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ABSTRACT

Purpose: *Vegetable production plays a vital role for the existence of human society. It is very much essential for the proper care of vegetable plants for better production of vegetables. However, vegetable plant leaf disease is a major concern in the current scenario. Tomato leaf disease is one of them. So, preventive measures should be taken to avoid the rise of tomatoes and other leaf diseases at the earliest for better production of vegetables.*

Approach: *In this work, a machine intelligent (MI) based approach is proposed for the classification of tomato leaf disease images (TLDIs) into the bacterial spot (BS), early blight (EB), late blight (LB), leaf mold (LM), septoria leaf spot (SLS), tomato mosaic virus (TMV), tomato yellow leaf curl virus (TYLCV) and healthy (HL) types. The proposed approach is focused on the stacking (hybridization) of Logistic Regression (LRG), Support Vector Machine (SVMN), Random Forest (RFS) and Neural Network (NNT) methods to carry out such classification. The proposed method is compared with other machine learning (ML) based methods such as LRG, SVMN, RFS, NNT, Decision Tree (DTR), AdaBoost (ADB), Naïve Bayes (NBY), K-Nearest Neighbor (KNNH) and Stochastic Gradient Descent (SGDC) for performance analysis.*

Result: *The proposed method and other ML based methods have been implemented using Python based Orange 3.26.0. In this work, 1600 TLDIs having 200 numbers of each type such as BS, EB, LB, LM, SLS, TMV, TYLCV and HL are taken from the Kaggle source. The performance of all the methods is assessed using the performance parameters such as classification accuracy (CA), F1, Precision (PR) and Recall (RC). From the results, it is found that the proposed method is capable of providing better classification results in terms of CA, F1, PR and RC as compared to other ML based methods such as LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH and SGD.*

Originality: *In this work, a MI based approach is proposed by focusing on the stacking of LRG, SVMN, RFS and NNT methods to carry out the classification of TLDIs into several types such as BS, EB, LB, LM, SLS, TMV, TYLCV and HL. The proposed approach performs better in terms of CA, F1, PR and RC as compared to LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH and SGDC methods.*

Paper Type: *Conceptual Research.*

Keywords: Tomato Leaf Disease, Machine Learning, Classification Accuracy, F1, Precision,

1. INTRODUCTION :

Several vegetables production is considered as an important concern in human society throughout the globe. Proper care of the vegetable plants is a key factor for better production of vegetables. The vegetables can be classified as tomato, potato, cabbage, cauliflower, broccoli, pumpkin, bean, etc. However, vegetable plant leaf diseases [1-6] and other diseases greatly hamper the production of vegetables. Tomato leaf diseases are focused in this work. The tomato plant leaf diseases [1-3] can be classified as BS, EB, LB, LM, SLS, TMV, TYLCV, etc. So, it is very much essential to classify the TLDIs [4-6] into several categories for taking preventive measures at the earliest to avoid the rise of such tomato leaf diseases.

ML [7-11] can be considered as a solution for the classification of TLDIs into several categories. The ML based methods can be broadly classified as supervised and unsupervised. The supervised ML [8-10] based methods such as LRG, SVMN, RFS, NNT, DTR, ADB, etc. play a significant role to accomplish the classification mechanism. However, each ML based method is not capable of providing better classification results in several situations. The performance of each ML [7, 8, 10] based method varies from one scenario to another scenario. So, it is a very challenging task to perform the classification mechanism accurately in different scenarios. Therefore, there is a need for some enhanced methods to carry out the categorization mechanism in a better way.

In this work, the main focus is given to the classification of TLDIs into several categories such as BS, EB, LB, LM, SLS, TMV, TYLCV and HL [12] in a better way. Here, a MI based approach is proposed to carry out the classification of TLDIs into several types. This approach is focused on the stacking of LRG, SVMN, RFS and NNT methods to carry out such classification. The proposed method is able to perform better in terms of CA, F1, PR and RC than LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH and SGDC methods. Here, the proposed work tries to provide better classification results than other methods.

The contributions in this work are mentioned as follows.

(1) In this work, a MI based approach is proposed for the classification of TLDIs into BS, EB, LB, LM, SLS, TMV, TYLCV and HL types.
(2) The proposed approach is focused on the stacking of LRG, SVMN, RFS and NNT methods to carry out such classification mechanisms.
(3) The proposed method is compared with other ML based methods such as LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH and SGDC in terms of CA, F1, PR and RC for performance analysis.
(4) The Simulation of this work is accomplished using python based Orange 3.26.0.
(5) From the results, it is found that the proposed method is capable of providing better classification results than other ML based methods in this scenario.

The rest of this work is presented as follows. Section 2 to Section 7 describes the related works, the objective of the work, methodology, results and discussion, recommendation and conclusion respectively.

2. RELATED WORKS :

Many research works have been accomplished related to the TLDIs processing and analysis [1-6, 13-32]. Some of the works are mentioned as follows. Paymode et al. [1] concentrated on the convolutional neural network (CNN) and transfer learning (TL) mechanism for the classification of multi-crop leaf disease images. Shruthi et al. [2] focused on the review of deep learning (DL) architectures for the classification of tomato plant disease. Mohanty et al. [3] concentrated on the ML mechanism for the recognition of tomato plant leaves disease. Al-gaashani et al. [4] concentrated on TL and feature concatenation process for the classification of tomato leaf disease. Wadadare et al. [5] focused on DL based CNN for the recognition of tomato leaves disease with the inception process. Tan et al. [6] emphasized on the comparison of ML and DL methods for the categorization of tomato leaf diseases by recognizing several leaf images. Abbas et al. [13] focused on the TL process for the recognition of tomato plant disease. Thangaraj et al. [14] emphasized on TL based deep CNN for the classification of tomato leaf disease. Gadekallu et al. [15] focused on principal component analysis-whale optimization (PCA-WO) based deep NNT model to categorize tomato plant diseases. Nandhini et al. [16] focused on an enhanced crossover based monarch butterfly optimization (BO) mechanism with the help of CNN process for the categorization of tomato leaf disease. Ngugi et al. [17] emphasized on tomato leaf segmentation algorithms with the help of DL mechanism for mobile phone applications. Mkonyi et al. [18] concentrated on the DL mechanism to early identify the tuta absoluta in tomato plants. The review of some articles related to TLDIs categorization is mentioned in Table 1.

