Using Deep learning to Improve the Classification of Weather Phenomena from Images

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Abstract

One of the most important phenomena at the moment is the identification of weather phenomena, which are crucial for numerous facets of daily life and are especially important for weather forecasts, transportation, tracking road conditions, farming, and forest management to protect of environment.

Contrarily, few studies have attempted to classify images of actual weather events because it is challenging to do so using pictures, which are primarily reliant on human visual observations. This lessens the possibility of changing weather patterns. As far as we can determine, it takes time and is difficult to accurately distinguish between various weather events using traditional artificial vision. Even though some research has increased precision, also efficacy to recognizing phenomena employing artificial intelligence and even though AI approaches are better suited for categorization, they have discovered less different weather phenomena. This study suggests five artificial intelligence classification methods for meteorological events.

In the meantime, we created a brand- The Weather Phenomenon Database (WEAPD), a brand-new dataset with 6,691 photos and 11 different types of weather phenomena, was just released. The categorization accuracy for AI methods in the WEAPD test group is about 84%. and the experimental results show how effective and better the models are for the specified AI

tactics. Next studies on the classification of weather photographs and weather forecasting may use the creation of automatic, high-quality categorization of weather photos as a benchmark. The proportion is not higher than these values since the images are difficult to categorizes because they combine a variety of events.

Keyword:

Classification of meteorological phenomena, Deep Learning, Weather forecasting, and Databases of meteorological phenomena.

1. Introduction

The analysis of meteorological occurrences is crucial for many applications, such as environmental monitoring, predicting the weather, and evaluating the state of the environment. A range of weather events also have an impact on agriculture in different ways. Therefore, accurate classification of climatic events can improve agricultural planning. In addition, weather occurrences affect our daily lives through affecting items like solar technology [1], clothes, and transportation. Due to things like snow, sandstorms, haze, etc., they have a substantial impact on car assistant driving systems as well. Meanwhile, weather conditions can affect the operation of different visual systems, including outside video monitoring.

The weather during the next few days will be influenced by weather from the day before, such as the haze, snow, sandstorm, and so forth. Sandstorms, downpours, rime, hazardous local or regional weather conditions include snow, thick fog, and others. Also, the factor in a considerable number of expressway accidents. In light of the foregoing, it is clear that categorization Understanding weather events is vital and can assist meteorologists comprehend climatic conditions and enhance weather forecasting [2].

The bulk of the time, traditional techniques of recognizing meteorological phenomena rely on human observation. The artificial visual differentiation used in the past to distinguish between different climatic occurrences, however, is slow and prone to inaccuracy. Therefore, developing highly accurate, efficient, and automated techniques for identifying meteorological phenomena is essential. In recent years, a collaborative learning approach has been used to classify weather into two categories (cloudy and sunny). Furthermore, a simple linear classifier successfully distinguished between scenes with and without fog. Now that machine learning is developing swiftly, academics can use it in a variety of academic fields. Meteorological phenomena were recognized as weather conditions utilizing K-Nearest Neighbor and feature extraction[3].

Nevertheless, weather phenomenon recognition based on standard machine learning cannot accurately learn the features of weather phenomena. Artificial intelligence (AI) and deep learning are both algorithms. Due to the use of deep structure, local receptive fields, spatial sub-sampling, shared weights, and other techniques, it can produce effective feature representations for images, also other methods [4].

Since the AlexNet model took first place when participating in the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC), a number of problems, such as object detection, face recognition, and regression prediction, have been tackled using AI. A growing number of studies have recently applied AI methods to solve meteorological issues. [5] used deep learning to extract the snow cover from remote sensing data. Using AI methods, [6] created two cloud recognition architectures that improved cloud recognition's precision. Additionally, [7] merged Using a simple deep learning architecture, one framework can separate images into day and night. also did better than rivals in research from accessible databases.

In summary, it is evident to AI methods has numerous benefits for identifying meteorological imagery. In order to identify different weather events, including two-departments climate (sunny and cloudy) and three-class weather phenomena, some studies examined the potential of AI Techniques (AI) (rainy, foggy, and snowy). Additionally, using deep learning, [8] developed six fictitious meteorological occurrences (such as Rain, dust, and dew, freezing, haze, and snow) and effectively detected all. Additionally, a convolutional neural network with three channels was successfully used to classify six meteorological phenomena (3C-CNN). In addition, [9] managed the multi-label task of classifying weather-related events. These studies, however, only think of a little portion different weather type, but kinds of climate occurrences we experience daily are significantly more diverse and numerous. As a result, there are now more categories of meteorological phenomena that need to be considered while studying and identifying them [10].

