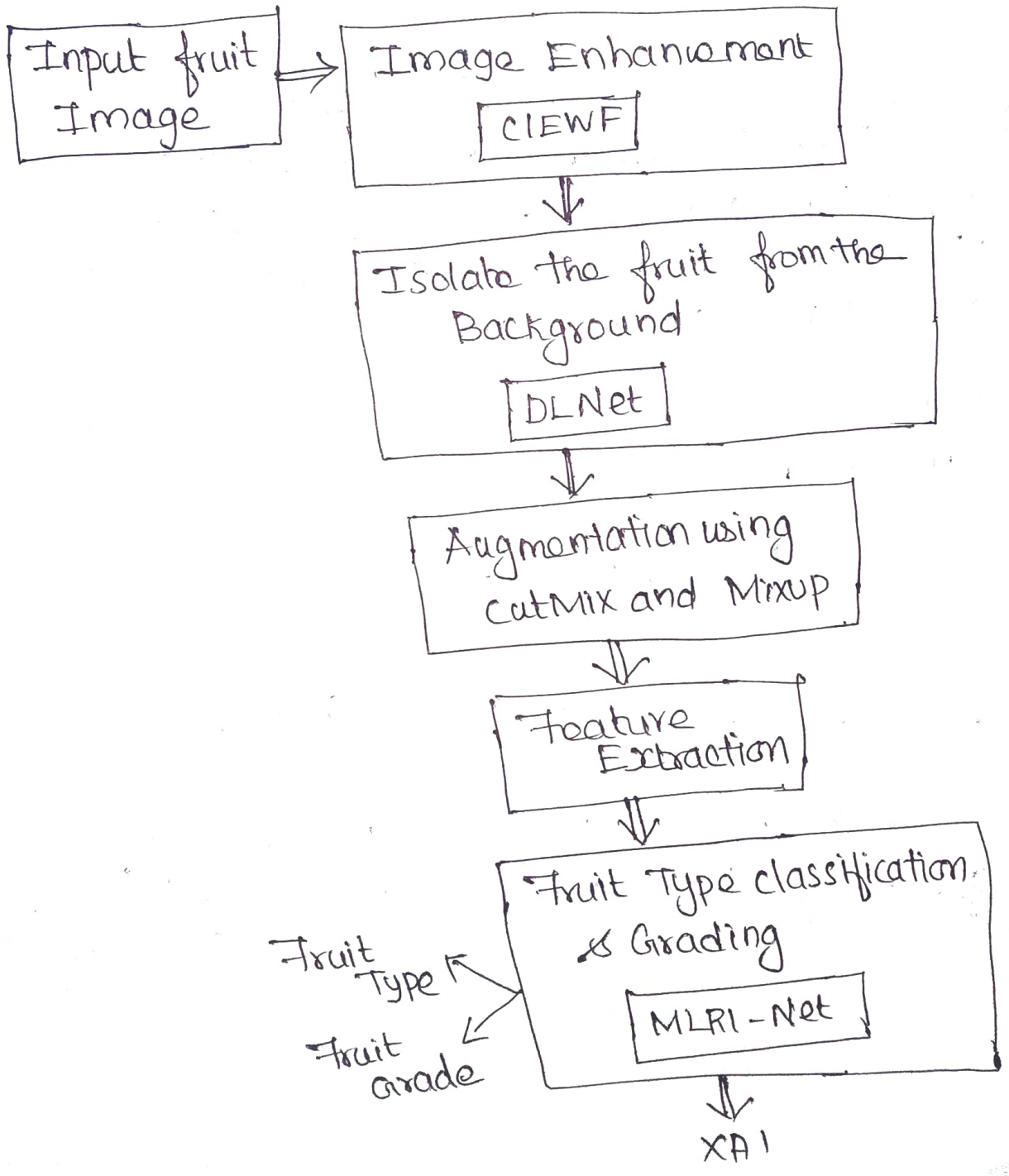
Fruit classification and Grading

MLRI-Net : A Novel Deep Learning Framework for Automated Fruit classification and Quality Grading using Attention based Residual Inception Networks.

