Classification and Analysis of Weather Images Using Machine Intelligent Based Approach

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ABSTRACT

Purpose: *Weather information plays a crucial role in the human society. It helps to lower the weather related losses and enhance the societal benefits such as the protection of life, health, property, etc., It is very much essential for the proper classification of weather images (WIs) into several categories such as dew, fogsmog, frost, glaze, hail, lightning, rain, rainbow, rime, sandstorm, snow, etc. so that appropriate information can be provided to the people as well as organizations for further analysis.*

Approach: *In this work, a machine intelligent (MI) based approach is proposed for the classification of WIs into the dew, fogsmog, frost, glaze, hail, lightning, rain, rainbow, rime, sandstorm, and snow 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, 1604 WIs having 149, 141, 146, 150, 144, 146, 142, 147, 149, 147, 143 numbers of dew, fogsmog, frost, glaze, hail, lightning, rain, rainbow, rime, sandstorm, and snow types respectively 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 WIs into several types such as dew, fogsmog, frost, glaze, hail, lightning, rain, rainbow, rime, sandstorm, and snow type. 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: Weather Image, Machine Learning, Classification Accuracy, F1, Precision, Machine intelligent

1. INTRODUCTION :

Weather information [1-16] is an important concern throughout the globe. It has the capability of lowering the weather related losses and enhancing societal benefits such as the protection of life, health, property, etc., if the weather information is shared among the entire human society at the right time properly. The proper classification of weather images (WIs) into several categories such as dew, fogsmog, frost, glaze, hail, lightning, rain, rainbow, rime, sandstorm, snow, etc. is an essential concern

so that appropriate information can be provided to the people and for further analysis.
Machine Learning (ML) [17-22] can be considered as a solution for the classification of WIs into several categories. The ML based methods can be broadly classified as supervised and unsupervised. The supervised ML [18, 19, 22] 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 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 WIs into several categories such as dew, fogsmog, frost, glaze, hail, lightning, rain, rainbow, rime, sandstorm, and snow [23] in a better way. Here, a MI [1-22] based approach is proposed to carry out the classification of WIs 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 WIs into dew, fogsmog, frost, glaze, hail, lightning, rain, rainbow, rime, sandstorm, and snow 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 of 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, conclusion and recommendation respectively.

2. RELATED WORKS :

Many research works have been carried out related to the WIs processing and analysis [1-16]. Some of the works are described as follows. Khan et al. [1] emphasized on the detection of multilevel weather by the help of ML mechanism by focusing on histogram of oriented gradient as well as local binary pattern based features. Osipov et al. [2] focused on the recognition and classification of images from video recorders by the help of deep learning (DL) mechanism in difficult weather conditions. Xiao et al. [3] focused on the deep convolutional neural network (CNN) for the classification of weather phenomenon. Dash et al. [4] emphasized on ML mechanism for the classification of crop on the basis of macronutrients and weather data. Schultz et al. [5] focused on ML mechanism to classify and understand the weather impact on airport performance. Purwandari et al. [6] emphasized on ML mechanism for multi-class weather forecasting from twitter. Togacar et al. [7] emphasized on spiking NN of DL mechanisms for the detection of WIs. Chandrayan et al. [8] emphasized on ML mechanism to predict the atmospheric weather fluctuation. Tao et al. [9] focused on ML and extreme gradient boosting feature selection mechanism for the prediction of weather relative humidity. Siddique et al. [10] focused on survey of uncertainty quantification in ML to predict the space weather. Jayasingh et al. [11] focused on ML based approach for the prediction of smart weather. The review of some articles related to WIs categorization is mentioned in Table 1.

Table 1: Review of some articles related to WIs classification Source: [1-8]

S. No.	Field of Research	Focus	Outcome	Reference

1	Image Processing	ML	Recognition of multilevel weather	Khan et al. (2021). [1]
2	Image Processing	DL	Recognition and categorization of WIs	Osipov et al. (2022). [2]
3	Image Processing	Deep CNN	Categorization of weather phenomenon	Xiao et al. (2021). [3]
4	Image Processing	ML	Categorization of crop on the basis of macronutrients and weather data	Dash et al. (2021). [4]
5	Image Processing	ML	Classify and understand the weather impact on airport performance	Schultz et al. (2021). [5]
6	Image Processing	ML	Multi-class weather forecasting from twitter	Purwandari et al. (2021). [6]
7	Image Processing	DL	Recognition of WIs	Togacar et al. (2021). [7]
8	Image Processing	ML	Prediction of atmospheric weather fluctuation	Chandrayan et al. (2022). [8]

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 WIs in all scenarios. A method which is working well in a scenario may not perform well in other scenarios. So, accurate classification of WIs 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 WIs 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. OBJECTIVE :

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 WIs into dew, fogsmog, frost, glaze, hail, lightning, rain, rainbow, rime, sandstorm and snow 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 [1-22] based approach is proposed for the classification of WIs [23] into dew, fogsmog, frost, glaze, hail, lightning, rain, rainbow, rime, sandstorm, and snow 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.
At first, the WIs are imported to Orange 3.26.0 [24] through the Import Images option. Afterwards, the image embedding (IED) process is accomplished on the WIs 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.