According to several countries, the method for manually determining cloud coverage in meteorological stations goes like this. First, field observers send satellite-free photos of clouds to the ground-based stations, it may include balloons or observation towers but not satellites. The gathered photos are then divided equivalent to eight into halves, which are then sent to human analysts for independent review. Each piece has three possible results: cloudy, clear, or no result if there are no sky pieces present and the piece includes irrelevant information for weather forecasting [11]. The item is regarded to have significant noise and is disqualified from the procedure if it has no sky sections and contains irrelevant information for weather forecasting. After determining how foggy each element is, depending on whether the cloudy portions make up 50% or more of the entire image when the non-noise bits are combined to form the original image [12], it can be said if the image is cloudy or clear. The flow described is using a solid architecture for deep learning, a big dataset will be trained, its volume would be continually increased, and the data would be processed instead of gathering weekly or daily image data and using human experts to analyses it. This would provide a contemporary viewpoint and increase predicting accuracy at an exponential rate. Technologies utilizing artificial intelligence with large data (AI) make it possible to convert a difficult human task into an automated computation. Systems based on deep learning are capable of labelling new data using the knowledge they have learned from training on similar massive amounts of data. Several layers are used in the machine learning subfield known as deep learning that learn by developing hypotheses and analyzing data [13]. Despite having various definitions, Artificial intelligence, machine learning, and deep learning (AI) are all subsets of one another. As an illustration, while AI is a methodology, deep learning is a subset of machine learning, which is a subset of it with its own distinct set of unique techniques and architecture [14].

2. Related Work

The application of AI technology has increased recently while they are still evolving. In accordance with this, several nations are testing or have already implemented a number of AI technology initiatives in the meteorological sector, a history of combining deep learning with certain AI techniques for weather forecasting. [15] They employed AI algorithms to forecast fundamental meteorological factors globally. In the course of their inquiry, the temperature is measured. Observation, analysis, and prediction are the three phases of weather forecasting. During these phases, a number of factors including atmospheric pressure, air temperature, humidity, wind speed, and cloud cover are taken into consideration [16].

One of these crucial elements is cloud coverage, also known as cloudiness, cloud quantity, or cloudiness in the sky. Cloud coverage is the number of clouds present in the sky.

Traditionally speaking, utilizing cloud coverage typically entails dispatching staff to the field to take ground-level photos during the observation stage, having knowledgeable staff analyses for images while in stations for the analysis phase [17], and then computing the desired outcome in a weather prediction using all additional information mentioned before, encompassing clouds, during the prediction phase. It is acknowledged on a global scale that a traditional meteorological institution may make forecasts with varied levels of approximation accuracy for particular time frames: 90% for a period of five days, 80% for a period of 50% after seven days for a period of 10 days [18]. Analysis for prediction tools and methodologies are still far from error-free, especially over longer time periods, despite the use of sophisticated technologies and procedures. Additionally, when humans are affected by human-based systems, they make more mistakes than usual in unexpected situations, such as the COVID-19 pandemic [19]. Due to field personnel, experts at stations, and meteorology regularly reporting weather forecasting at work worsened during the epidemic. Errors in meteorology increased as a result.

3. Methodology

3.1 Dataset Description:

Classify the weather based on an image using this dataset, which consists of 6691 images of various weather conditions that have been tagged with specific meteorological conditions. The photographs are separated to dew, fog/smog, frost, glazing, hail, lightning, rain, rainbow, rime, sandstorm, and snow are among the eleven categories. To the best of our knowledge, before any classification models in supervised learning can be proposed, a sizeable, labelled dataset must be used [20]. The size and caliber of the dataset have an important effect for classification effectiveness of the model, and by creating a sizable training and test database, It is possible to considerably increase categorization accuracy. Therefore, it is essential to take enough images of weather occurrences and mark them appropriately.

In this paper, JPG images of weather events were first acquired through the internet and academic exchanges, and then the images were manually categorized according to meteorological standards. Finally, based on visual shape and color attributes, a database of weather phenomena (WEAPD) was developed and divided into 11 classes [21].

This database includes different and exemplary images of meteorological events. The primary elements of the WEAPD include hail (591), rainbow (232), Frost (475), dew (698), sandstorm (692), snow (621), rain (526), lightning (377), fog/smog (851), rime (1160), and glazing (639). the validation set, testing set, and training set that we divided WEAPD into do not have any image overlap.

In this study, we used a set of 6691 pictures grouped into 11 categories of weather occurrences to construct a network called AI Techniques, a deep learning algorithm, for classifying weather phenomena [22]. The AI methods were subsequently taught to validate them. The trained AI Techniques model was then assessed using the testing set.

