Cloudburst Prediction in India Using Machine Learning

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***Abstract*— Cloudbursts pose a significant threat in India, especially during the South-West Monsoon season that commences in June. India's diverse climate regions, including the northern Himalayan region, Indo-Gangetic Plain, southern peninsula, and coastal areas, experience sporadic cloudbursts, with only 31 recorded instances, mainly in Himachal Pradesh, Uttarakhand, and Jammu and Kashmir. To address the lack of comprehensive Indian cloudburst data, we've curated a dataset, incorporating meteorological factors for cloudburst prediction. This dataset encompasses variables such as Temperature, Wind Gust, Wind Gust Speed, Humidity, Monsoon patterns, Air Pressure, and Cloud Density. Our goal is to improve preparedness and mitigation strategies, safeguarding lives, and property in cloudburst-prone areas. Employing optimized machine learning algorithms, our model analyzes these parameters alongside prevailing weather conditions, facilitating cloudburst event prediction. We evaluate the prediction performance of machine learning algorithms, including Random Forest, CatBoost, XGBoost, and Decision Tree. The CatBoost algorithm outperformed others with an accuracy of 86.18%. Moreover, we provide graphical insights into the correlation between humidity and cloudburst occurrence, emphasizing the importance of weather variables in prediction models. This research contributes to cloudburst forecasting, even with limited Indian data, and highlights the potential of utilizing diverse machine learning techniques for improved accuracy.**

I. Introduction

A cloudburst is a brief but intense precipitation event, often accompanied by hail and thunder, capable of causing flooding. These events can deposit a staggering 72,300 tons of water over a single area. Cloudbursts typically occur when the rainfall rate exceeds 100mm per hour. Traditional prediction methods include weather forecasting, data mining techniques for meteorological data modeling, and laser beam atmospheric extinction measurements from both manned and unmanned aerospace vehicles. Hailstorms and thunder can sometimes accompany these intense rain events [1].

Cloudburst events are commonly observed in mountainous regions, where warm air currents ascend, carrying raindrops upwards. This prevents spontaneous rainfall and leads to significant cloud condensation. As water accumulates at higher altitudes, the warmth below hinders its descent. The upward air currents weaken, resulting in a sudden downpour. Cloudbursts typically occur at elevations ranging from 1000 to 2,500 meters above sea level [2].

India is recognized as a monsoon-driven nation on the global climate map, experiencing several cloudburst events in recent years, particularly in the western Himalayas and along the west coast. To enhance our understanding and prediction of cloudbursts, India has established the Cloud Observatories, a network of four high-altitude physics observatories equipped with advanced technology. These observatories aim to investigate cloud and rain dynamics in high-altitude regions, focusing on cloud interactions, convection, circulation, and improving forecasting and monitoring of cloudburst incidents. Their ultimate goal is to mitigate the impact of such events in these areas [3]. In-depth research into cloudburst events through numerical modeling, as conducted by [1], revealed valuable insights into the dynamic structures and interactions with local topography. The author in[4], proposed that monsoonal low- pressure systems amplify low-level convergence and upper- level divergence, contributing to intense monsoonal heavy rainfall in orographic regions. Various studies have attributed the occurrence of heavy rainfall (ranging from 200 to 1000 mm/h) within a brief span to the presence of cumulonimbus clouds in the area. Gupta et al. [5] further emphasize that cloudburst events often result from convective systems trapped in enclosed valleys surrounded by mountainous terrain.

Sudden and intense short-term heavy rainfall events can be influenced by convective cloud feedbacks, whose connection to climate change remains uncertain due to their sensitivity to temperature stratification and large-scale atmospheric circulation changes. Climate change may lead to variations in storm size, either increasing or decreasing. Nevertheless, it's likely to result in higher rainfall intensity and expanded storm coverage, which can contribute to elevated rainfall levels. This, in turn, may lead to an increase in flash flooding, posing substantial regional concerns. Consequently, adapting to rapid climate change is essential to address the potential global impact of intensified flash floods [6].

Scientists examine historical data and climate models to understand the impact of rising global temperatures on heavy rainfall patterns. The 2018 Kerala floods, triggered by exceptionally intense monsoon rains, resulted in widespread devastation, causing significant loss of life and displacement. Kerala, often the first to receive monsoon rains in India, faced additional challenges due to heavy rainfall events in 2018 and 2019, as confirmed by various observational and modeling studies, attributed in part to regional climate changes [7], [8]. Predicting cloudbursts in the Himalayan region is crucial to minimize potential damage and loss of life. Due to limited observations in this area, utilizing reanalysis data is necessary to understand the cloudburst formation process. Historical data is integrated through data assimilation techniques to create consistent gridded reanalysis data, offering insight into atmospheric conditions. Accurate forecasting of cloudburst events requires comprehensive data sources and analytical methods. Enhancing our understanding of cloudburst mechanisms is essential for proactive disaster management in the Himalayan region. Thus the proposed approach combines historical data and modern machine learning methods to improve cloudburst prediction and reduce its impact.

This paper's key contributions can be summarized as follows: 1) We have curated a dataset specifically for Indian cloudburst analysis. 2) We've utilized machine learning algorithms to forecast cloudburst events in the Indian subcontinent.