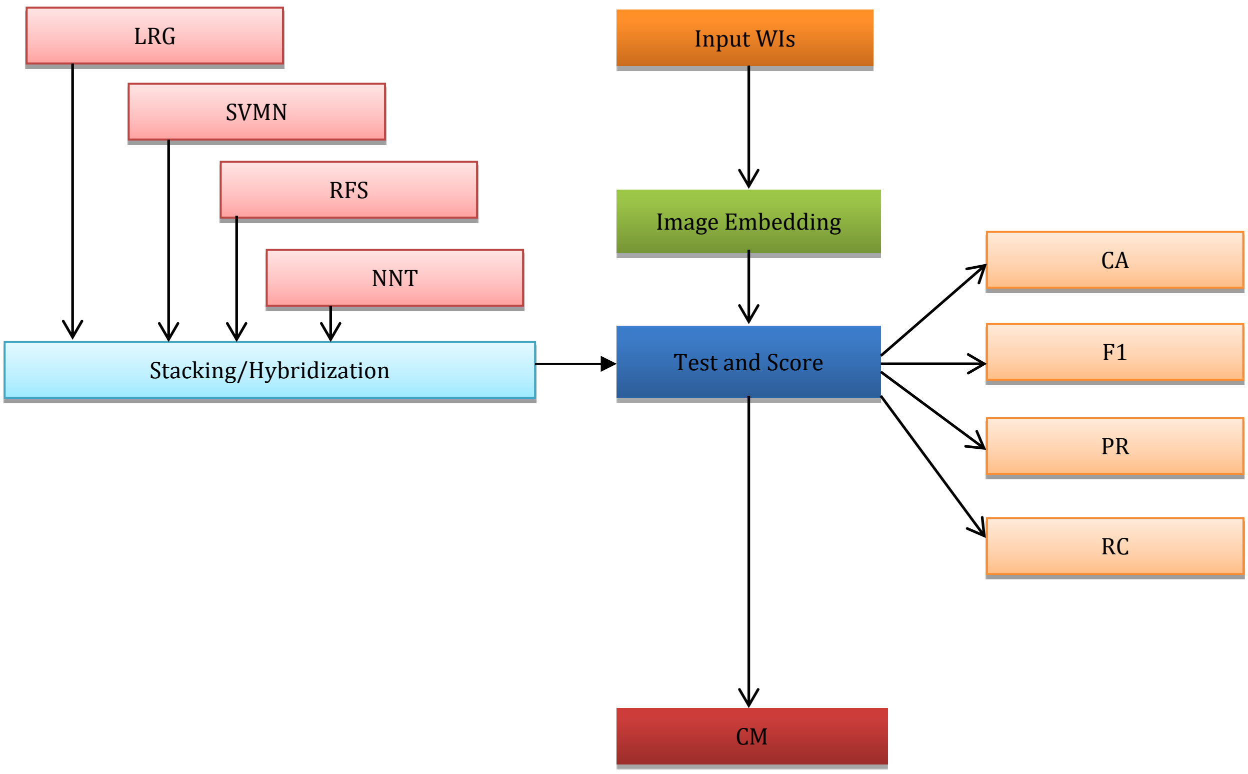


Fig. 1: Methodology

Source: [24]

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 ------ (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 ------- (2)

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

NBTR=50 (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 WIs into Dew, Fogsmog, Frost, Glaze, Hail, Lightning, Rain, Rainbow, Rime, Sandstorm and Snow types is described in Algorithm 1.

Algorithm 1: WI Classification
Input: WIs
Output: Dew, Fogsmog, Frost, Glaze, Hail, Lightning, Rain, Rainbow, Rime, Sandstorm and Snow Type

Step 1: Start
Step 2: Input WIs
Step 3: IED (WIs)
Step 4: Test and Score (LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC, Proposed Method)
Step 5: Compute CA, F1, Precision, Recall 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 [24]. In this work, 1604 different size WIs having 149, 141, 146, 150, 144, 146, 142, 147, 149, 147, 143 numbers of dew, fogsmog, frost, glaze, hail, lightning, rain, rainbow, rime, sandstorm, and snow types respectively taken from the source [23].The Orange workflow setup diagram is mentioned in Fig. 2. The sample representation of dew, fogsmog, frost, glaze, hail, lightning, rain, rainbow, rime, sandstorm, and snow types are mentioned in Fig. 3 to Fig. 13 respectively. The WIs 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 of 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. 13 to Fig. 17 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. 18 to Fig. 27 respectively. In CM, the actual values are represented using light blue color and the predicted values are represented using light pink color.