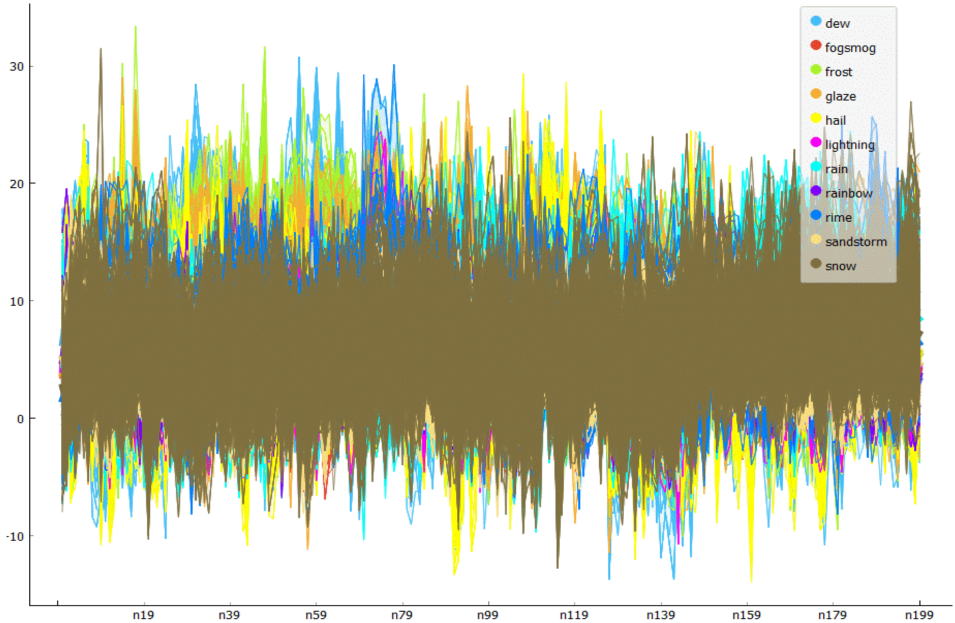

Figure (1) Plot a line representing meteorological phenomena

This essay's remaining sections are set up as follows. We present the information. Information on the experimental use of the suggested classification model presents the experiment's results before assessing the AI Techniques model using a range of evaluation metrics. This paper discusses the opportunities for additional research. This study divided equal amounts of ground-based cloud photographs into equal grid squares, and each square was labelled as either clear or cloudy [23].

In contrast, objects with a high level of undesirable unclassifiable noise are considered, eliminated from information set data. Following this step, the collection is fed into pretrained model-based architectures in four different forms, including method VGG-19 and Squeeze Net (local), in order to undergo training and testing of deep learning system of classification [24]. To create a robust model for image identification that reaches AlexNet-Level accuracy on ImageNet with 50x less parameters, we worked on two image processing algorithms in this study:

1 – Squeeze - Net (local) 2 – VGG -19.

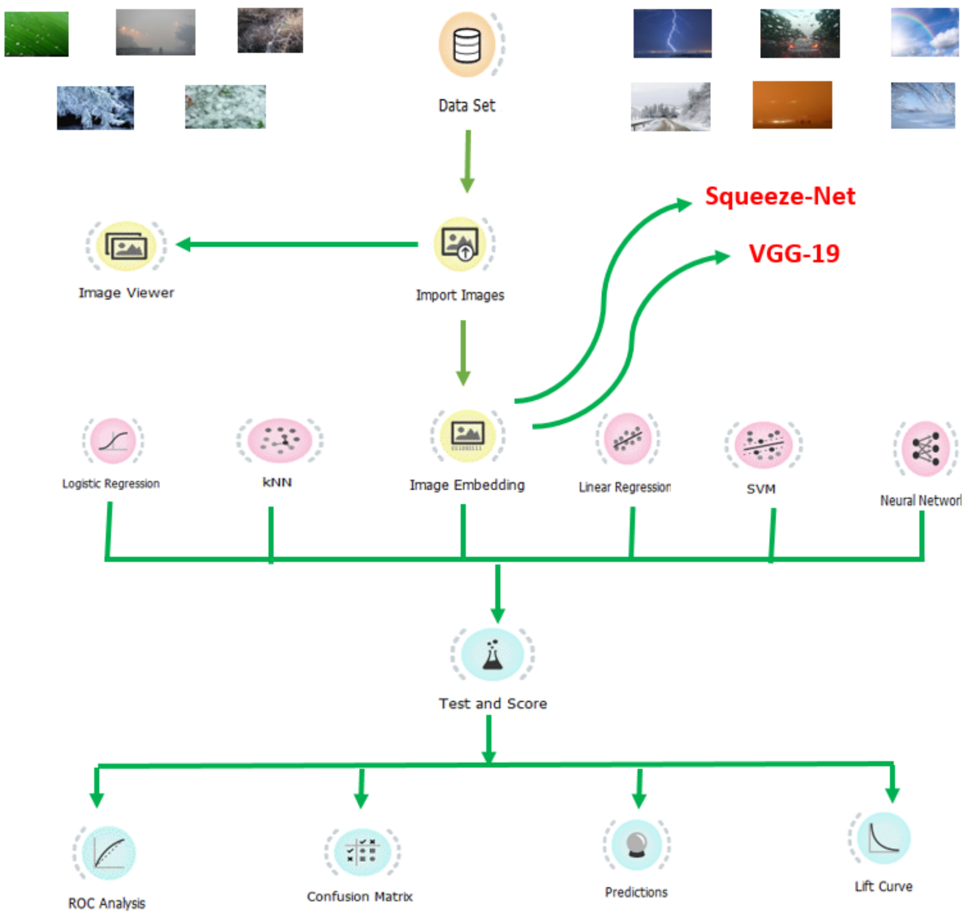

Figure (2) Steps for Deep learning

3.2. Model Architecture

An optimized approach to classifying photographs of weather phenomena is AI techniques. AI techniques develop as VGG19 is improved. In comparison to other popular models, VGG19 of straightforward framework and has rapid training, takes up little memory, as well as prevent overfitting regarding tiny information sets [25]. As a result, the decision to use VGG19 as the foundation for our suggested AI Techniques model. AI techniques have a quality classification impact and may correctly understand for characteristics to each weather condition phenomena.