3. Proposed Method :-



3.1. Input Fruit Image Acquisition:—

consider the fruits type with quality dataset consists of 'n' number of Images.

$$D = \{I_1, I_2, \ldots I_m, \ldots I_n\}$$

3.2. Image Enhancement using Contextual Image Enhancement Wiener Filter:-

$I_m \Rightarrow$ [CIEWF] $\Rightarrow P_m$

$P_m \downarrow$ enhanced Image

Refer, "High Performance parallel multi scale attention network with explainable AI for intelligent diagnosis of leaf diseases in agricultural systems" pg. No: 5

3.3. Isolation of fruit from the background using DLNet:—

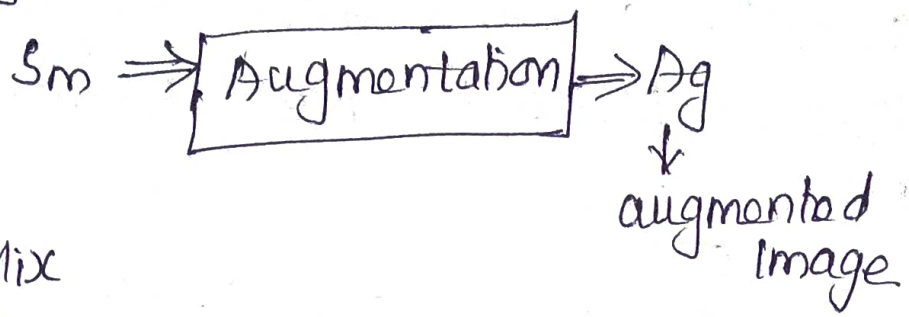
$P_m \Rightarrow$ [DLNet] $\Rightarrow S_m$

$S_m \downarrow$ Segmented Image.

3.3.1. Architecture of DLNet:—

Refer, "DLNet: Accurate segmentation of green fruit in obscured environments" sec: 3-2.

3.4. Augmentation of Image:-

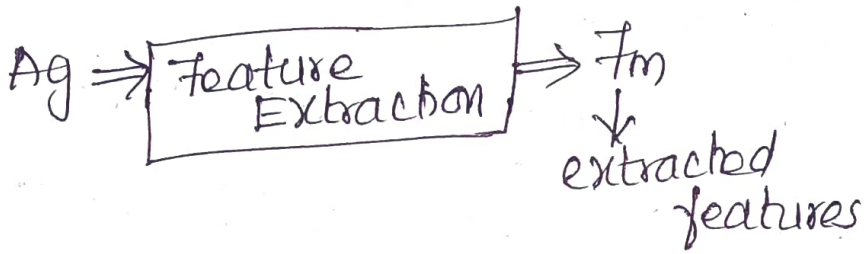


i) CutMix

ii) MixUp

Refer, "Multi-fruit classification and grading using a same domain Transfer learning approach" sec: III-B

3.5. Handcrafted and Deep feature Representation:-



i) CS-LMP (f1):-

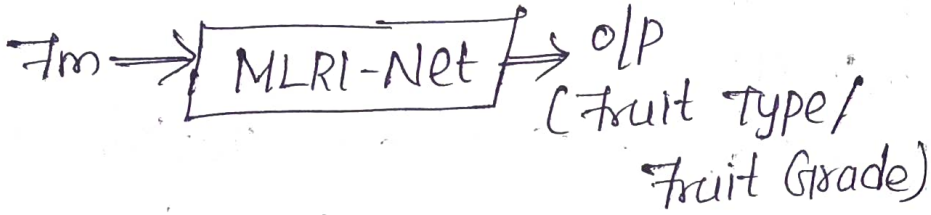
Refer, "An enhanced LBP-based technique with various size of sliding window approach for handwritten Arabic digit Recognition" sec: 2.1.4

ii) Deep feature extraction using ResNext-101(f2):-

Refer, "vegetable and fruit freshness detection based on deep features and principal component analysis" sec: 3.3.2.

$$fm = \{f_1, f_2\}$$

3.6. Joint Fruit Type classification and Quality Grading using proposed Mean Squared Logcosh loss based Residual Inception Network:-



3.6.1. Architecture of RAI-Net:-

Refer, "RAI-Net: Tomato Plant Disease classification using Residual Attention Inception Network"

3.6.2. Lossfunction Modification:-

→ The lossfunction will be modified using Mean squared logcosh loss, Combination of Root Mean Squared Logarithmic Error (RMSLE) and Logcosh loss.

i) RMSLE:-

$$L_R = \sqrt{\frac{1}{N}\sum_{i=0}^{N}(\log(y_i+1) - \log(\hat{y}_i+1))^2}$$

where,

$N \rightarrow$ No. of data samples

$y_i \rightarrow$ true value

$\hat{y}_i \rightarrow$ Predicted value

ii) Logcosh loss:-

$$L_{Lc} = \sum_{i=1}^{N} \log(\cosh(\hat{y}_i - y_i))$$

Refer, "A comprehensive survey of Regression based loss functions for Time series forecasting" sec: III - I & M

Total Loss function,

$$L_{Tot} = \lambda_1 L_R + \lambda_2 L_{Lc}$$

where,

$\lambda_1, \lambda_2 \rightarrow$ scaling factors.