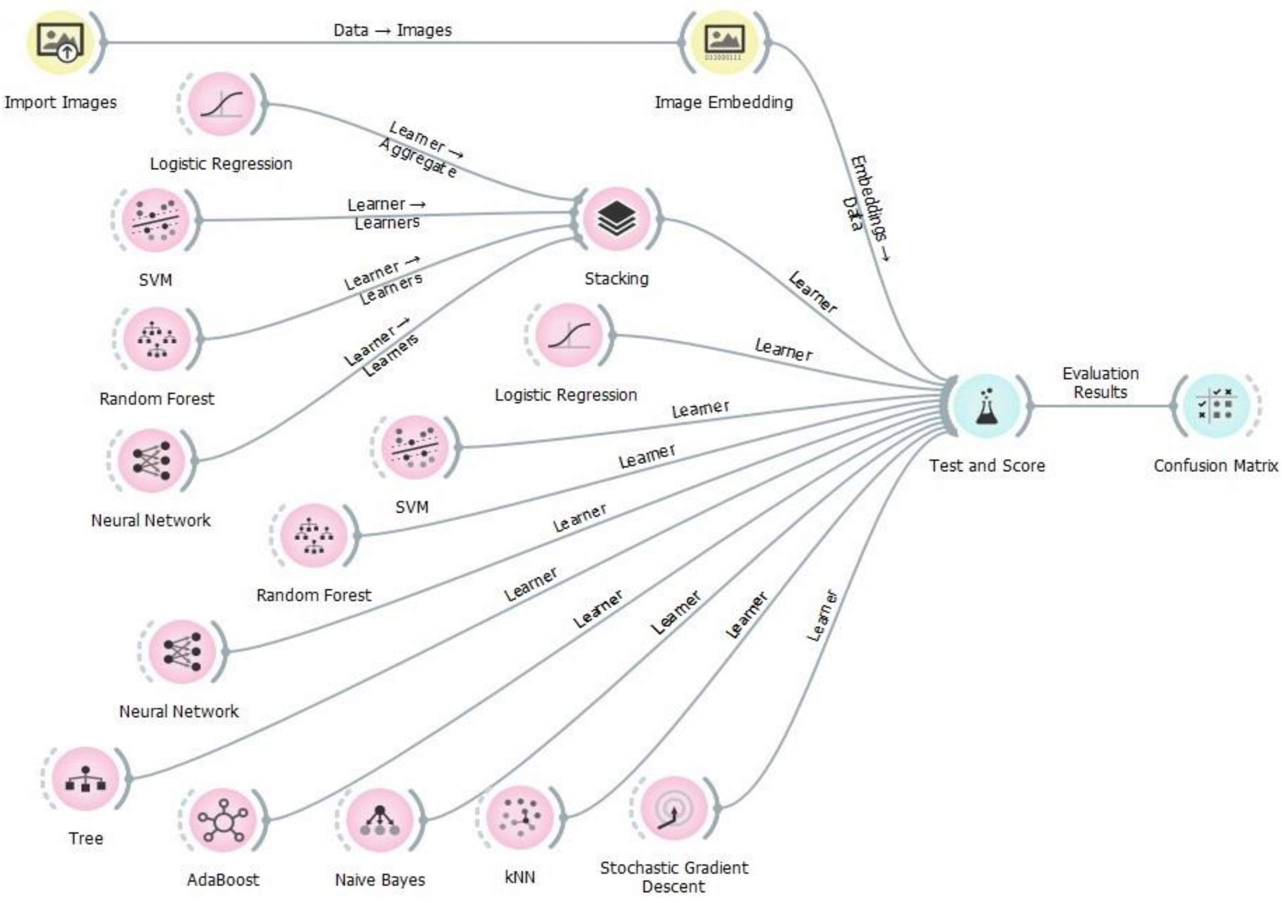


Fig. 2: Orange workflow setup diagram [24]

Fig. 3: Sample depiction of Dew type [23]

(1) (2) (3)

Fig. 4: Sample depiction of Fogsmog type [23]

(1) (2) (3)

Fig. 5: Sample depiction of Frost type [23]

(1) (2) (3)

Fig. 6: Sample depiction of Glaze type [23]

(1) (2) (3)

Fig. 7: Sample depiction of Hail type [23]

(1) (2) (3)

Fig. 8: Sample depiction of Lightning type [23]

(1) (2) (3)

Fig. 9: Sample depiction of Rain type [23]

(1) (2) (3)

Fig. 10: Sample depiction of Rainbow type [23]

(1) (2) (3)

Fig. 11: Sample depiction of Rime type [23]

(1) (2) (3)

Fig. 12: Sample depiction of Sandstorm type [23]

(1) (2) (3)

Fig. 13: Sample depiction of Snow type [23]

Table 2: Comparison of proposed method with other MI based methods [24]

Method	CA	F1	PR	RC
LRG	0.803	0.804	0.805	0.803
SVMN	0.794	0.794	0.795	0.794
RFS	0.736	0.731	0.731	0.736
NNT	0.822	0.822	0.823	0.822
DTR	0.562	0.562	0.563	0.562
ADB	0.541	0.540	0.540	0.541
NBY	0.645	0.638	0.644	0.645
KNNH	0.746	0.740	0.747	0.746
SGDC	0.787	0.783	0.783	0.787
Proposed Method	0.828	0.828	0.828	0.828