Table 1: Review of some articles related to TLDIs classification Source: [1-6, 13-16]

S. No	Field of Research	Focus	Outcome	Reference
1	Image Processing	CNN and TL	Categorization of multi-crop leaf disease images	Paymode et al. (2022). [1]
2	Image Processing	DL architectures	Categorization of tomato plant disease	Shruthi et al. (2022). [2]
3	Image Processing	ML	Recognition of tomato plant leaves disease	Mohanty et al. (2022). [3]
4	Image Processing	TL and feature concatenation	Categorization of tomato leaf disease	Al-gaashani et al. (2022). [4]
5	Image Processing	DL and CNN	Recognition of tomato leaves disease	Wadadare et al. (2022). [5]
6	Image Processing	ML and DL	Categorization of tomato leaf disease	Tan et al. (2021). [6]
7	Image Processing	TL	Recognition of tomato plant disease	Abbas et al. (2021). [13]
8	Image Processing	TL and Deep CNN	Categorization of tomato leaf disease	Thangaraj et al. (2021). [14]
9	Image Processing	PCA-WO and deep NNT	Categorization of tomato plant disease	Gadekallu et al. (2021). [15]
10	Image Processing	BO and CNN	Categorization of tomato leaf disease	Nandhini et al. (2021). [16]

3. RESEARCH GAP :

From the literature survey, it is observed that a single method may not be efficient enough to accomplish the classification process of TLDIs [1-6, 13-32] in all scenarios. A method which is working well in a scenario may not perform well in other scenarios. So, accurate classification of TLDIs into several categories by applying different methods is a challenging task. So, there is a need for the development of enhanced methods to carry out the categorization mechanism in a better way to solve the mentioned issues.

4. RESEARCH AGENDA :

The main focus of the research agenda is mentioned as follows.
(1) To apply different existing ML based methods for the categorization of TLDIs into several types.
(2) To propose a MI based method to accomplish such a categorization process in a better way as compared to other methods.
(3) To analyze the performance of all the methods in terms of CA, F1, PR and RC.

5. OBJECTIVES :

The key objectives of this work are presented as follows.
(1) To propose a MI based method by focusing on stacking mechanism for the classification of TLDIs into BS, EB, LB, LM, SLS, TMV, TYLCV and HL types in a better way.
(2) To compare the proposed method with other ML based methods such as LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH and SGDC in terms of CA, F1, PR and RC.

6. METHODOLOGY :

In this work, a MI [19-32] based approach is proposed for the classification of TLDIs into BS, EB, LB, LM, SLS, TMV, TYLCV and HL types. The proposed approach is focused on the stacking of LRG, SVMN, RFS and NNT methods to carry out such classification. The proposed method is compared with other ML based methods such as LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH and SGDC in terms of CA, F1, PR and RC for performance analysis. The methodology is described in Fig. 1.

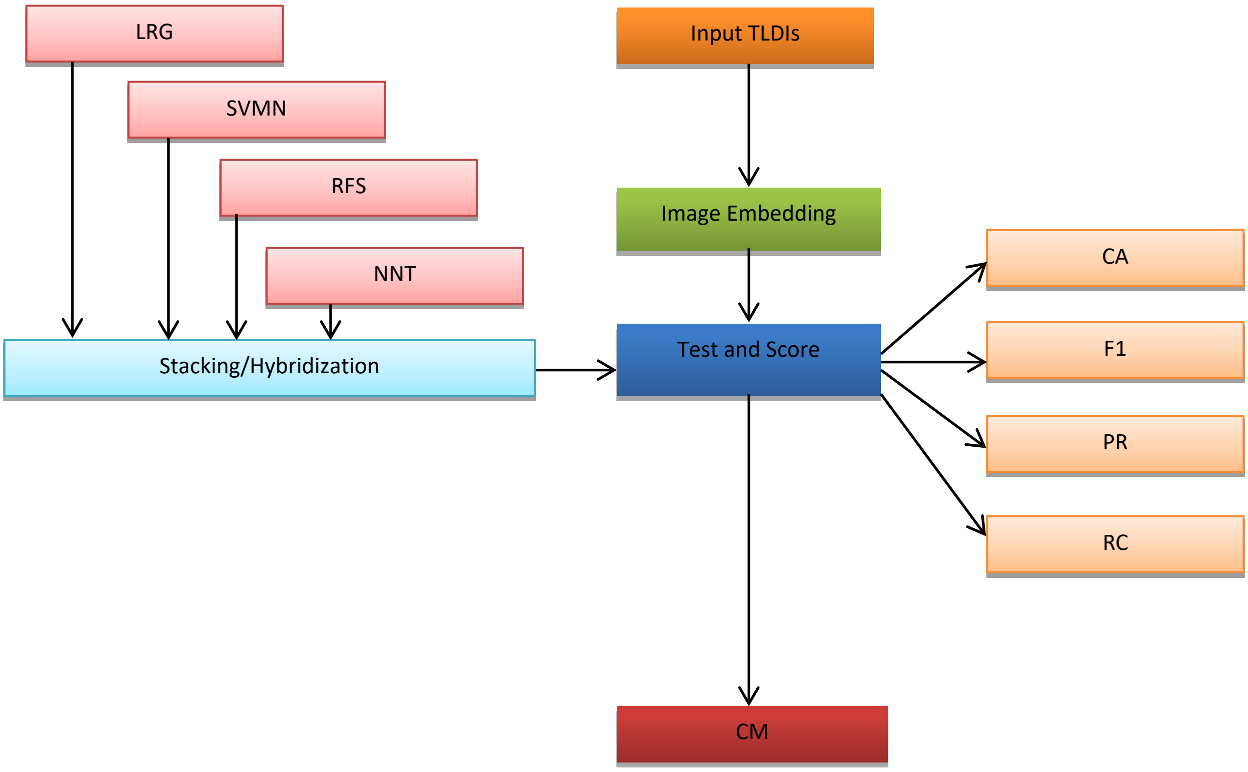


Fig. 1: Methodology [33]

At first, the TLDIs are imported to Orange 3.26.0 [33] through the Import Images option. Afterwards, the image embedding (IED) process is accomplished on the TLDIs to extract the essential features such as height, width, etc. For IED, several embedders such as SqueezeNet, Inception v3, DeepLoc, etc. can be used. In this work, SqueezeNet (local) embedder is considered for processing. After the completion of the IED process, test and score computation will be performed by considering the ML based methods such as LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC and the proposed method to find out the CA, F1, PR and RC values in units. The test and score computation can be performed by considering cross validation (CRV) as well as random sampling mechanisms. In this work, the CRV process is focused. The CRV process can be carried out by recognizing the number of folds (NF) as 2, 3, 5, 10, 20, etc. But, in this work, the NF value is considered as 5 to accomplish the classification mechanism.