4. Results and Discussion:-

4.1. Tool : PYTHON

4.2. Performance Indicators:-

i) Accuracy
ii) MCC
iii) F1-score

4.3. Dataset Description:-

[DS1] → FruitNet dataset [Mendeley]

[DS2] → Fruit 360 dataset [kaggle]

4.4. Parameter settings:-

4.4.1. Experimental Parameters:-

Parameter	Range
Epoch	
optimizer	
learning rate	
Kernel size	
Beta 1	
Beta 2	
Batchsize	
Epsilon	
loss	
Activation	

4.5. Experimental Results:-

4.5.1. Image Results:-

→ i/p, enhanced image, segmented, augmented, feature extracted

4.5.2. UMAP visualisation:-

Refer," Firmness classification in 'Rojo Brillante' persimmon fruit after cold storage using hyperspectral imaging and deep learning with variational autoencoders" Fig:13

4.6. Explainability Results:—

→ based on Lovi saliency maps

Refer, "cathAI: Fully automated coronary angiography interpretation and stenosis estimation" Fig: 4(b)

→ based on LRP (Layerwise Relevance Propagation)

Refer, "Explaining decisions of a light-weight deep neural network for real-time coronary artery disease classification in magnetic Resonance Imaging" Fig: 5.

4.7. Analysis:—

4.7.1. Confidence Analysis:— [violin + Swamplot]

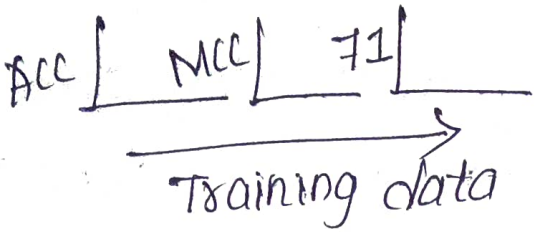
[3] + [3]

ACC | MCC | F1 | → Methods

confidence score

Refer, "LSTM-SHAP based academic performance prediction for disabled learners in virtual learning environments: a statistical analysis approach" Fig: 13

4.7.2. Ablation analysis:- [Raincloud plot] [3]+[3]



i) W/O DLNet
ii) W/O augmentation
iii) Proposed MLRI-Net

Refer, "AI driven fusion of multimodal data for Alzheimer's disease biomarker assessment" Fig: 4(a)

4.7.3. Foldwise AUC curve:- [1]+[1]



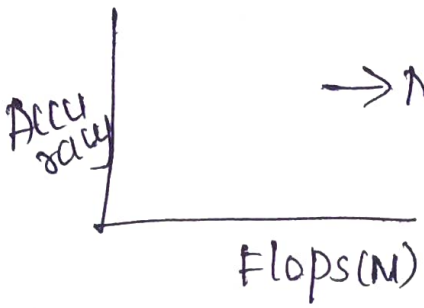
Refer, "Attention driven graph based machine Learning for non-Invasive diagnosis of NAFLD" Fig: 7

4.7.4. AUPR violin plot:- [1]+[1]



Refer, "HiGLDP: a hierarchical graph neural network for predicting lncRNA-disease associations through multi-omic integration" Fig: 5.

4.7.5. Trade-off analysis:- [1] + [1]



Refer, "MultiResFF-Net: Multilevel Residual Block-based Lightweight feature fused network with attention for Gastrointestinal disease diagnosis" Fig: 12

4.7.6. Confusion Matrix:- [1] + [1]

(20 graphs)

4.8. Summary:-

4.8.1. Discussion Table graph

4.8.2. Paired t-test box plot:-

Refer, "A Novel XAI framework for explainable AI-ECG using generative counterfactual XAI (GCX)" Fig: 4.

Extra Results:-

Sensitivity Analysis:- [Radar plot] [3] + [3]

→ Batch size: 16, 32, 64, 128.