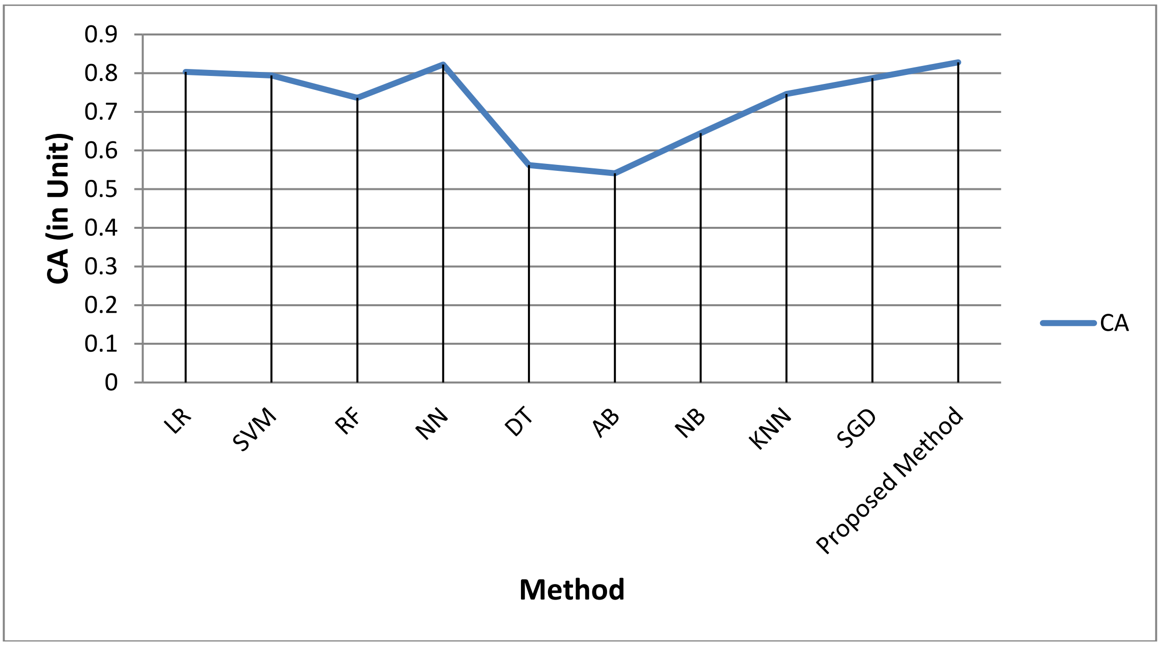


Fig. 14: Comparison results representation of all methods in terms of CA [24]

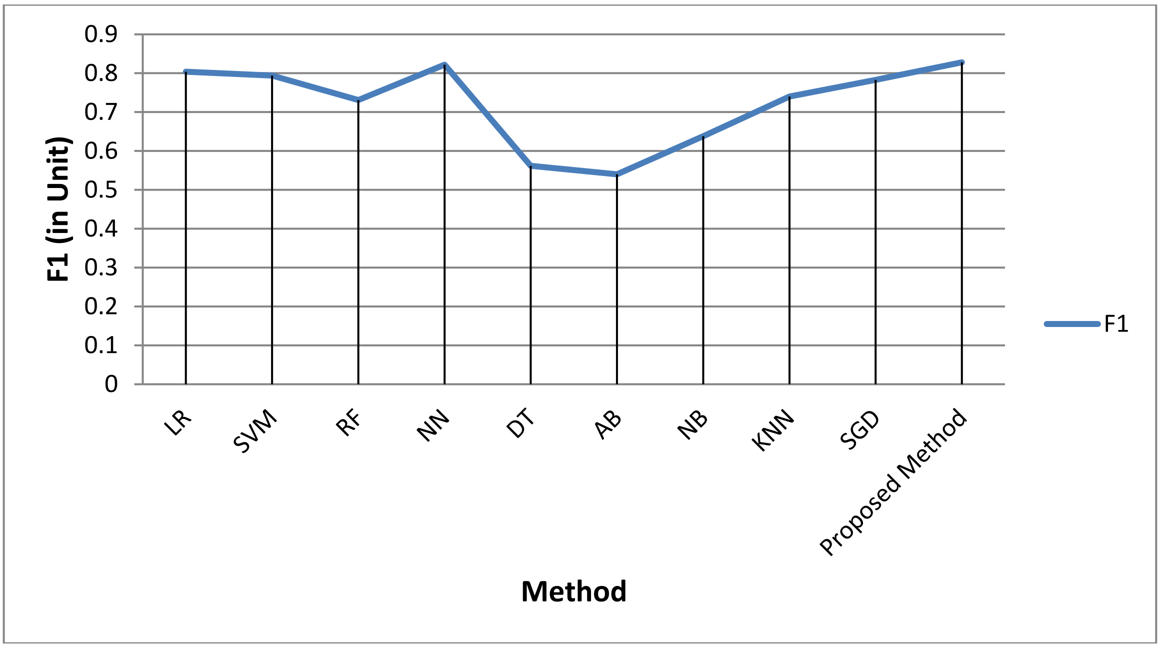


Fig. 15: Comparison results representation of all methods in terms of F1 [24]

