & SRWDVVLXP DQG PDLQWDLQLQJ RYHUDOO KHDOWK >@ 7KH\ SDFNHG ZLWK DQWLR[LGDQWV RXU ERGLHV IURP FKURQLF GLVHDVHV [3]. $GGLWLRQDOO\ IUXLWV DUH DQ ILEHU ZKLFK DLGV LQ GLJHVWLRQ levels, and promotes a feeling of fullness [4].

7R SURFXUH D SDUWLFXODU W\SH RI IUXLW WKH VLJQLILFDQFH of fruit classification becomes abundantly clear. Fruit classification is the systematic categorization of fruits based on various criteria such as botanical characteristics, PRUSKRORJ\ DQG XVDJH 7KLV SUR differentiate fruits and group them into categories, facilitating a deeper understanding of their diversity and FKDUDFWHULVWLFV >@ )UXLWV DUH ... from a single ... RYDU\ DJJUHJDWH IUXLWV IURP PXOWLSOH RYDULHV >@ DQG $ PXOWLSOH IXVLRQ RI RYDULHV IURP PXOWLSOH types is further subdivided based on specific attributes OLNH ZKHWKHU WKH IUXLW LV IOHVK\ RU GU\ GHKLVFHQW RU indehiscent, and more.

([SORULQJ WKH FODVVLILFDWLRQ R ... WUDGLWLRQDO DSSURDFKHV ... size, shape, color, and seeds. It's vital in agriculture, ERWDQ\ DQG WD[RQRP\ IRU FDWHJ ... understanding their diversity. In contrast, the modern era has ushered in automated methods for fruit classification, driven by technological advancements, particularly in the fields of machine learning and computer vision [6].

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$XWRPDWHG IUXLW FODVVLILFD
algorithms and artificial intelligence to identify and
FDWHJRUL]H IUXLWV EDVHG RQ
involves training machine learning models, such as
&RQYROXWLRQDO 1HXUDO 1HWZRUNV
datasets of fruit images.

1.1 Deep learning

'HHS /HDUQLQJ '/ D VXEVHW RI PDFKLQH OHDUQLQJ KDV
profoundly transformed various domains, ushering in a paradigm shift in academia, healthcare, finance, and agriculture [7,8]. In education, DL has revolutionized pedagogical strategies through personalized learning platforms, adaptive assessment systems, and intelligent tutoring systems, tailoring education to individual needs [9]. In healthcare, DL's image and speech recognition
FDSDELOLWLHV KDYH DFFHOHUDWHG GLVHDVH GLDJQRVLV
predictive models have enhanced patient outcomes
WKURXJK HDUO\ LQWHUYHQWLRQ [10–16]. Financial institutions
EHQHILW IURP '/ V ULVN DVVHVVPHQW IUDXG GHWHFWLRQ DQG
algorithmic trading algorithms, enhancing decision
PDNLQJ SURFHVVHV > @ 0RUHRYHU
agriculture by enabling precision farming through data driven decision-PDNLQJ HQKDQFLQJ FURS GLVHDVH
detection, predicting yields, and optimizing resource utilization [18–21]. DL-SRZHUHG ZHHG PDQDJHPHQW DQG
OLYHVWRFN PRQLWRULQJ SURPRWH VXVWDLQDELOLW\ DQG DQLPDO
ZHOIDUH )XUWKHUPRUH '/ DVVLVWV LQ VXSSO\ FKDLQ
PDQDJHPHQW FOLPDWH UHVLOLHQFH
HQVXULQJ IRRG VDIHW\ UHGXFLQJ ZDVWH DQG DPSOLI\LQJ
profits.