In this work, the parameter setup for each method is described as follows. For LRG, the regularization type can be considered as Lasso (L1) and Ridge (L2). İn this work, Ridge (L2) is considered for processing. The strength value (SV) for this work is considered as per equation (1).

$$SV=1 \qquad (1)$$

For SVMN, the kernel can be considered as Linear, Polynomial, RBF and Sigmoid. In this work, the kernel is considered as a radial basis function and the iteration limit is taken as 100. Here, the numerical tolerance (NTL) value is taken for processing as per equation (2).

$$NTL=0.0010 \qquad (2)$$

In this work, for RFS the number of trees (NBTR) considered for processing is mentioned in equation (3).

$$NBTR=50 \quad \text{---------} \quad (3)$$

For NNT, the activation function can be considered as ReLu, Logistic, tanh, etc. The solver can be considered as Adam, SGDC, L-BFGS-B, etc. In this work, the activation function is considered as ReLu and the solver is considered as Adam with the maximal number of iterations as 100. The neurons (NR) in hidden layers and regularization (RE) value are considered in this work as per equation (4) and equation (5) respectively.

NR=200 ----------- (4)

RE=0.0001 ----------- (5)

For DTR, the maximum tree depth (MTDPT) is considered as per equation (6) with the minimum number of instances in leaves as 4.

MTDPT=100 ----------- (6)

For KNNH, the metric can be considered as Euclidean, Manhattan, Chebyshev and Mahalanobis and the weight(WT) can be considered as distance (ds) and uniform (u). In this work, for KNNH weight value is mentioned in equation (7) by considering the number of neighbors as 10 and the metric as Manhattan.

WT=ds ---------- (7)

At the test and score computation , the CA, F1, PR and RC values (in units) are computed. Then, the confusion matrix (CM) representation can be carried out. The CM can be represented by considering the number of instances, proportion of predicted and proportion of actual values. However, in this work, the number of instances is considered for processing. The methodology used in this work for the classification of TLDIs into BS, EB, LB, LM, SLS, TMV, TYLCV and HL types is described in Algorithm 1.

Algorithm 1: TLDI Classification
Input: TLDIs
Output: BS, EB, LB, LM, SLS, TMV and TYLCV Type
Step 1: Start
Step 2: Input TLDIs
Step 3: IED (TLDIs)
Step 4: Test and Score (LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC, Proposed Method)
Step 5: Compute CA, F1, PR, RC by applying LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC and Proposed Method
Step 6: Create (CM) for each method to analyze the classification results
Step 7: Stop

7. RESULTS AND DISCUSSION :

The simulation of this work is accomplished using Python based Orange 3.26.0 [33]. In this work, 1600 different size TLDIs having 200 numbers of each type such as BS, EB, LB, LM, SLS, TMV, TYLCV and HL are taken from the source [12].The Orange workflow setup diagram is mentioned in Fig. 2. The sample representation of BS, EB, LB, LM, SLS, TMV, TYLCV and HL types are mentioned in Fig. 3 to Fig. 10 respectively. The TLDIs are processed using several ML based methods such as LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC and the proposed method when the NF value is recognized as 5. The performance of all the methods is accessed using performance parameters such as CA, F1, PR and RC which are described as follows.

- **CA:** It refers to the rate of correct classification. It is represented in equation (8) by considering the number of corrected predictions (CP) and the total number of input samples (IS).

  CA= CP / IS ---------- (8)

- **F1:** It is the harmonic mean of PR and RC. It is mentioned in equation (9).

  F1= 2* (PR * RC) / (PR + RC) ----------- (9)

- **PR:** It is represented in equation (10) by considering the true positives (TP) and false positives (FP).

  PR= TP / (TP+FP) ------------- (10)

- **RC:** It is represented in equation (11) by considering the TP and false negatives (FN).

  RC= TP / (TP+FN) --------- (11)

The classification results are better when the CA,F1, PR and RC values are higher. Table 2 describes the CA, F1, PR and RC computed values (in units) of the proposed method and other methods. Fig. 11 to Fig. 14 represents the comparison results of all methods graphically in terms of CA, F1, PR and RC respectively. This work is also focused on CM representation. The CM represents the actual and predicted values by showing the number of instances for each of these methods. The CM representation for LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC and the proposed method are mentioned in Fig. 15 to Fig. 24 respectively. In the representation of CM (Fig. 15 to Fig. 24), the TMV, TYLCV types are displayed as (Tomato Mosaic ...) and (Tomato Yellow ...) by the Orange 3.26.0. In CM, the actual values are represented using light blue color and the predicted values are represented using light pink color.