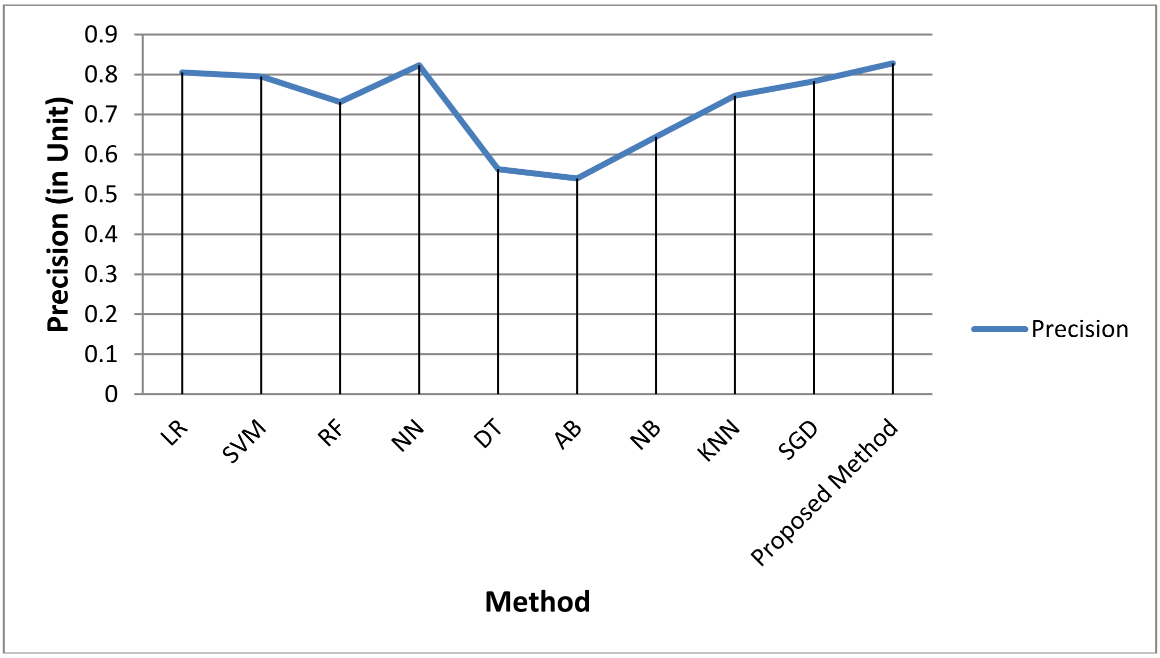


Fig. 16: Comparison results representation of all methods in terms of PR [24]

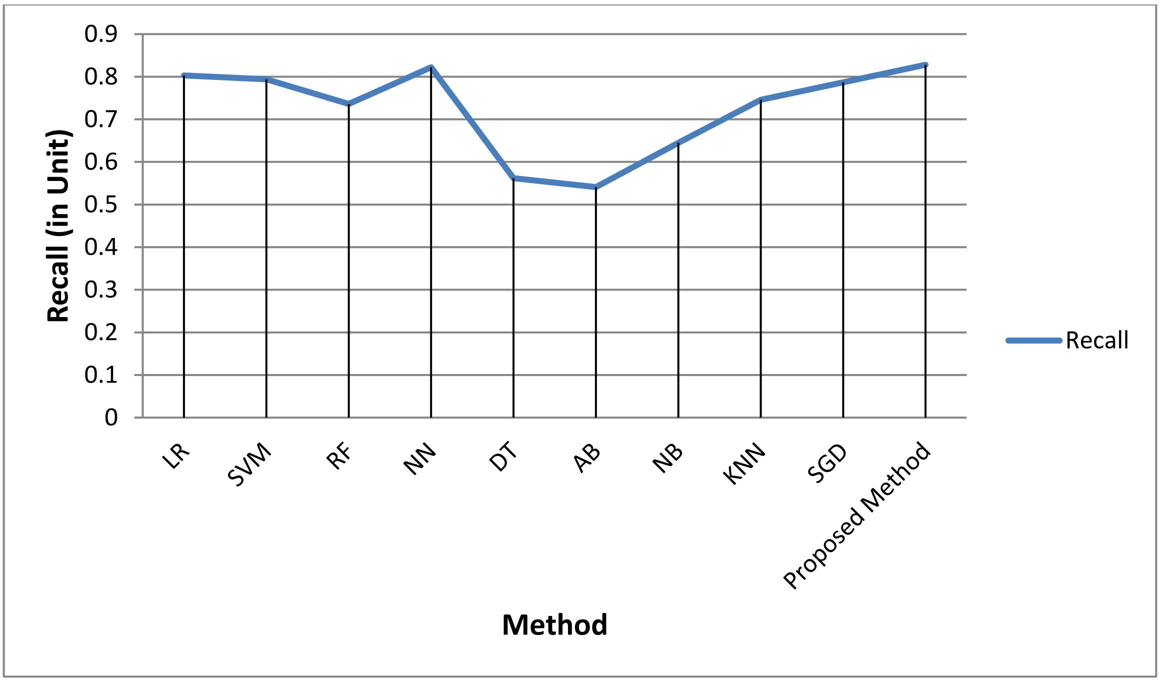


Fig. 17: Comparison results representation of all methods in terms of RC [24]

Predicted

Actual	Dew	Fogsmog	Frost	Glaze	Hail	Lightning	Rain	Rainbow	Rime	Sandstorm	Snow	Σ
Dew	132	0	5	7	1	1	1	2	0	0	0	149
Fogsmog	0	116	0	1	0	2	2	2	0	11	7	141
Frost	4	0	106	17	5	0	1	1	5	1	6	146
Glaze	2	0	20	93	1	1	1	0	12	0	20	150
Hail	4	0	5	1	125	0	6	0	1	0	2	144
Lightning	1	1	1	0	0	135	0	2	0	5	1	146
Rain	2	3	1	2	5	0	112	1	0	2	14	142
Rainbow	2	1	1	0	1	2	3	133	0	3	1	147
Rime	0	0	3	12	1	1	1	0	120	1	10	149
Sandstorm	0	12	0	0	0	1	2	1	0	128	3	147
Snow	1	2	5	15	2	0	13	0	14	3	88	143
Σ	148	135	147	148	141	143	142	142	152	154	152	1604

Fig. 18: CM of LRG [24]