When it comes to fruit classification, deep learning has turned out very effective, offering numerous advantages in automating and optimizing the sorting and grading processes in agriculture and the food industry. Using
&RQYROXWLRQDO 1HXUDO 1HWZRUNV &11V and other DL
architectures, fruit classification systems can accurately
GLVWLQJXLVK EHWZHHQ GLIIHUHQW IUXLW W\SHV
grades based on visual attributes, such as size, color,
WH[WXUH DQG VKDSH

One significant application of DL in fruit
FODVVLILFDWLRQ LV LQ WKH DJULFXOWXUDO VHFWRU ZKHUH LW LV
utilized for sorting and grading fruits as they are harvested. DL-SRZHUHG VRUWLQJ PDFKLQHV FDQ UDSLGO\
SURFHVV ODUJH TXDQWLWLHV RI IUXLWV FODVVLI\LQJ WKHP into
GLIIHUHQW FDWHJRULHV EDVHG RQ SUHGHILQHG TXDOLW\ FULWHULD
7KLV DXWRPDWLRQ UHGXFHV ODERU FRVWV LPSURYHV HIILFLHQF\
DQG HQVXUHV FRQVLVWHQW TXDOLW\ LQ WKH ILQDO SURGXFW

1.2 Objectives

7KH REMHFWLYH RI WKLV FULWLFDO UHYLHZ LV WR
comprehensively assess the state of the art in fruit classification utilizing deep OHDUQLQJ PHWKRGRORJLHV 7KLV
UHYLHZ DLPV WR

1. /LWHUDWXUH 5HYLHZ &RQGXFW D WKRURXJK OLWHUDWXUH
UHYLHZ RQ GHHS OHDUQLQJ DSSOLFDWLRQV LQ IUXLW FODVVLILFDWLRQ
to understand the current state of research.
2. 'DWD ([WUDFWLRQ DQG $QDO\VLV ([WUDFW UHOHYDQW GDWD
from the Web of Science database and analyze it to identify trends and distribution of research articles and conference papers.
3. Model Performance Assessment: Evaluate the reported model performance metrics, focusing on accuracy, and identify factors influencing model performance, such as dataset size and model choice.
4. Challenges and Limitations Identification: Identify
DQG GLVFXVV WKH FKDOOHQJHV DQG
deep learning-based fruit classification, including dataset size disparities and model interpretability.
5. )XWXUH 'LUHFWLRQV ([SORUDWLRQ
trends and future directions in the field, considering areas
OLNH multi-modal sensing, interpretable AI, and human-AI collaboration in fruit classification.

## 2 Material and method

,Q WKLV FULWLFDO UHYLHZ ZH PRQG
:HE RI 6FLHQFH GDWDEDVH :H XWLO
VHDUFK VWULQJ WR H[WUDFW GDWD I
Search String "Deep Learning" AND "Fruit
&ODVVLILFDWLRQ´ 127 ³'LVHDVH´
1RWH WKDW DOO RI WKHVH NH\ZRUGV ZHU
data from various fields, including the title, abstract,
DXWKRU NH\ZRUGV DQG .H\ZRUGV 3O
,Q RXU TXHVW WR UHWULHYH UHVH
DIRUHPHQWLRQHG VHDUFK VWULQJ Z
VWXGLHV DV RI 6HSWHPEHU
VWXGLHV ZH GLVFRYHUHG WKH IROO
research articles and 12 conference papers. 6XEVHTXHQ
ZH QDUURZHG RXU IRFXV WR UHVHDU
on classification, resulting in a selection of 21 articles for
IXUWKHU H[DPLQDWLRQ

In the pursuit of advancing fruit classification using deep learning, researchers have employed diverse methodologies and datasets to develop accurate and
HIILFLHQW PRGHOV 7KLV VHFWLRQ VX
methodologies commonly utilized in the cited studies
VXPPDUL]HG LQ 7DEOH DQG KLJKOLJ
of the datasets employed for training and evaluation.

## 3 Results

### 3.1 Model architectures

'HHS OHDUQLQJ PRGHOV VHUYH DV
FODVVLILFDWLRQ V\VWHPV HPSOR\LQJ
spectrum of architectures tailored to their specific
REMHFWLYHV 7KHVH PRGHOV HQFRPS
novel approaches:

- 3URSRVHG 0RGHOV +RVVDLQ HW D
QRYHO DUFKLWHFWXUH LQ WKHLU VWX
leveraged pre-WUDLQHG 9** DQG $OH[1HW
Similarly, Faisal et al. [26] and Faisal et al. [27] adopted VGG19 and ResNet, respectively, as their base models.
1L HW DO > @ H[SORUHG *RRJ/H1HW
employed MobileNetV2.
- ,QVWDQFH 6HJPHQWDWLRQ /H HW
0DVN 5&11 DUFKLWHFWXUH SDUWLFXOD
UHTXLULQJ LQVWDQFH VHJPHQWDWLRQ 7KL

WR GLIIHUHQWLDWH DQG FODVVLI\ same image.