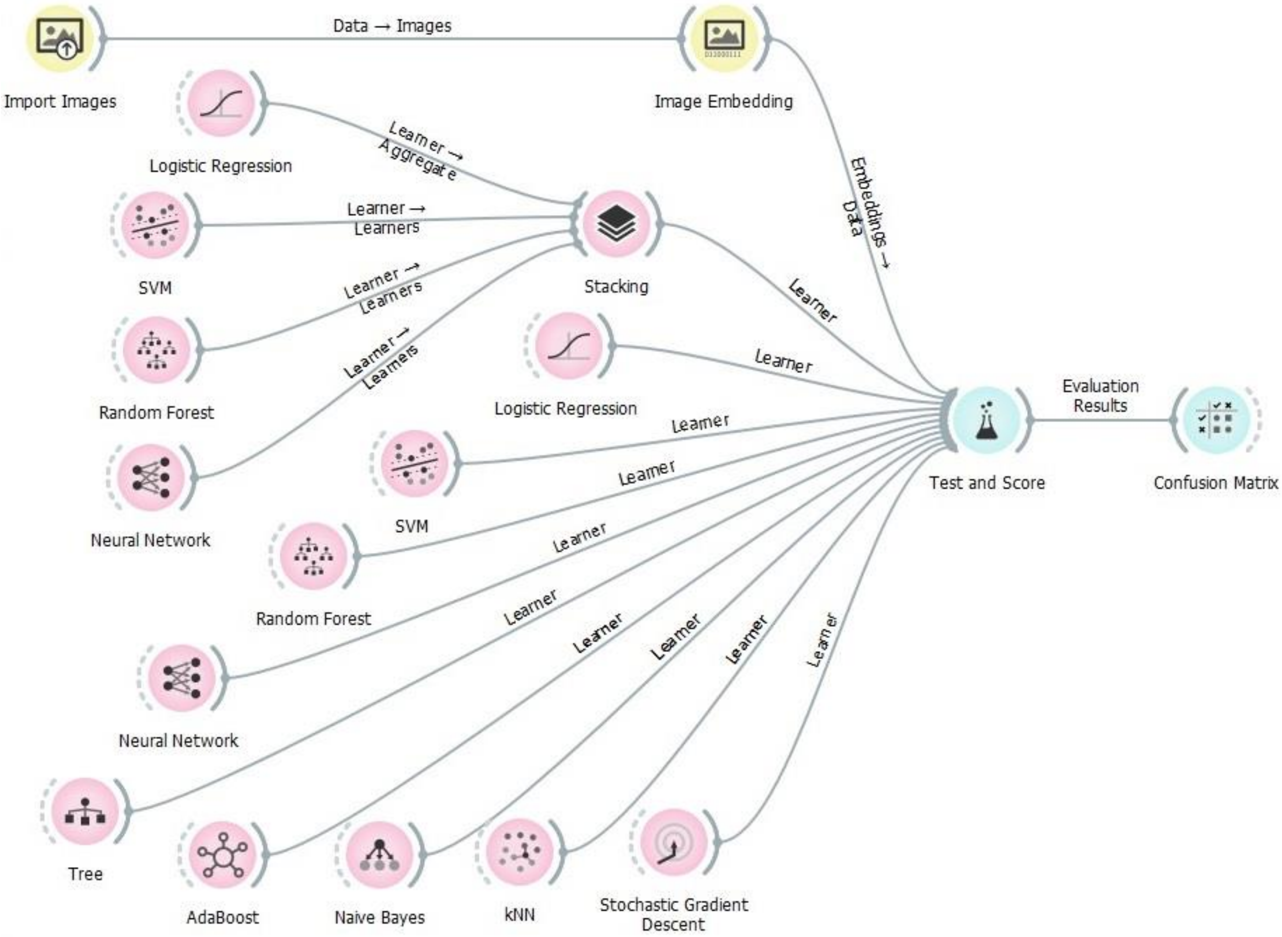


Fig. 2: Orange workflow setup diagram [33]

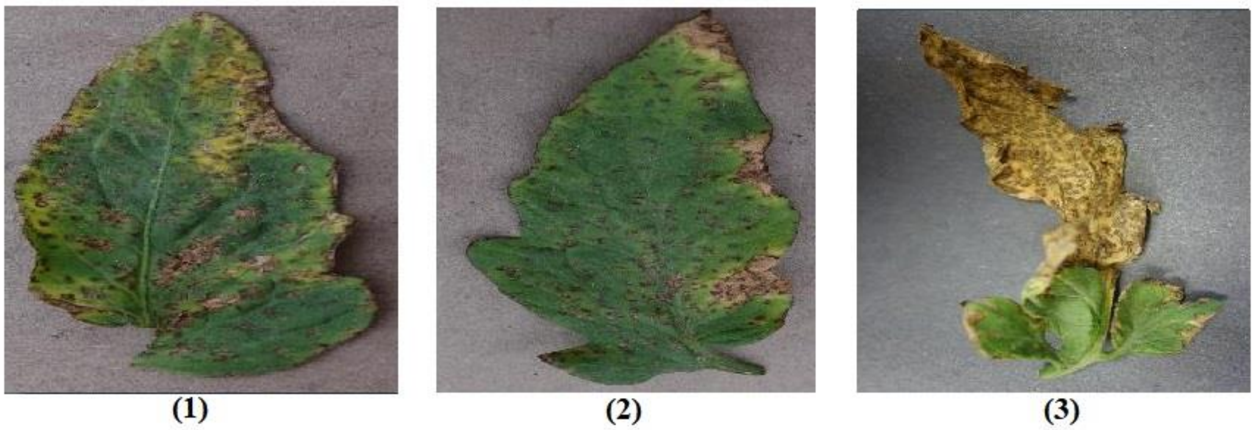


Fig. 3: Sample depiction of BS type [12]

(1) (2) (3)

Fig. 4: Sample depiction of EB type [12]

(1) (2) (3)

Fig. 5: Sample depiction of LB type [12]

(1) (2) (3)

Fig. 6: Sample depiction of LM type [12]

(1) (2) (3)

Fig. 7: Sample depiction of SLS type [12]

(1) (2) (3)

Fig. 8: Sample depiction of TMV type [12]

(1) (2) (3)

Fig. 9: Sample depiction of TYLCV type [12]

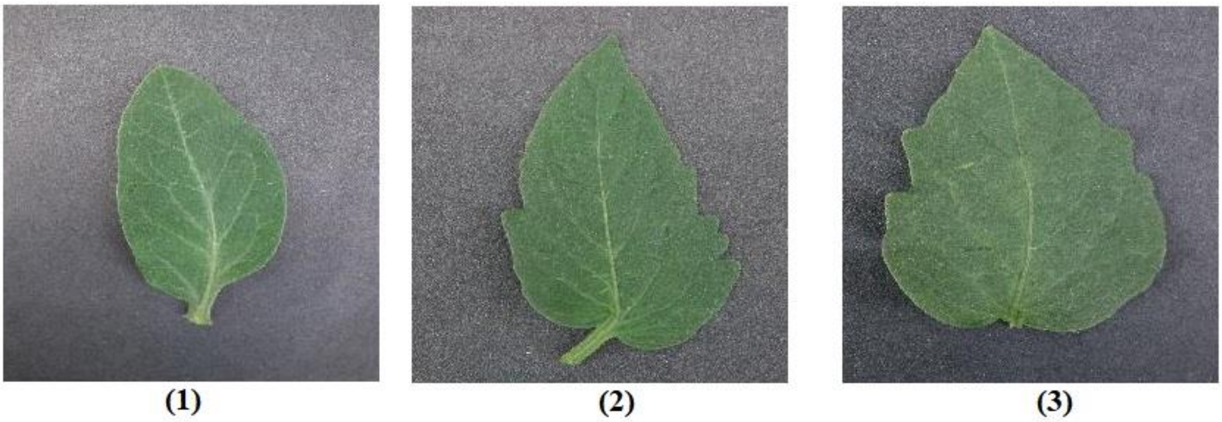


Fig. 10: Sample depiction of HL type [12]

Table 2: Comparison of the proposed method with other MI based methods [33]