Predicted

Actual	Dew	Fogsmog	Frost	Glaze	Hail	Lightning	Rain	Rainbow	Rime	Sandstorm	Snow	Σ
Dew	137	0	4	6	0	1	0	0	0	0	1	149
Fogsmog	0	123	0	0	0	1	1	2	0	12	2	141
Frost	4	0	93	28	5	0	0	0	10	1	5	146
Glaze	6	1	25	92	3	0	0	0	14	0	9	150
Hail	2	0	8	0	126	0	2	0	1	0	5	144
Lightning	0	2	1	1	0	133	0	5	0	3	1	146
Rain	1	5	1	2	5	1	111	0	0	4	12	142
Rainbow	1	0	1	1	0	2	1	133	0	7	1	147
Rime	0	0	2	15	1	0	0	0	118	0	13	149
Sandstorm	0	14	0	0	0	0	2	3	0	125	3	147
Snow	0	6	7	12	1	1	16	0	16	2	82	143
Σ	151	151	142	157	141	139	133	143	159	154	134	1604

Fig. 19: CM of SVMN [24]

Predicted

Actual	Dew	Fogsmog	Frost	Glaze	Hail	Lightning	Rain	Rainbow	Rime	Sandstorm	Snow	Σ
Dew	132	0	5	5	3	1	2	1	0	0	0	149
Fogsmog	0	112	0	0	0	6	3	4	0	14	2	141
Frost	2	0	86	34	7	0	0	2	8	2	5	146
Glaze	11	1	21	83	4	1	1	1	17	1	9	150
Hail	3	1	17	0	109	0	3	1	2	1	7	144
Lightning	0	3	0	2	0	135	0	4	0	1	1	146
Rain	2	6	0	1	3	1	108	1	5	5	10	142
Rainbow	3	1	0	1	1	1	3	128	2	6	1	147
Rime	0	1	3	8	2	0	1	0	119	2	13	149
Sandstorm	0	17	0	0	0	1	1	5	4	115	4	147
Snow	0	8	3	14	5	1	30	0	24	5	53	143
Σ	153	150	135	148	134	147	152	147	181	152	105	1604

Fig. 20: CM of RFS [24]

Predicted

Actual	Dew	Fogsmog	Frost	Glaze	Hail	Lightning	Rain	Rainbow	Rime	Sandstorm	Snow	Σ
Dew	137	0	4	4	1	1	1	0	0	0	1	149
Fogsmog	0	129	0	0	0	1	1	0	0	9	1	141
Frost	5	0	106	17	5	1	2	0	5	0	5	146
Glaze	4	0	16	101	3	1	0	0	11	0	14	150
Hail	1	0	7	1	130	0	3	0	1	0	1	144
Lightning	0	2	1	0	0	137	0	1	0	4	1	146
Rain	2	4	1	2	3	0	113	1	1	2	13	142
Rainbow	1	0	0	0	0	4	2	133	0	6	1	147
Rime	0	0	2	17	0	0	2	0	119	0	9	149
Sandstorm	0	14	0	0	0	1	3	1	0	126	2	147
Snow	0	2	7	14	3	1	15	0	11	2	88	143
Σ	150	151	144	156	145	147	142	136	148	149	136	1604

Fig. 21: CM of NNT [24]

Predicted

Actual	Dew	Fogsmog	Frost	Glaze	Hail	Lightning	Rain	Rainbow	Rime	Sandstorm	Snow	Σ
Dew	111	0	9	14	3	4	4	2	0	1	1	149
Fogsmog	2	86	1	0	0	10	4	5	0	26	7	141
Frost	18	0	57	39	10	1	1	3	6	1	10	146
Glaze	5	3	35	55	10	2	7	4	14	1	14	150
Hail	2	1	19	6	91	1	8	3	7	0	6	144
Lightning	5	2	5	4	2	105	1	12	1	6	3	146
Rain	0	4	2	3	6	1	86	6	4	8	22	142
Rainbow	6	2	3	3	4	9	2	110	2	4	2	147
Rime	0	1	11	22	1	2	6	5	75	1	25	149
Sandstorm	5	22	2	1	3	6	8	10	1	82	7	147
Snow	2	9	8	14	7	2	26	2	22	8	43	143
Σ	156	130	152	161	137	143	153	162	132	138	140	1604

Fig. 22: CM of DTR [24]