• Ensemble Approaches: In some instances, researchers amalgamated multiple deep learning models to enhance classification performance. For instance,

\OLWDQGKLHYLG XHDW EDQ D>Q D@ ZLWPKLQ HWGKH DFKLHYLQJ UHPDUNDEOH DFFXUDF\

• 6SHFLDOL]HG $UFKLWHFWXUHV $ SURSRVHG D FXVWRP DUFKLWHFWXU FODVVLILFDWLRQ ZKLOH 3KDQ HW DO for tomato classification.

Table 1. Summary of Deep Learning Approaches in Fruit Classification Studies

| Paper | Base Model/ Proposed | Dataset | Public/Private (self-created) | Classes | Number of images | Data augmentation | Transfer Learning | Accuracy |
|---|---|---|---|---|---|---|---|---|
| +RVV[ et al.[22] | Proposed | Date Fruit | Public | 4 | | Yes | Yes | 99.2 |
| Altaheri et al.[23] | VGG16, $OH[1H | Date Fruit | Private | | | Yes | Yes | |
| +RVV[ et al.[24] | VGG16 | MIX Fruit | Private | | | Yes | Yes | |
| Le et al. > @ | 0DVN 5 CNN | Banana | Public | 2 | 194 | Yes | Yes | |
| Faisal et al.[26] | VGG19 | Date Fruit | Public | 7 | | Yes | Yes | 99.4 |
| Faisal at al. [27] | ResNet | Date Fruit | Public | | | Yes | Yes | |
| Ni et al. [28] | GoogLeNet | Banana | Private | 6 | - | Yes | Yes | 98.92 |
| Xue at al. [29] | CAE-AND | MIX fruit | Public | 26 | 124,212 | No | Yes | 93.78 |
| Chen et al. > @ | Proposed | MIX fruit | Public | | | No | No | |
| Gill et al.[31] | Proposed | MIX fruit | - | | | No | No | - |
| Kang et al.[32] | ResNet | MIX Fruit | Public | 7 | 11,632 | Yes | Yes | 97.43 |
| Ufuah et al. [33] | DenseNet | Date Fruit | Private | 3 | | Yes | Yes | |
| 6LGG [34] | VGG16 | MIX Fruit | Private | 7 | | Yes | Yes | 94.82 |
| Shahi et al. > @ | MobileNetV2 | MIX Fruit | Public | | | Yes | Yes | 96.24 |
| $OEDU et al.[36] | MobileNetV2 | Date fruit | Private | 8 | 917 | Yes | Yes | |
| 6KDQ et al[37] | DenseNet169 | MIX Fruit | Public | | 2633 | Yes | Yes | 99.84 |
| Mimma et al[38] | RestNet | MIX fruit | Public | | 971 | Yes | Yes | |
| Wang et al.[39] | MobileNetV3 | 0L[ IUXLW | Public | 11 | 2278 | Yes | Yes | |
| Azadnia et al.> @ | Proposed | +DZWKRUQ | Private | 3 | | Yes | Yes | 99.63 |
| Phan et al.[41] | ResNet | 7RPDWR | Private | 3 | | Yes | No | 98 |
| Gulzar [42] | MobileNetV2 | 0L[ IUXLW | Public | | 26,149 | Yes | Yes | 99 |

### 3.2 Data augmentation

7KH DXJPHQWDWLRQ RI WUDLQLQJ enhancing model robustness and generalization [43, 44]. 0RVW VWXGLHV LQFRUSRUDWHG such as rotation, scaling, flipping, and introducing noise WR DUWLILFLDOO\ GLYHUVLI\ augmentation strategy helped mitigate overfitting and enabled models to handle variations in fruit appearance effectively.