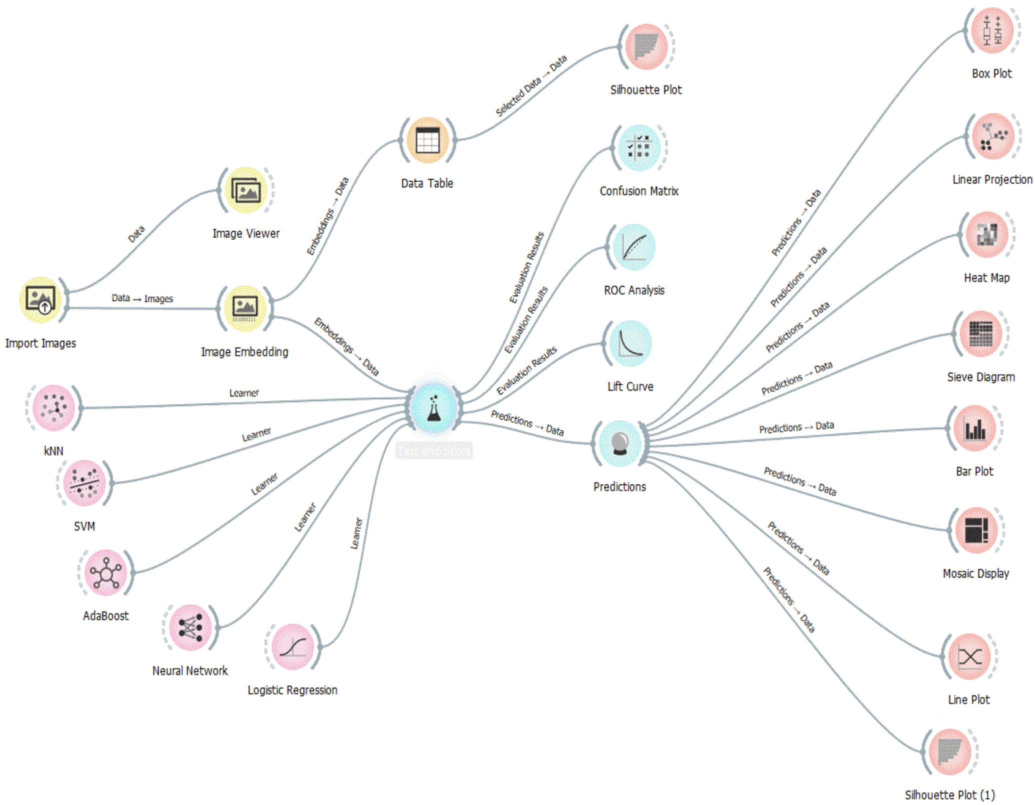

Figure (3) Represent Model Architecture for study

In contrast to VGG19, our AI Techniques employ the squeeze and excitation module. A collection of fixed-size photos representing meteorological phenomena provides the input for AI techniques [26]. The AI Techniques layers serve as a feature extractor, turning input photos into representations of abstract weather phenomena features. A variety of feature maps are produced by each layer of AI techniques utilizing a trainable. A collection of fixed-size photos representing meteorological phenomena provides the input for AI techniques. The AI Techniques layers serve as a feature extractor, turning input photos into representations of abstract weather phenomena features. Using a trainable, each layer of AI techniques generates a variety of feature maps [27].

4. Analysis of Results

where stands for the expected label for the sample, and is the corresponding true label. Furthermore, the trained AI Techniques model was assessed using quantitative evaluation indicators. In this research, we specifically implemented the Precision (P), Recall (R), and -measure (F1). Precision is the model's capacity to avoid making a positive prediction when the Analyte is unfavorable [28]. And Recall is a measurement to locate everything of the samples that are positive. An average of Precision and Recall, that is weighted, is denoted by symbol measure. Using False positives, genuine positives, true negatives, and false positives, the concepts of P, R, and F1 are defined. where the values of the assessment metrics are uniformly between 0 and 1. The model's classification performance improves when macro-average values, F1-measure, accuracy, precision, recall increase [29].