Method	CA	F1	PR	RC
LRG	0.861	0.861	0.861	0.861
SVMN	0.843	0.843	0.843	0.843
RFS	0.738	0.736	0.737	0.738
NNT	0.863	0.862	0.862	0.863
DTR	0.501	0.501	0.501	0.501
ADB	0.504	0.503	0.503	0.504
NBY	0.621	0.625	0.647	0.621
KNNH	0.711	0.697	0.722	0.711
SGDC	0.840	0.839	0.839	0.840
Proposed Method	0.870	0.870	0.870	0.870

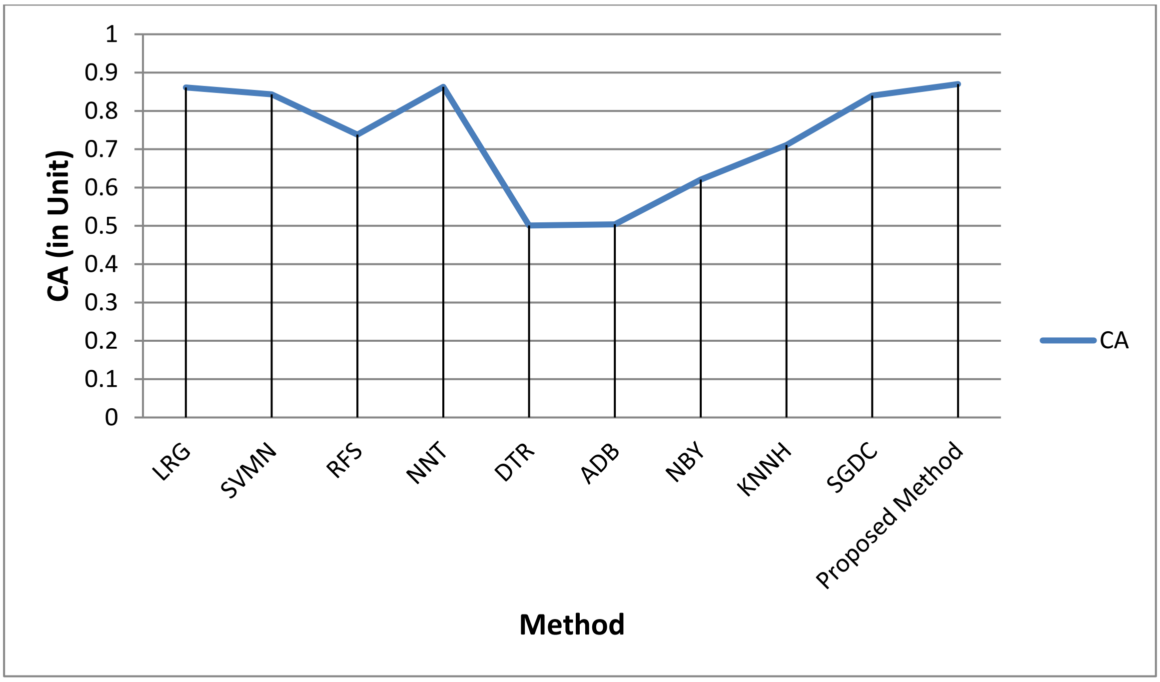


Fig. 11: Comparison results representation of all methods in terms of CA [33]

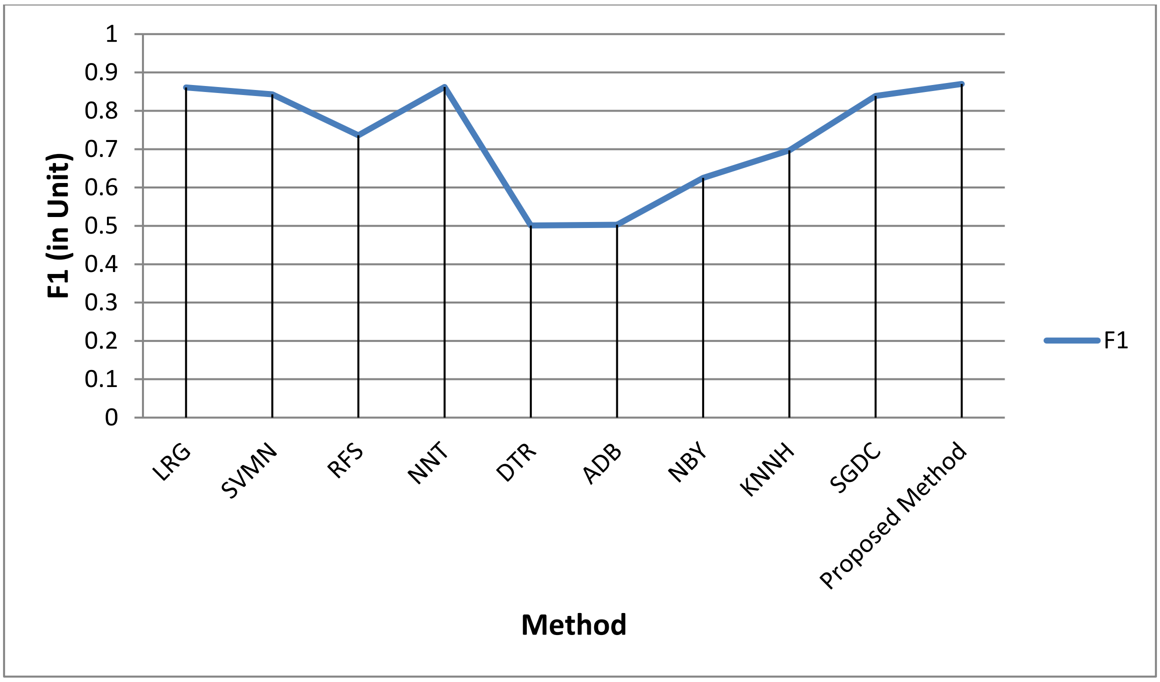


Fig. 12: Comparison results representation of all methods in terms of F1 [33]