### 3.3 Transfer learning

7UDQVIHU OHDUQLQJ SOD\HG D SLYRWDO UROH LQLWLDOL]LQJ -PRGHOV ZLWK SUH large-scale datasets, researchers fine-tuned these models on their specific fruit WKH WUDLQLQJ GDWDVHW 7KLV convergence and leveraged previously learned features for improved performance.

3.4 Datasets

Public Datasets: Several publicly available fruit datasets served as the foundation for numerous studies. Notable among them is the "Date Fruit" dataset, a standardized EHQFKPDUN IRU GDWH IUXLW FODVVLILFDWLRQ. $GGLWLRQDOO\, PL[HG IUXLW GDWDVHWV ZLWK YDU\LQJ QXPEHUV RI FODVVHV ZHUH employed, offering a comprehensive range of fruit types for training and evaluation.

Private Datasets: In certain cases, researchers collected and curated their private datasets to address specific UHVHDUFK REMHFWLYHV RU IUXLW W\SHV QRW DGHTXDWHO\ UHSUHVHQWHG LQ SXEOLF GDWDVHWV. 7KHVH SULYDWH GDWDVHWV DOORZHG IRU FXVWRPL]HG GDWD FROOHFWLRQ and labeling.

3.5 Dataset characteristics

- 1XPEHU RI &ODVVHV: 7KH QXPEHU RI IUXLW FODVVHV ZLWKLQ WKHVH GDWDVHWV YDULHG FRQVLGHUDEO\ UDQJLQJ IURP D IHZ FODVVHV. 7KLV YDULDELOLW\ FDWHUHG WR WKH GLYHUVH UDQJH RI fruit types and research goals.
- Number of Images: Datasets contained varying TXDQWLWLHV RI LPDJHV, VSDQQLQJ IURP D IHZ KXQGUHG WR RYHU D KXQGUHG WKRXVDQG. 7KH VL]H RI WKH GDWDVHW VLJQLILFDQWO\ influenced model performance.
- 'DWD $XJPHQWDWLRQ: 'DWD DXJPHQWDWLRQ WHFKQLTXHV ZHUH H[WHQVLYHO\ DSSOLHG LQ ERWK SXEOLF DQG SULYDWH datasets to enrich the training data.
- 7UDQVIHU /HDUQLQJ: 7UDQVIHU OHDUQLQJ ZDV D FRPPRQ practice, enabling models to benefit from pre-trained NQRZOHGJH DQG DGDSW LW WR IUXLW FODVVLILFDWLRQ WDVNV.

3.6 Model performance

Model performance in fruit classification studies is typically measured by accuracy, and the table presents a variety of accuracy scores from different research papers. +HUH ZH ZLOO DQDO\]H DQG GLVFXVV WKH PRGHO SHUIRUPDQFH trends and highlights:

- +LJK $FFXUDF\ $FURVV WKH %RDUG: 2QH QRWDEOH WUHQG in the table is the consistently high accuracy achieved by most of the models. Many studies report accuracy scores ZHOO DERYH ZLWK VHYHUDO HYHQ VXUSDVVLQJ WKH PDUN. 7KLV LQGLFDWHV WKDW GHHS OHDUQLQJ models are highly HIIHFWLYH LQ IUXLW FODVVLILFDWLRQ WDVNV, UHJDUGOHVV RI WKH specific architecture or dataset used.
- Influence of Dataset Size: Larger datasets often result in better model performance. For instance, the "MIX )UXLW GDWDVHW XVHG E\ &KHQ HW DO. [ ] DQG WKH 0RELOH1HW9 GDWDVHW E\ *XO]DU [ ] ERWK ZLWK substantial numbers of images, achieved accuracy scores RI DQG UHVSHFWLYHO\. 6LPLODUO\, WKH 'DWH )UXLW GDWDVHW ZLWK LPDJHV XVHG E\ )DLVDO HW DO. [ ] and Faisal et al. [26] also yielded high accuracy scores of DQG
- Effect of Model Choice: While the choice of deep learning model architecture varies across studies, it is evident that several models, including VGG16, ResNet, DQG 0RELOH1HW9 FRQVLVWHQWO\ SHUIRUP ZHOO. )RU H[DPSOH 6KDKL HW DO. [ ] RI@ DFKLHYHG DQ DFFXUDF\ XVLQJ 0RELOH1HW9 ZKLOH 6KDQNDU HW DO. LPSUHVVLYH DFFXUDF\ ZLWK 'HQVH1HW demonstrates the robustness of these architectures in fruit FODVVLILFDWLRQ WDVNV.
- 3ULYDWH YV. 3XEOLF 'DWDVHWV: 7KH that used both public and private datasets. Interestingly, some private datasets, such as those used by Altaheri et al. [ ] DQG $OEDUUDN HW DO. [ ] RXW in terms of accuracy, indicating the potential benefits of curated, domain-specific datasets.
- Specialized Architectures: In some cases, specialized DUFKLWHFWXUHV WDLORUHG IRU VSHFLILF KDZWKRUQ IUXLW LQ $]DGQLD HW H[FHSWLRQDOO\ ZHOO DFKLHYLQJ D 7KLV VXJJHVWV WKDW FXVWRP tures can be KLJKO\ HIIHFWLYH IRU QLFKH IUXLW F
- ,PSDFW RI 'DWD $XJPHQWDWLRQ DQ Most studies employed data augmentation and transfer OHDUQLQJ. ZKLFK FRQWULEXWHG WR LPSURYHG JHQHUDOL]DWLRQ DQG DFFXUDF\. 7KL models to adapt to variations in fruit appearance and leverage pre-WUDLQHG NQRZOHGJH IURP OD-scale datasets.

# 4 Challenges and limitations

In the realm of fruit classification using deep learning, numerous challenges and limitations shape the landscape. 7KHVH FKDOOHQJHV DQG OLPLWDWLRQ

- Dataset Size Disparities: One of the primary challenges in fruit classification using deep learning is the variability in dataset sizes. While some studies have DFFHVV WR H[WHQVLYH GDWDVHWV Z images, others are constrained by smaller GDWDVHWV size disparity can significantly impact model SHUIRUPDQFH ZLWK ODUJHU GDWDVH PRUH UREXVW PRGHOV. 5HVHDUFKHU data may face challenges in achieving comparable accuracy levels.
- Private Dataset Dependency: Several studies rely on private datasets that are not publicly accessible. While private datasets offer the advantage of customization and domain-specific labeling, they can also limit the reproducibility and comparability of UHVHDUFK. 7KH OD standardized public datasets for specific fruit types may KLQGHU FROODERUDWLRQ DQG EHQFK
- &ODVV ,PEDODQFH: ,Q IUXLW FODV LPEDODQFH LV D FRPPRQ LVVXH SDU ZLWK GDWDVHWV FRQWDLQLQJ QXPHU OHDG WR ELDVHG PRGHOV WKDW SH FODVVHV EXW VWUXJJOH ZLWK PLQR classes. Addressing FODVV LPEDODQFH WKURXJK WHFKQL undersampling, or generating synthetic data can be FKDOOHQJLQJ DQG UHTXLUHV FDUHIX
- Computational Resources: Deep learning models, HVSHFLDOO\ WKRVH ZLWK FRPSOH[ D datasets, demand substantial computational resources. 7UDLQLQJ DQG ILQH-tuning models can be computationally H[SHQVLYH DQG WLPH-consuming, limiting the accessibility RI WKLV WHFKQRORJ\ WR UHVHDUFKH
- *HQHUDOL]DWLRQ WR 1HZ )UXLW 7 focus on specific fruit types or a limited number of fruit

 https://doi.org/10.1051/bioconf/20248501020

YDULHWLHV 7KH FKDOOHQJH OLHV
of models to novel or previously unencountered fruit types. Models trained on one set of fruits may not JHQHUDOL]H ZHOO WR HQWLUHO\ retraining or adaptation.