Squeeze Net, VGG-19, and F1-measure were used to evaluate accuracy, against the popular models, a macro-average of Precision, Recall, and

F1-measure. Within a 5% improvement, there was a considerable improvement in the classification results utilizing the (VGG-19) approach as opposed to the (Squeeze-Net) method. The parameter maps that the feature extractor creates hierarchical layers inside AI Techniques, can disclose the many semantic meanings. The experiments demonstrated that while the deeper levels are more likely to exhibit high-level and sophisticated semantic properties [30], the thinner layers have a higher likelihood of collecting details about the texture. This is confirmed, and the feature maps of AI techniques are understood. In conclusion, with the development of AI techniques, it will be possible to identify more subtle semantic properties of weather photos, such as some non-linear image attributes. The outcome is consistent with earlier studies.

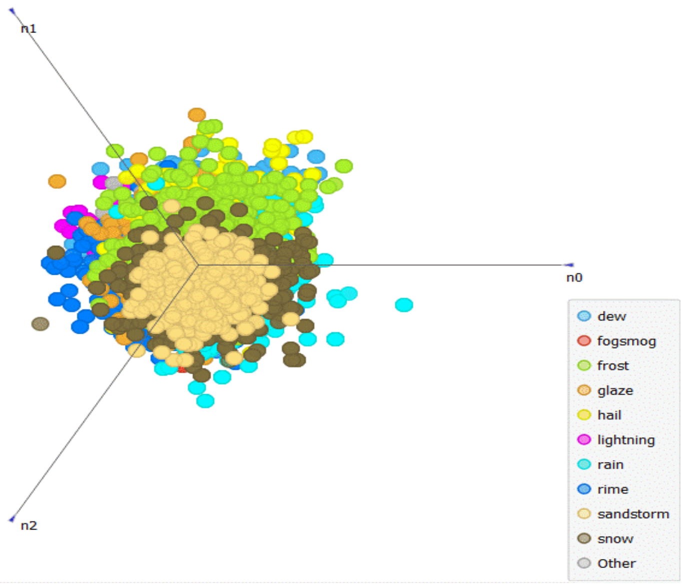

Figure (4) Linear Projection

The five models significantly improved when the model (VGG-19) was used, thus the training time was raised to further enhance the models, and the test duration was also increased [31]. The best models for classification were (Squeeze-Net) and (Logistic Regression), which produced results with classification accuracy of 0.980 in the VGG-19 model and (Precision of 0.980) in the Logistic Regression model. Additionally, the result (0.836) in the (VGG-19) model, whereas the results (Precision= 0.822) in the (Squeeze-Net) model, followed by the model (Support Vector Machine) in the prediction values showing for every table (1, also 2).

Table (1) Evaluation of Classification Performance of AI Techniques by Precision, for Squeeze- Net.

Model	Train time [s]	Test time [s]	AUC	CA	F1	Precision	Recall	Specificity
Logistic Regression	1617.492	3.348	0.974	0.822	0.821	0.822	0.822	0.979
SVM	112.456	64.388	0.970	0.738	0.736	0.738	0.738	0.971
kNN	7.150	14.908	0.948	0.766	0.759	0.766	0.766	0.971
Neural Network	35.714	6.725	0.886	0.378	0.219	0.222	0.378	0.894
AdaBoost	3604.622	10.705	0.846	0.705	0.702	0.701	0.705	0.965

Table (2) The classification performance of AI Techniques Precision and Recall Modeling For VGG-19.

Model	Train time [s]	Test time [s]	AUC	CA	F1	Precision	Recall	Specificity
Logistic Regression	341.873	22.789	0.981	0.836	0.835	0.835	0.836	0.980
SVM	875.512	369.536	0.970	0.732	0.731	0.734	0.732	0.969
kNN	51.172	50.300	0.940	0.727	0.720	0.740	0.727	0.965
AdaBoost	6477.481	55.697	0.844	0.700	0.698	0.698	0.700	0.964
Neural Network	182.286	43.519	0.899	0.418	0.288	0.335	0.418	0.900

ples. Even if there are few images in some categories, the suggested model can nevertheless correctly categories them with a Recall of 1 and 0.98, respectively (Table 1). Fog/smog (1160) and rime (1160) are the categories with the most and second-most images, respectively (851). Nevertheless, a little or high number of photos (such as a rainbow or a snowflake) had no discernible impact on the categorization outcomes, showing that the data set's quantity distribution is appropriate [32].

The confusion matrix was utilized as additional evidence of Performance in terms of classification for AI Techniques design of meteorological occurrence (Figure 3 to 7). The AI Techniques model's categorization accuracy for weather phenomena is greater than 89%. The AI Techniques model still makes some classification mistakes, though. This might be the case, for instance, because glaze's sceneries and shapes are fairly similar to those of it has rime or frost on it.

It is difficult for AI systems to tell each person apart. Also, the proposed model has a 3.9% risk of mistaking rime for snow, which may be caused by how similar the colors in the two types of images are. The suggested model, in general, simply detects incorrect meteorological information.