Predicted

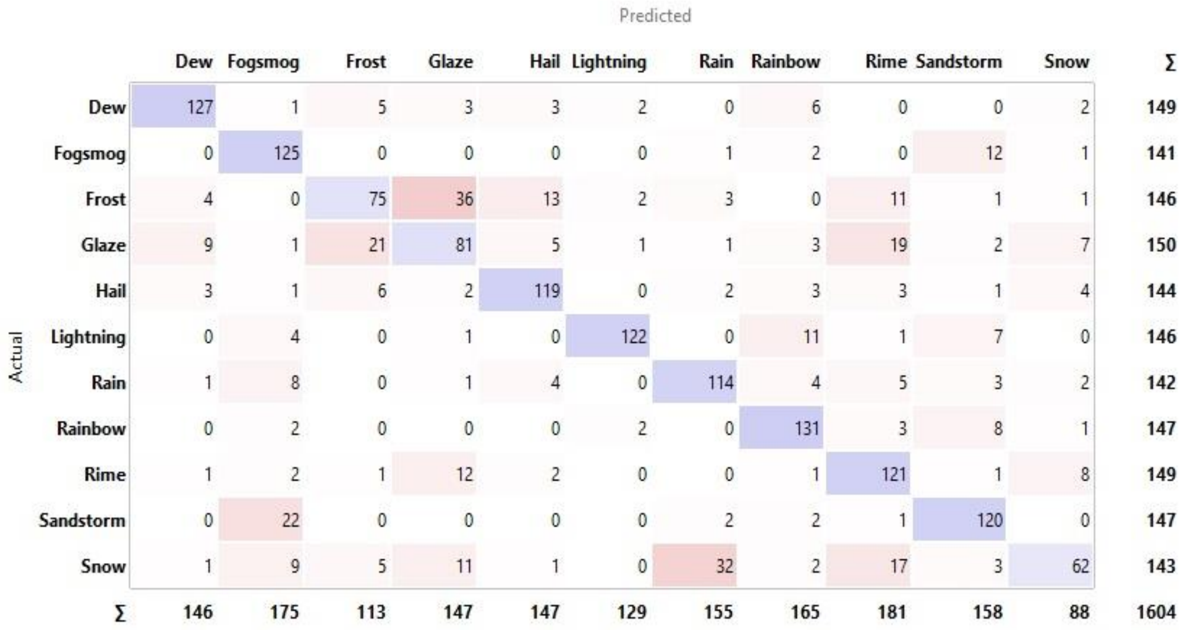
Actual	Dew	Fogsmog	Frost	Glaze	Hail	Lightning	Rain	Rainbow	Rime	Sandstorm	Snow	Σ
Dew	111	0	11	12	2	5	4	2	1	0	1	149
Fogsmog	2	80	2	2	2	6	7	4	2	29	5	141
Frost	10	0	69	27	12	7	0	3	9	2	7	146
Glaze	5	1	36	51	9	3	4	3	19	2	17	150
Hail	1	2	11	5	91	5	5	6	4	4	10	144
Lightning	2	8	2	4	3	106	1	10	2	4	4	146
Rain	1	8	1	11	5	2	69	4	3	10	28	142
Rainbow	3	9	3	2	5	9	4	98	6	5	3	147
Rime	0	3	9	13	5	2	6	8	79	5	19	149
Sandstorm	0	28	4	1	1	6	9	7	5	79	7	147
Snow	2	6	11	11	4	10	27	5	20	13	34	143
Σ	137	145	159	139	139	161	136	150	150	153	135	1604

Fig. 23: CM of ADB [24]

Predicted

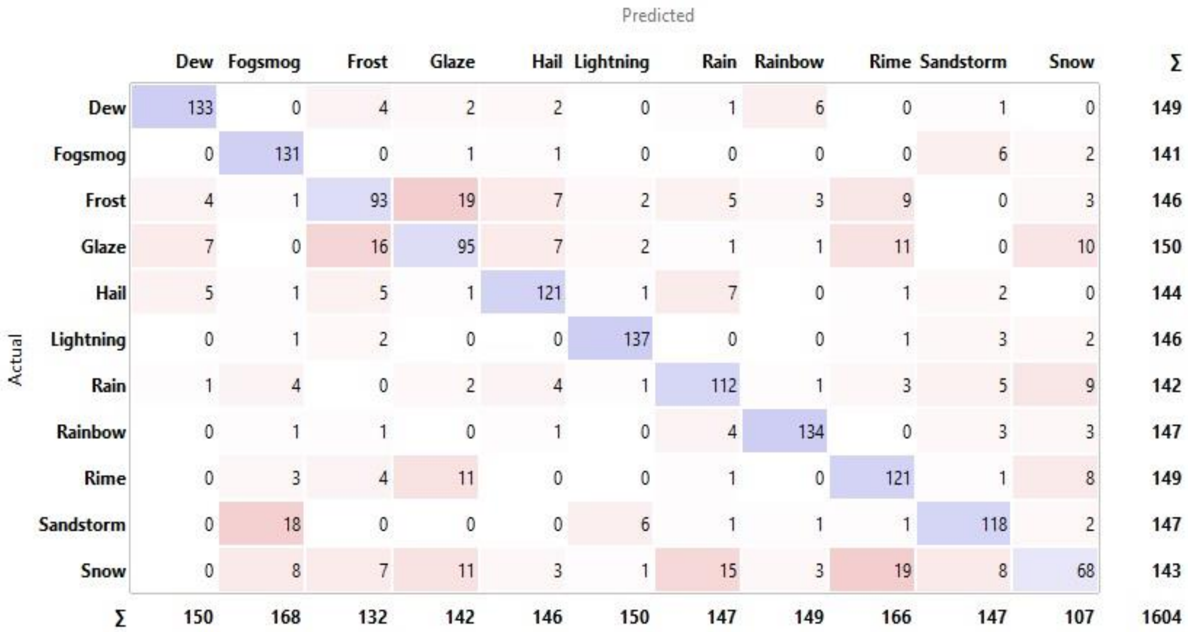
Actual	Dew	Fogsmog	Frost	Glaze	Hail	Lightning	Rain	Rainbow	Rime	Sandstorm	Snow	Σ
Dew	121	2	13	6	3	2	0	1	0	0	1	149
Fogsmog	0	106	0	0	0	2	5	3	0	23	2	141
Frost	12	0	78	24	8	1	0	0	17	1	5	146
Glaze	19	1	38	50	3	0	2	1	27	1	8	150
Hail	5	3	18	0	96	1	3	3	9	1	5	144
Lightning	2	5	3	5	0	115	1	11	0	3	1	146
Rain	2	1	2	1	2	0	116	0	6	8	4	142
Rainbow	5	3	1	1	0	2	2	116	5	7	5	147
Rime	0	0	4	10	3	0	0	0	107	3	22	149
Sandstorm	0	28	0	0	0	1	8	3	5	96	6	147
Snow	1	8	5	9	2	0	47	0	29	9	33	143
Σ	167	157	162	106	117	124	184	138	205	152	92	1604