• Interpretable Models: Deep learning models, SDUWLFXODUO\ WKRVH ZLWK LQWULFDWH DUFKLWHFWXUHV FDQ EH FKDOOHQJLQJ WR LQWHUSUHW 8QGHUVWDQGLQJ ZK\ D PRGHO PDNHV D VSHFLILF FODVVLILFDWLRQ GHFLVLRQ LV HVVHQWLDO HVSHFLDOO\ LQ DSSOLFDWLRQV ZKHUH LQWHUSUHWDELOL is crucial, VXFK DV TXDOLW\ FRQWURO LQ WKH IRRG LQGXVWU\

• Model Robustness: While high accuracy rates are impressive, the robustness of models in real-world VFHQDULRV ZLWK YDULDWLRQV LQ OLJKWLQJ EDFNJURXQG DQG fruit deformities remains a limitation. Ensuring that PRGHOV SHUIRUP ZHOO XQGHU GLYHUVH FRQGLWLRQV LV DQ ongoing challenge.

• 6FDODELOLW\ 7KH VFDODELOLW\ RI IUXLW FODVVLILFDWLRQ models for large-scale agricultural or industrial applications is a concern. Deploying these models across vast fruit processing facilities or agricultural fields UHTXLUHV HIILFLHQW KDUGZDUH UHDO-time processing capabilities, and scalability considerations.

## 5 Applications and implications

Fruit classification using deep learning holds immense promise and is poised to revolutionize several industries DQG GRPDLQV 7KLV WHFKQRORJ\ V implications are far-reaching. Some of them are PHQWLRQHG DV IROORZV

• Agriculture and Quality Control: Fruit classification using deep learning has significant implications in agriculture. Accurate identification of fruit types and TXDOLW\ DVVHVVPHQW FDQ DLG LQ DXWRPDWHG KDUYHVWLQJ VRUWLQJ DQG TXDOLW\ 7KLV WHFKQRORJ\ FDQ RSWLPL]H UHVRXUFH DOORFDWLRQ production.

• )RRG 3URFHVVLQJ ,QGXVWU\ classification of fruits can enhance the efficiency of fruit SURFHVVLQJ IDFLOLWLHV $XWRPDWHG VRUWLQJ EDVHG RQ TXDOLW\ DQG ULSHQHVV FDQ OHDG WR LPSURYHG SURGXFW TXDOLW\ DQG UHGXFHG SURFHVVLQJ WLPHV quality control. LQ LQGXVWULHV VXFK DV MXLFH

• Consumer Convenience: Deep learning-based fruit FODVVLILFDWLRQ FDQ H[WHQG WR FRQVXPHU DSSOLFDWLRQV including mobile apps and devices that help consumers LGHQWLI\ IUXLWV TXLFNO\ DQG DFFXUDWHO\ 7KLV FDQ DVVLVW LQ PDNLQJ LQIRUPHG GLHWDU\ FKRLFHV DQG SURYL de information on fruit ripeness.

• Disease Detection: Beyond classification, deep learning models can be adapted for disease detection in fruit crops. Early detection of diseases or pests can enable timely intervention and reduce crop losses, contributing to sustainable agriculture.

• Research and Biodiversity Conservation: Fruit classification aids researchers in studying fruit varieties, WUDFNLQJ ELRGLYHUVLW\ DQG -bearing SODQW VSHFLHV 7KLV LQIRUPDWLRQ FDQ EH FUXFLDO IRU ecological and conservation studies.

• LQ DGYHUVH ... FODVVLILFDWLRQ FDQ KHOS PHHW PD WKDW WKH ULJKW W\SHV DQG TXDOLW\ DUH GHOLYHUHG WR FRQVXPHUV international standards.

## 6 Emerging trends and future directions

• Multi-Modal Sensing: Integrating multiple sensing modalities, such as vision and spectroscopy, can enhance IUXLW FODVVLILFDWLRQ DFFXUDF\ WR H[SORUH WKH IXVLRQ RI GDWD I improve fruit assessment.

• Edge Computing: Future directions may involve the GHSOR\PHQW RI OLJKWZHLJKW GHHS GHYLFHV time fruit classification directly in WKH ILHOG RU DW SURFHVVLQJ IDFLO and minimizes the need for H[WHQVLYH FRPSXWD resources.