It can be brought on by how similar and intricate the visuals are. Utilizing the confusion matrix on test was designed to assess its effectiveness in the AI Techniques model. As is well known, a probability mask representing the projected probability of several types of weather occurrences is the result of AI techniques. The potential must be converted into a particular kind of meteorological for phenomenon. We employ the Receiver Operating Curve (ROC) method in this study to examine the model's capacity for classification using AI techniques. Figure (6) shows ROC graph for AI Techniques simulate different probability thresholds in the range [0,1] for the testing set. False Positive Rate (FPR) and True Positive Rate (TPR) are also variable when the probability threshold shifts from 0 to 1. Each class of meteorological occurrence has an area behind the ROC curve (AUC) value that is greater than 0.96; in particular, the AUC values for hail, rainbows, lightning, sandstorms, and dew are close to 1.00. It once more demonstrates how the AI techniques model can reorganize hail, rainbows, lightning, sandstorms, and dew with almost perfect accuracy. Additionally, the ROCs on a large-scale AUC value is 0.99, highlighting for model's excellent classification performance.

Predicted

Actual	dew	fogsmog	frost	glaze	hail	lightning	rain	rainbow	rime	sandstorm	snow	∑
dew	4380	14	104	75	83	24	24	6	9	0	3	4722
fogsmog	7	4185	8	4	4	7	78	18	43	1172	50	5576
frost	183	6	1991	471	141	0	34	2	251	8	133	3220
glaze	211	29	946	2093	93	1	40	0	620	14	311	4358
hail	108	2	122	60	3410	0	129	2	9	0	36	3878
lightning	15	26	10	10	0	2399	3	14	1	16	5	2499
rain	50	164	54	60	153	2	2632	11	16	31	182	3355
rainbow	25	29	4	1	1	28	41	1380	5	50	0	1564
rime	26	114	563	634	17	12	26	9	5302	7	767	7677
sandstorm	1	762	11	13	2	14	40	37	15	3627	21	4543
snow	31	231	219	377	119	5	661	1	437	47	1980	4108
∑	5037	5562	4032	3798	4023	2492	3708	1480	6908	4972	3488	45500

Predicted

Actual	dew	fogsmog	frost	glaze	hail	lightning	rain	rainbow	rime	sandstorm	snow	∑
dew	4256	19	127	116	108	28	33	9	16	8	2	4722
fogsmog	21	3823	0	7	8	16	58	15	43	1519	74	5576
frost	216	13	2195	415	69	6	30	3	212	10	51	3220
glaze	287	20	757	2471	68	2	43	0	502	3	205	4358
hail	133	0	49	83	3514	0	68	0	8	0	23	3878
lightning	15	25	13	9	0	2384	2	15	7	29	0	2499
rain	67	126	29	38	103	4	2758	2	25	33	170	3355
rainbow	5	76	11	3	3	24	41	1314	9	77	1	1564
rime	23	141	463	658	5	20	24	7	5208	36	1092	7677
sandstorm	12	870	39	18	2	36	53	61	102	3313	37	4543
snow	41	214	146	356	103	0	585	5	526	47	2085	4108
∑	5076	5527	3829	4174	3975	2520	3695	1431	6658	5075	3740	45500

Table (3) Confusion Matrix to SVM (a) Squeeze - Net, (b) VGG-19.

Predicted

Actual	dew	fogsmog	frost	glaze	hail	lightning	rain	rainbow	rime	sandstorm	snow	∑
dew	3988	37	153	205	102	66	32	36	46	21	36	4722
fogsmog	21	4369	18	27	27	64	110	68	104	589	179	5576
frost	172	12	1610	581	212	16	47	14	434	39	103	3220
glaze	226	66	466	2480	131	31	50	3	657	20	226	4358
hail	109	25	207	109	3010	21	131	20	89	52	105	3878
lightning	70	92	16	38	21	1987	18	60	62	113	22	2499
rain	38	175	39	63	121	24	2185	18	146	106	440	3355
rainbow	54	122	15	12	37	72	37	1030	35	129	21	1564
rime	40	87	214	494	87	45	68	26	6110	92	414	7677
sandstorm	13	700	20	28	29	62	106	68	89	3292	136	4543
snow	54	255	94	235	116	27	484	26	647	166	2004	4108
∑	4785	5940	2852	4272	3893	2417	3268	1369	8399	4619	3686	45500

Predicted

Actual	dew	fogsmog	frost	glaze	hail	lightning	rain	rainbow	rime	sandstorm	snow	∑
dew	3767	85	221	199	156	58	67	46	51	40	32	4722
fogsmog	40	4339	10	18	11	94	112	43	140	655	114	5576
frost	236	8	1706	563	137	13	37	7	381	26	106	3220
glaze	223	43	404	2610	96	10	81	5	671	42	173	4358
hail	126	25	103	135	3152	6	136	12	57	31	100	3878
lightning	74	152	12	17	10	1963	25	48	49	135	14	2499
rain	98	158	36	40	132	29	2186	22	122	172	360	3355
rainbow	34	94	10	7	11	40	49	1060	49	169	13	1564
rime	34	93	204	547	35	35	70	12	6073	136	438	7677
sandstorm	35	899	22	31	28	77	119	72	209	2902	149	4543
snow	37	171	94	257	119	13	385	17	796	142	2077	4108
∑	4724	6067	2822	4424	3887	2338	3267	1352	8593	4450	3576	45500

Table (4) Confusion Matrix to AdaBoost (a) Squeeze - Net, (b) VGG-19.