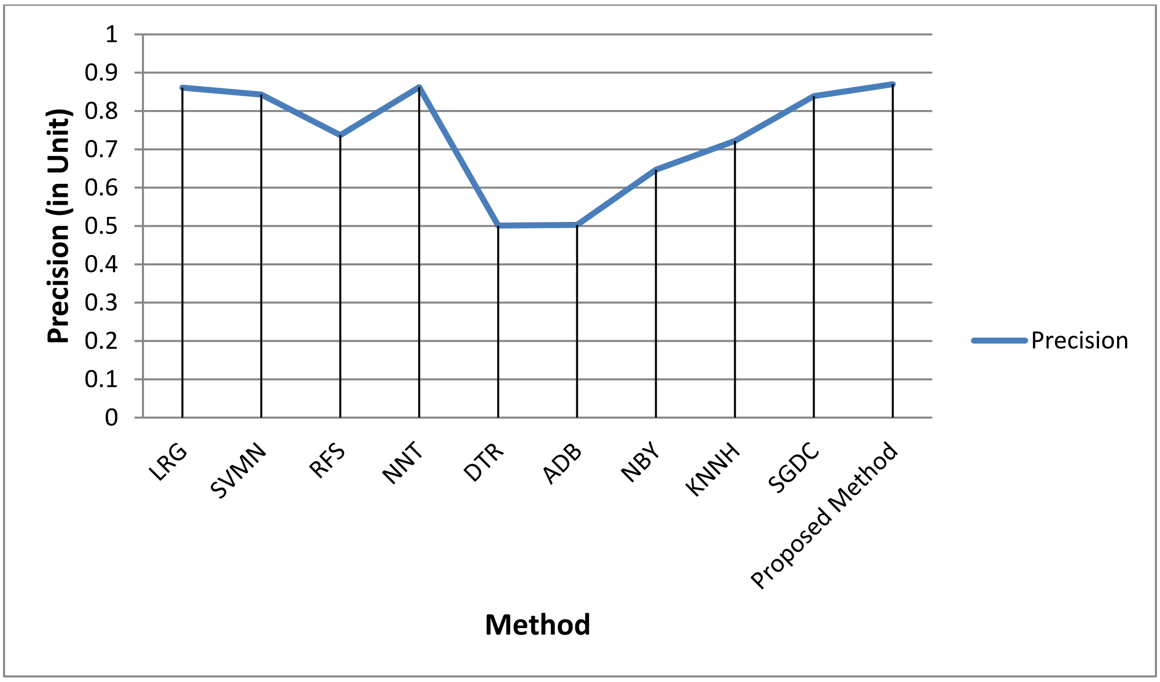


Fig. 13: Comparison results representation of all methods in terms of PR [33]

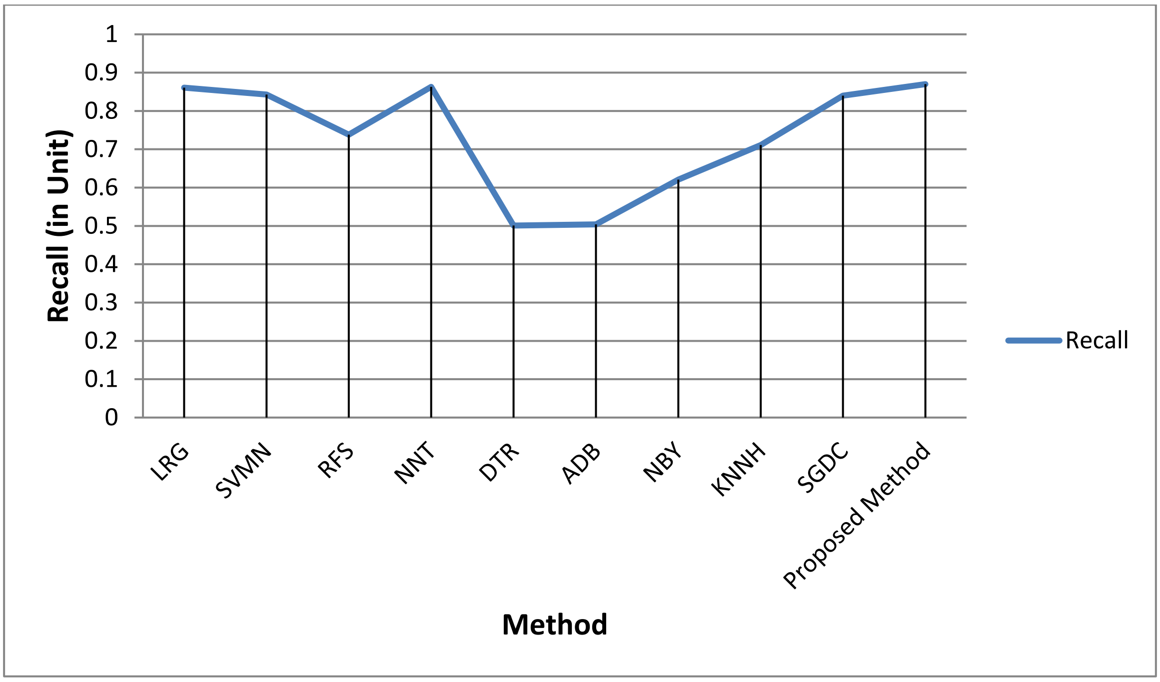


Fig. 14: Comparison results representation of all methods in terms of RC [33]

Predicted

Actual	Bacterial Spot	Early Blight	Healthy	Late Blight	Leaf Mold	Septoria Leaf Spot	Tomato Mosaic ...	Tomato Yellow ...	Σ
Bacterial Spot	172	12	0	2	1	8	0	5	200
Early Blight	8	150	0	22	4	8	2	6	200
Healthy	1	0	192	0	2	2	3	0	200
Late Blight	3	19	1	165	6	2	1	3	200
Leaf Mold	1	6	0	6	168	5	10	4	200
Septoria Leaf Spot	6	6	1	2	7	172	4	2	200
Tomato Mosaic ...	0	4	4	0	10	5	177	0	200
Tomato Yellow ...	7	5	0	3	4	0	0	181	200
Σ	198	202	198	200	202	202	197	201	1600

Fig. 15: CM of LRG [33]

Predicted

Actual	Bacterial Spot	Early Blight	Healthy	Late Blight	Leaf Mold	Septoria Leaf Spot	Tomato Mosaic ...	Tomato Yellow ...	Σ
Bacterial Spot	180	8	1	4	1	5	0	1	200
Early Blight	15	147	2	14	4	10	4	4	200
Healthy	0	1	193	0	0	3	3	0	200
Late Blight	6	22	0	155	13	4	0	0	200
Leaf Mold	1	8	0	7	169	6	8	1	200
Septoria Leaf Spot	11	15	3	9	14	142	5	1	200
Tomato Mosaic ...	0	4	0	0	11	2	183	0	200
Tomato Yellow ...	12	2	0	2	3	0	1	180	200
Σ	225	207	199	191	215	172	204	187	1600

Fig. 16: CM of SVMN [33]