Fig. 24: CM of NBY [24]



Actual \ Predicted	Dew	Fogsmog	Frost	Glaze	Hail	Lightning	Rain	Rainbow	Rime	Sandstorm	Snow	Σ
Dew	127	1	5	3	3	2	0	6	0	0	2	149
Fogsmog	0	125	0	0	0	0	1	2	0	12	1	141
Frost	4	0	75	36	13	2	3	0	11	1	1	146
Glaze	9	1	21	81	5	1	1	3	19	2	7	150
Hail	3	1	6	2	119	0	2	3	3	1	4	144
Lightning	0	4	0	1	0	122	0	11	1	7	0	146
Rain	1	8	0	1	4	0	114	4	5	3	2	142
Rainbow	0	2	0	0	0	2	0	131	3	8	1	147
Rime	1	2	1	12	2	0	0	1	121	1	8	149
Sandstorm	0	22	0	0	0	0	2	2	1	120	0	147
Snow	1	9	5	11	1	0	32	2	17	3	62	143
Σ	146	175	113	147	147	129	155	165	181	158	88	1604

Fig. 25: CM of KNNH [24]



Actual \ Predicted	Dew	Fogsmog	Frost	Glaze	Hail	Lightning	Rain	Rainbow	Rime	Sandstorm	Snow	Σ
Dew	133	0	4	2	2	0	1	6	0	1	0	149
Fogsmog	0	131	0	1	1	0	0	0	0	6	2	141
Frost	4	1	93	19	7	2	5	3	9	0	3	146
Glaze	7	0	16	95	7	2	1	1	11	0	10	150
Hail	5	1	5	1	121	1	7	0	1	2	0	144
Lightning	0	1	2	0	0	137	0	0	1	3	2	146
Rain	1	4	0	2	4	1	112	1	3	5	9	142
Rainbow	0	1	1	0	1	0	4	134	0	3	3	147
Rime	0	3	4	11	0	0	1	0	121	1	8	149
Sandstorm	0	18	0	0	0	6	1	1	1	118	2	147
Snow	0	8	7	11	3	1	15	3	19	8	68	143
Σ	150	168	132	142	146	150	147	149	166	147	107	1604

Fig. 26: CM of SGDC [24]

Actual \ Predicted	Dew	Fogsmog	Frost	Glaze	Hail	Lightning	Rain	Rainbow	Rime	Sandstorm	Snow	Σ
Dew	135	0	5	6	1	1	1	0	0	0	0	149
Fogsmog	0	126	0	0	0	2	1	1	0	9	2	141
Frost	3	0	101	26	5	1	1	0	5	0	4	146
Glaze	4	1	16	101	4	1	0	0	12	0	11	150
Hail	4	0	7	0	126	0	4	0	1	0	2	144
Lightning	0	1	2	0	0	137	0	1	0	5	0	146
Rain	3	3	1	1	4	0	117	1	0	2	10	142
Rainbow	0	0	1	1	0	2	3	136	0	4	0	147
Rime	0	0	2	11	0	0	0	0	130	0	6	149
Sandstorm	0	13	0	0	0	2	2	1	1	127	1	147
Snow	0	2	5	13	1	1	14	0	13	2	92	143
Σ	149	146	140	159	141	147	143	140	162	149	128	1604

Fig. 27: CM of Proposed Method [24]

From Table 2 and Fig. 14 to Fig. 27, it is observed that LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC and proposed method are able to provide 0.803, 0.794, 0.736, 0.822, 0.562, 0.541, 0.645, 0.746, 0.787 and 0.828 CA values (in unit) respectively. LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC and proposed method are able to provide 0.804, 0.794, 0.731, 0.822, 0.562, 0.540, 0.638, 0.740, 0.738 and 0.828 F1 values (in unit) respectively. LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC and proposed method are able to provide 0.805, 0.795, 0.731, 0.823, 0.563, 0.540, 0.644, 0.747, 0.783 and 0.828 PR values (in unit) respectively. LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC and proposed method are able to provide 0.803, 0.794, 0.736, 0.822, 0.562, 0.541, 0.645, 0.746, 0.787 and 0.828 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 0.828 CA, F1, PR and RC values in units. However, the ADB method is not capable of providing better categorization results than other methods and it is having 0.541, 0.540, 0.540 and 0.541 CA, F1, PR and RC values in units respectively. Thus the decreasing order of performance of these methods is Proposed method, NNT, LRG, SVMN, SGDC, KNNH, RFS, NBY, DTR and ADB.

8. RECOMMENDATION :

This work can be extended to develop improved methods to carry out the classification of WIs 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 WIs and other types of images by applying DL based methods.

9. CONCLUSION :

This paper proposed a MI based approach for the classification of WIs into dew, fogsmog, frost, glaze, hail, lightning, rain, rainbow, rime, sandstorm, and snow types. The proposed approach is focused on the stacking of LRG, SVMN, RFS and NNT methods to carry out the classification of WIs 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 0.828 which are higher as compared to other ML based methods. However, in this scenario, the ADB method is unable to perform better than other methods. The CA, F1, PR and RC values in units using the ADB method are computed as 0.541, 0.540, 0.540 and 0.541 respectively 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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