Predicted

Actual	dew	fogsmog	frost	glaze	hail	lightning	rain	rainbow	rime	sandstorm	snow	∑
dew	4181	17	75	162	118	90	2	42	22	13	0	4722
fogsmog	0	5059	0	4	0	10	39	38	79	303	46	5576
frost	155	13	1636	653	255	8	35	10	403	22	30	3220
glaze	246	79	381	2712	189	32	17	3	571	23	105	4358
hail	57	18	139	95	3405	0	74	16	19	25	30	3878
lightning	2	104	1	19	0	2276	1	38	18	40	0	2499
rain	39	262	18	31	106	6	2457	12	120	136	168	3355
rainbow	3	97	0	1	7	18	39	1369	12	103	0	1564
rime	8	75	82	575	28	30	18	16	6640	47	158	7677
sandstorm	0	846	2	6	0	9	21	45	36	3573	5	4543
snow	27	416	70	326	114	2	609	28	761	125	1630	4108
∑	4718	6986	2404	4584	4222	2481	3293	1549	8681	4410	2172	45500

Predicted

Actual	dew	fogsmog	frost	glaze	hail	lightning	rain	rainbow	rime	sandstorm	snow	∑
dew	3868	123	159	182	86	104	41	18	38	23	0	4722
fogsmog	0	5091	0	0	0	23	13	13	98	330	8	5576
frost	228	18	1722	662	133	7	13	0	383	18	24	3220
glaze	228	53	414	2717	89	30	43	3	697	35	49	4358
hail	97	30	75	132	3317	5	104	2	54	23	39	3878
lightning	3	252	7	1	0	2139	2	3	28	62	2	2499
rain	71	373	21	43	64	22	2303	4	113	199	142	3355
rainbow	3	230	0	0	5	106	16	1073	38	93	0	1564
rime	36	113	89	618	11	41	15	0	6581	51	122	7677
sandstorm	9	1472	1	13	0	44	16	14	197	2762	15	4543
snow	15	402	65	382	72	12	519	0	1017	176	1528	4108
∑	4558	8149	2553	4690	3777	2613	3085	1130	9244	3772	1929	45500

Table (5) Confusion Matrix to KNN (a) Squeeze - Net, (b) VGG-19.

Actual \ Predicted	dew	fogsmog	frost	glaze	hail	lightning	rain	rainbow	rime	sandstorm	snow	Σ
dew	4256	31	95	131	72	33	32	12	27	9	24	4722
fogsmog	12	4904	23	35	5	16	74	9	64	338	96	5576
frost	104	12	2093	490	76	5	56	8	215	10	151	3220
glaze	102	29	429	2960	79	4	36	3	475	21	220	4358
hail	59	5	102	49	3451	2	110	3	16	24	57	3878
lightning	10	25	11	7	0	2397	7	12	15	12	3	2499
rain	40	119	47	61	89	3	2704	9	46	38	199	3355
rainbow	20	36	3	0	1	16	33	1401	6	46	2	1564
rime	13	41	174	482	15	10	31	0	6491	13	407	7677
sandstorm	1	465	13	8	3	6	23	20	18	3944	42	4543
snow	14	99	119	211	104	5	274	0	430	68	2784	4108
Σ	4631	5766	3109	4434	3895	2497	3380	1477	7803	4523	3985	45500

Actual \ Predicted	dew	fogsmog	frost	glaze	hail	lightning	rain	rainbow	rime	sandstorm	snow	Σ
dew	4250	27	115	140	102	33	28	6	10	2	9	4722
fogsmog	9	5048	1	1	0	7	55	13	79	295	68	5576
frost	110	2	2272	339	90	3	37	12	282	17	56	3220
glaze	115	24	341	3044	93	4	35	0	520	9	173	4358
hail	64	6	57	71	3524	0	94	0	19	6	37	3878
lightning	1	32	10	5	0	2373	0	6	14	58	0	2499
rain	61	93	30	24	72	17	2792	4	33	52	177	3355
rainbow	1	57	6	5	4	8	35	1339	14	95	0	1564
rime	16	61	128	366	6	15	17	0	6781	35	252	7677
sandstorm	7	565	8	6	0	14	42	12	54	3793	42	4543
snow	9	144	41	192	83	5	205	0	553	60	2816	4108
Σ	4643	6059	3009	4193	3974	2479	3340	1392	8359	4422	3630	45500

Table (6) Confusion Matrix to Logistic Regression (a) Squeeze - Net, (b) VGG-19.