Predicted

Actual	Bacterial Spot	Early Blight	Healthy	Late Blight	Leaf Mold	Septoria Leaf Spot	Tomato Mosaic ...	Tomato Yellow ...	Σ
Bacterial Spot	146	14	3	5	6	14	2	10	200
Early Blight	23	119	1	15	10	16	6	10	200
Healthy	1	1	187	0	0	6	4	1	200
Late Blight	6	29	5	122	21	10	3	4	200
Leaf Mold	3	15	3	5	145	9	13	7	200
Septoria Leaf Spot	15	23	7	11	14	117	10	3	200
Tomato Mosaic ...	1	0	2	0	15	7	174	1	200
Tomato Yellow ...	12	9	0	4	3	1	1	170	200
Σ	207	210	208	162	214	180	213	206	1600

Fig. 17: CM of RFS [33]

Actual \ Predicted	Bacterial Spot	Early Blight	Healthy	Late Blight	Leaf Mold	Septoria Leaf Spot	Tomato Mosaic ...	Tomato Yellow ...	Σ
Bacterial Spot	178	5	0	3	2	6	0	6	200
Early Blight	11	152	3	10	4	10	3	7	200
Healthy	0	0	194	0	2	1	3	0	200
Late Blight	1	17	3	167	8	3	0	1	200
Leaf Mold	0	8	2	4	166	5	11	4	200
Septoria Leaf Spot	7	7	1	7	13	156	6	3	200
Tomato Mosaic ...	0	4	3	0	8	3	182	0	200
Tomato Yellow ...	8	2	1	0	2	0	1	186	200
Σ	205	195	207	191	205	184	206	207	1600

Fig. 18: CM of NNT [33]

Actual \ Predicted	Bacterial Spot	Early Blight	Healthy	Late Blight	Leaf Mold	Septoria Leaf Spot	Tomato Mosaic ...	Tomato Yellow ...	Σ
Bacterial Spot	108	15	15	13	7	25	6	11	200
Early Blight	30	64	6	28	26	24	10	12	200
Healthy	12	5	148	5	9	8	13	0	200
Late Blight	15	42	2	80	23	15	10	13	200
Leaf Mold	8	18	6	24	90	27	22	5	200
Septoria Leaf Spot	29	19	20	21	16	72	20	3	200
Tomato Mosaic ...	9	17	18	8	19	22	102	5	200
Tomato Yellow ...	16	10	0	23	6	5	2	138	200
Σ	227	190	215	202	196	198	185	187	1600

Fig. 19: CM of DTR [33]

Predicted

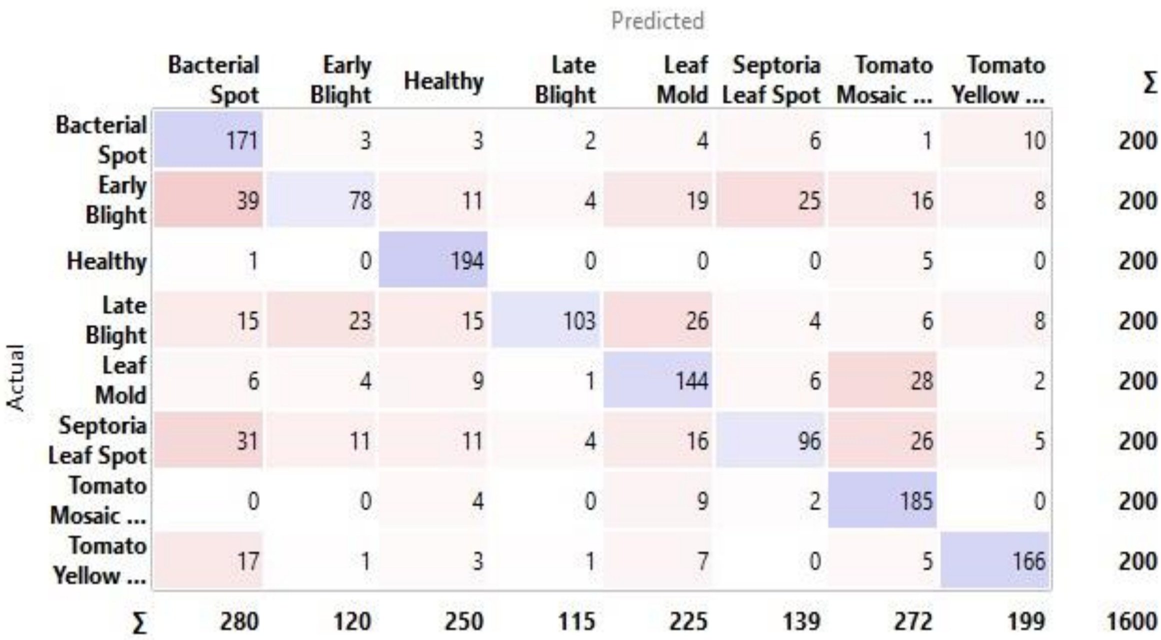
Actual	Bacterial Spot	Early Blight	Healthy	Late Blight	Leaf Mold	Septoria Leaf Spot	Tomato Mosaic ...	Tomato Yellow ...	Σ
Bacterial Spot	91	26	12	14	16	22	6	13	200
Early Blight	26	69	6	29	12	28	15	15	200
Healthy	13	4	146	4	9	12	10	2	200
Late Blight	22	34	7	77	23	19	5	13	200
Leaf Mold	10	16	4	16	91	17	33	13	200
Septoria Leaf Spot	21	22	9	16	19	88	18	7	200
Tomato Mosaic ...	6	8	11	5	27	18	118	7	200
Tomato Yellow ...	21	14	5	18	8	5	3	126	200
Σ	210	193	200	179	205	209	208	196	1600

Fig. 20: CM of ADB [33]

Predicted

Actual	Bacterial Spot	Early Blight	Healthy	Late Blight	Leaf Mold	Septoria Leaf Spot	Tomato Mosaic ...	Tomato Yellow ...	Σ
Bacterial Spot	129	11	10	3	3	24	1	19	200
Early Blight	22	104	8	6	16	25	6	13	200
Healthy	1	19	159	0	2	10	6	3	200
Late Blight	12	60	4	85	16	14	1	8	200
Leaf Mold	8	36	3	2	119	13	10	9	200
Septoria Leaf Spot	19	37	8	9	10	97	9	11	200
Tomato Mosaic ...	5	13	5	0	15	15	143	4	200
Tomato Yellow ...	14	16	0	4	7	0	2	157	200
Σ	210	296	197	109	188	198	178	224	1600

Fig. 21: CM of NBY [33]