• )HZ-Shot Learning: Developing models that can FODVVLI\ IUXLWV ZLWK PLQLPDO OD -shot OHDUQLQJ LV DQ HPHUJLQJ WUHQG YDOXDEOH IRU UDUH RU QHZO\ GLVFR

• Interpretable AI: As the demand for transparency and DFFRXQWDELOLW\ LQ $, V\VWHPV JUR focus on developing interpretable models that provide H[SODQDWLRQV IRU WKHLU FODVVLIL HVSHFLDOO\ UHOHYDQW LQ TXDOLW\ control and food safety applications. DSSOLFDWLRQV DQG

• 7UDQVIHU /HDUQLQJ $FURVV 'RP OHDUQLQJ WHFKQLTXHV FDQ EH H NQRZOHGJH IURP RQH IUXLW W\SH WR GLIIHUHQW GRPDLQV H J IURP YHJ can reduce the need for large labeled datasets for each fruit type.

• 5REXVWQHVV DQG $GDSWDELOLW\ adaptability to varying environmental conditions, including changes in lighting, fruit deformities, and EDFNJURXQG QRLVH

• +XPDQ-AI Collaboration:

## 7 Conclusion

7KH ODQGVFDSH RI IUXLW FODVVLILF LV PDUNHG E\ D GLYHUVH DUUD\ RI PHWKRGRORJLHV 7KH UHVHDUFK HIIR 2 have illuminated both the potential and the challenges of applying deep learning to IUXLW FODVVLILFDWL studies have underscored the significance of dataset size, ZLWK ODUJHU GDWDVHWV RIWHQ \LH but have also highlighted the limitations faced by UHVHDUFKHUV ZLWK FRQVWUDLQHG D )XUWKHUPRUH WKH UHOLDQFH RQ offering customization advantages, has raised concerns DERXW UHVHDUFK UHSURGXFLELOLW challenge of class imbalance in fruit datasets has been DFNQRZOHGJHG QHFHVVLWDWLQJ

VSHFLDOL]HG WHFKQLTXHV WR HQVXUH IDLU DQG PHDQLQJIXO training.

7KH GHPDQG IRU FRPSXWDWLRQDO UHVRXUFHV SDUWLFXODUO\ IRU FRPSOH[ PRGHOV DQG ODUJH GDWDVHWV KDV VXUIDFHG DV D QRWHZRUWK\ OLPLWDWLRQ SRWHQWLDOO\ UHVWULFWLQJ WKH accessibility of deep learning technology. Generalization WR QHZ DQG SUHYLRXVO\ XQHQFRXQWHUHG fruit types remains a challenge, calling for adaptability and retraining of models.
Additionally, the need for interpretable AI models has EHFRPH DSSDUHQW SDUWLFXODUO\ LQ FRQWH[WV VXFK DV IRRG TXDOLW\ FRQWURO (QVXULQJ PRGHO UREXVWQHVV XQGHU GLYHUVH conditions and scaling these technologies for large-scale applications present ongoing challenges in the field.

Despite these challenges, the studies in section 2 have VKRZFDVHG UHPDUNDEOH DFKLHYHPHQWV ZLWK VHYHUDO PRGHOV DFKLHYLQJ KLJK DFFXUDF\ UDWHV LQ IUXLW FODVVLILFDWLRQ $V ZH ORRN WR WKH IXWXUH WKH ILHOG LV SRLVHG IRU H[FLWLQJ developments, including multi-modal sensing, edge FRPSXWLQJ, self-learning, interpretable AI, transfer learning, and innovative human-AI collaboration models.

7KHVH HPHUJLQJ WUHQGV DQG IXWXUH GLUHFWLRQV KROG WKH SURPLVH RI PDNLQJ IUXLW FODVVLILFDWLRQ WHFKQRORJ\ PRUH versatile, accessible, and adaptable across various industries and research domains. Overall, the insights gained from the studies in section 2 pave WKH ZD\ IRU continued advancements in fruit classification using deep OHDUQLQJ ZLWK EURDG-reaching DSSOLFDWLRQV DQG implications in agriculture, food processing, consumer services, research, and beyond.

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