Actual \ Predicted	dew	fogsmog	frost	glaze	hail	lightning	rain	rainbow	rime	sandstorm	snow	Σ
dew	4348	76	0	0	0	0	0	0	298	0	0	4722
fogsmog	8	5176	0	0	0	0	0	0	392	0	0	5576
frost	490	0	0	0	0	0	0	0	2730	0	0	3220
glaze	736	68	0	0	0	0	0	0	3554	0	0	4358
hail	1940	161	0	0	0	0	0	0	1777	0	0	3878
lightning	252	1836	0	0	0	0	0	0	411	0	0	2499
rain	84	1203	0	0	0	0	41	0	2027	0	0	3355
rainbow	274	1025	0	0	0	0	0	0	265	0	0	1564
rime	40	19	0	0	0	0	0	0	7618	0	0	7677
sandstorm	0	3758	0	0	0	0	0	0	785	0	0	4543
snow	117	986	0	0	0	0	4	0	3001	0	0	4108
Σ	8289	14308	0	0	0	0	45	0	22858	0	0	45500

Actual \ Predicted	dew	fogsmog	frost	glaze	hail	lightning	rain	rainbow	rime	sandstorm	snow	Σ
dew	4026	337	0	27	80	0	0	0	252	0	0	4722
fogsmog	12	5254	0	0	0	0	0	0	310	0	0	5576
frost	469	8	0	103	142	0	0	0	2498	0	0	3220
glaze	468	56	0	62	111	0	0	0	3661	0	0	4358
hail	734	51	0	38	1988	0	0	0	1067	0	0	3878
lightning	50	2311	0	0	0	0	0	0	138	0	0	2499
rain	368	659	0	1	15	0	94	0	2218	0	0	3355
rainbow	49	1356	0	0	0	0	0	0	159	0	0	1564
rime	18	54	0	0	0	0	0	0	7605	0	0	7677
sandstorm	7	3533	0	0	0	0	2	0	1001	0	0	4543
snow	78	307	0	3	24	0	6	0	3690	0	0	4108
Σ	4279	13926	0	234	2360	0	102	0	22599	0	0	45500

Table (7) Confusion Matrix to Neural Network (a) Squeeze - Net, (b) VGG-19.

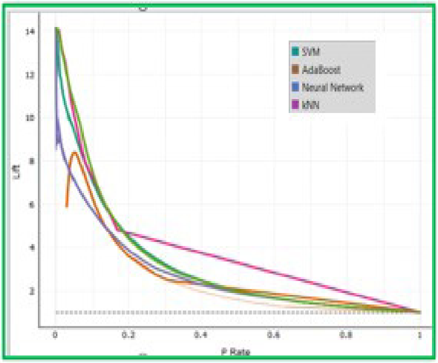

Figure (5) Lift Curve for Study

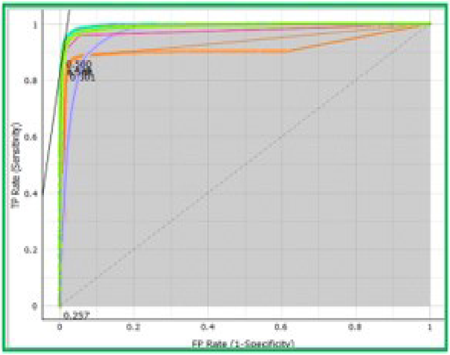

Figure (6) The ROC curve on the testing set.

Utilizing weather information criterion, in this study, we propose a fresh, representative library of images of meteorological phenomena. This database, which includes 6,691 photos of 11 different weather events, can be used as a study foundation for upcoming studies on weather public relations. In the meantime, we created a classification model for meteorological phenomena called AI Techniques. The AI techniques model is good at picking up on the characteristics of weather events. Numerous tests have demonstrated the effectiveness of the proposed AI techniques model for classifying weather occurrences and its ability to prevent errors brought on by subjectivity. making it better than conventional techniques. However, the AI techniques model misinterprets several types of meteorological occurrences, maybe as a result of how similar and intricate the images are. Overall, the AI techniques model's classification accuracy is as high as 84%, and on our dataset, it performs competitively with several widely used models (Squeeze - Net, Vgg19). Regarding the suggested approach, it can therefore be widely used to the daily observation of weather phenomenon photos and provides weather advise for environmental monitoring, agriculture, and transportation, particularly in relation to weather change and forecasting. We created a dataset with a complicated and interference-filled background. Each image consists of the object to be detected as well as other interference objects. Future study must therefore identify and discuss interference backgrounds. In addition, we are aware of the numerous weather events that affect our daily life. Therefore, new types of weather occurrences are important to consider in future studies. To improve classification results and enhance the classification model, the quantity of images of each weather phenomenon can be increased. Because consumers can quickly access weather forecasts via their mobile devices, for meteorological errors draw greater attention than they did in the past and undermine public faith in weather predictions. Error rates will be high as long as meteorological forecasts are made by humans. When people's participation levels drop, errors spike, especially in unusual situations.

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