Actual \ Predicted	Bacterial Spot	Early Blight	Healthy	Late Blight	Leaf Mold	Septoria Leaf Spot	Tomato Mosaic ...	Tomato Yellow ...	Σ
Bacterial Spot	171	3	3	2	4	6	1	10	200
Early Blight	39	78	11	4	19	25	16	8	200
Healthy	1	0	194	0	0	0	5	0	200
Late Blight	15	23	15	103	26	4	6	8	200
Leaf Mold	6	4	9	1	144	6	28	2	200
Septoria Leaf Spot	31	11	11	4	16	96	26	5	200
Tomato Mosaic ...	0	0	4	0	9	2	185	0	200
Tomato Yellow ...	17	1	3	1	7	0	5	166	200
Σ	280	120	250	115	225	139	272	199	1600

Fig. 22: CM of KNNH [33]

Actual \ Predicted	Bacterial Spot	Early Blight	Healthy	Late Blight	Leaf Mold	Septoria Leaf Spot	Tomato Mosaic ...	Tomato Yellow ...	Σ
Bacterial Spot	157	11	1	5	1	12	3	10	200
Early Blight	10	146	4	16	3	5	6	10	200
Healthy	0	2	189	1	0	2	6	0	200
Late Blight	1	21	8	156	10	3	0	1	200
Leaf Mold	1	4	2	7	165	9	10	2	200
Septoria Leaf Spot	11	4	1	4	11	163	5	1	200
Tomato Mosaic ...	0	2	0	0	5	4	189	0	200
Tomato Yellow ...	9	4	1	1	4	0	2	179	200
Σ	189	194	206	190	199	198	221	203	1600

Fig. 23: CM of SGDC [33]

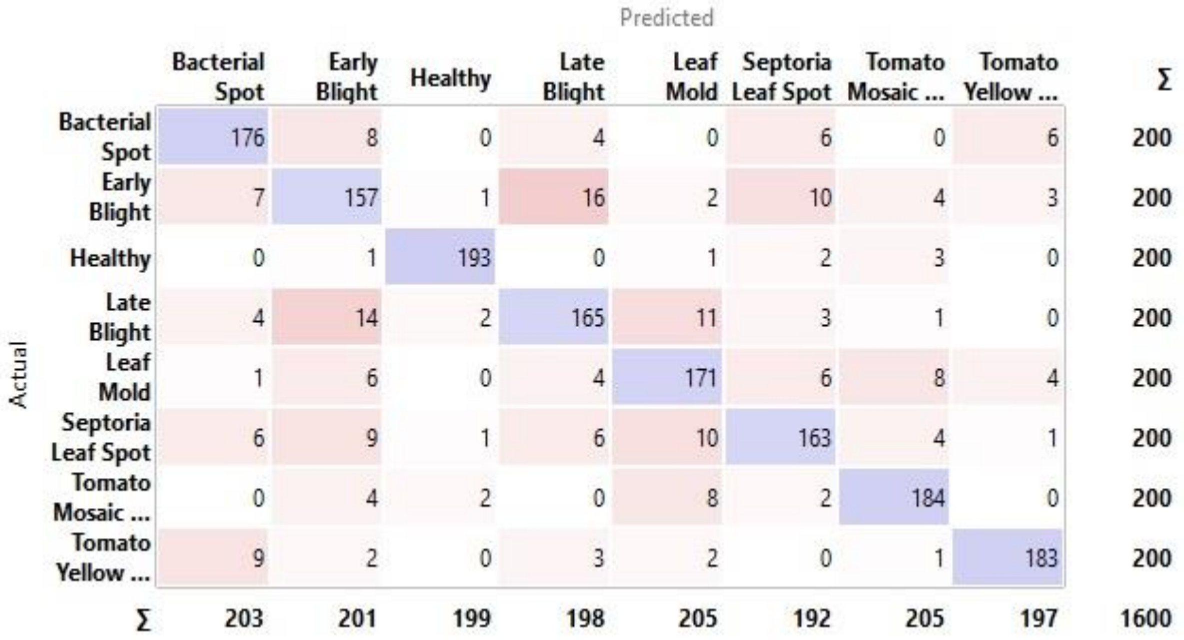


Fig. 24: CM of Proposed Method [33]

From Table 2 and Fig. 11 to Fig. 24, it is observed that LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC and proposed method are able to provide 0.861, 0.843, 0.738, 0.863, 0.501, 0.504, 0.621, 0.711, 0.840 and 0.870 CA values (in unit) respectively. LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC and proposed method are able to provide 0.861, 0.843, 0.736, 0.862, 0.501, 0.503, 0.625, 0.697, 0.839 and 0.870 F1 values (in unit) respectively. LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC and proposed method are able to provide 0.861, 0.843, 0.737, 0.862, 0.501, 0.503, 0.647, 0.722, 0.839 and 0.870 PR values (in unit) respectively. LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC and proposed method are able to provide 0.861, 0.843, 0.738, 0.863, 0.501, 0.504, 0.621, 0.711, 0.840 and 0.870 RC values (in unit) respectively. So, the proposed method is capable of providing better classification results as compared to LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC methods and it is having 0.870 CA, F1, PR and RC values in units. However, the DTR method is not capable of providing better categorization results than other methods and it is having 0.501 CA, F1, PR and RC values in units. The decreasing order of performance of these methods is proposed method, NNT, LRG, SVMN, SGDC, RFS, KNNH, NBY, ADB and DTR.

8. RECOMMENDATIONS :

This work can be extended to develop improved methods to carry out the classification of TLDIs and other types of images in terms of higher CA, F1, PR and RC. This work can also be extended to process and analyze the classification results of TLDIs and other types of images by applying DL based methods.

9. CONCLUSION :

This paper proposed a MI based approach for the classification of TLDIs into BS, EB, LB, LM, SLS, TMV, TYLCV and HL types. The proposed approach is focused on the stacking of LRG, SVMN, RFS and NNT methods to carry out the classification of TLDIs into such categories. From the results, it is found that the proposed method is capable of providing better classification results in terms of CA, F1, PR and RC as compared to other ML based methods such as LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH and SGDC. The CA, F1, PR and RC values in units using the proposed method are computed as 0.870 which are higher as compared to other ML based methods. However, in this scenario, the DTR method is unable to perform better than other methods. The CA, F1, PR and RC values in units using the DTR method are computed as 0.501 which are lower than other methods in this scenario. This approach can help the researchers to carry out the image classification mechanism in a better way for several applications.

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