II. Literature Survey

Numerical weather prediction (NWP) models offer moderate accuracy in large-scale medium-range weather forecasting, yet precipitation forecasting remains challenging. Mesoscale models rely on initial and boundary conditions from global models, which tend to oversimplify terrain, land cover, and vegetation. Both global and regional models neglect detailed geographical features for improved results. Operational forecasting centers utilize mesoscale models to deliver comprehensive weather forecasts for specific geographical regions with higher resolution [9]. Rising rainfall intensity and its correlation with temperature variations can lead to alterations in flood patterns, as demonstrated by [10]. Consequently, adjustments are required in flood forecasts to account for these evolving conditions. Back in 2008 [11], the cloudburst prediction model relied on an Arduino-connected rain gauge, but its primary drawback was the Arduino's processing limitations. The cloudburst prediction model employed in 2010 was the WRF mesoscale Model [12], notable for its effectiveness. However, it presented challenges in terms of implementation and demanded substantial data resources. The work in [13] focuses on rainfall prediction through empirical statistical methods. We utilize various datasets, including variables like minimum and maximum temperature, pressure, wind direction, and relative humidity. The prediction model is based on Multiple Linear Regression. Certain predictors, such as wind direction, are excluded due to limitations in data collection, which could enhance predictive accuracy.

Fluctuations in weather patterns pose a significant challenge to atmospheric research due to their profound impact on human society [14]. Various remote sensing satellites are routinely employed for data collection. This weather determinates exhibit evolving characteristics over time. Amidst a backdrop of increasing cloudburst frequency and severity, urban centers face an urgent need to adapt stormwater drainage systems and the associated decision-making processes. This study in [15] examines the evolving knowledge systems essential for addressing these challenges, analyzing case cities. The research also identifies knowledge gaps in dealing with a changing climate, the protection of private property, and the integration of cloudburst infrastructure within holistic water management approaches, highlighting avenues for further re- search to inform policy and decision-making. The study in [14] utilized weather data from the University of Columbia's weather station, focusing on thirteen variables from a larger set of fifty-one. A ten-fold cross-validation approach was employed to validate the model's performance. Enhancing the model's accuracy is possible by strategically incorporating additional attributes in the analysis. Researchers [16] aimed to create a predictive model for rainfall by employing decision tree and artificial neural network techniques. Their emphasis was primarily on climate parameters, including temperature, humidity, and wind speed. The model utilized an extensive historical dataset, potentially leading to limited knowledge retrieval and decreased prediction accuracy, high- lighting the need for further investigation in this area. Existing methods have shown limited effectiveness in handling cloud- burst data for the Indian subcontinent. To address this issue, the proposed approach utilizes various machine learning algorithms for cloudburst prediction. The models are trained on an Australian dataset and then tested using Indian data to enhance accuracy and reliability. This research aims to bridge the gap in cloudburst prediction methodologies, specifically tailored to the Indian region.

III. PROPOSED CLOUD BURST PREDICTION MECHANISM

To address the scarcity of Indian cloudburst data for model training and testing, our approach involved using an Australian dataset for training and an Indian dataset for testing. We ensured that the same attributes were applied to both datasets, maintaining consistency in our methodology. The India Meteorological Department (IMD) has undertaken the development of a cloudburst prediction system. This system incorporates historical cloudburst event data, weather patterns, topographic information, and area-specific vulnerability data to forecast the likelihood of cloudbursts in specific locations.

To overcome data limitations, several strategies can be considered:

1. Data Collection: Collaboration with meteorological agencies or research institutions is vital for acquiring pertinent data, whether it's real-time or historical, encompassing atmospheric conditions, rainfall patterns, and other relevant variables.

2. Data Augmentation: If acquiring an adequate dataset proves challenging, exploring data augmentation techniques

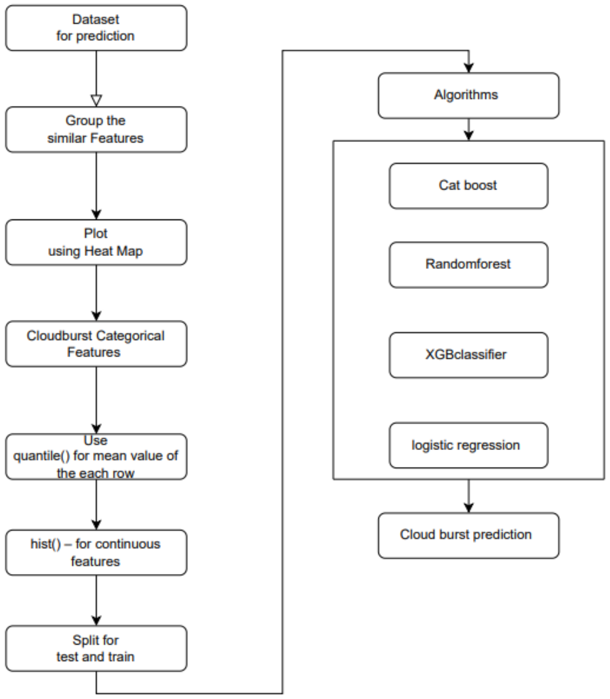

Fig 1: Proposed Model for Cloud Burst Prediction.

can be beneficial. This involves artificially expanding the dataset by introducing variations or synthetic samples, thereby enhancing prediction accuracy.

3. Transfer Learning: Another approach to address dataset limitations is employing transfer learning. Pre-trained models, particularly those related to relevant tasks or domains, can leverage knowledge from existing datasets to predict cloudbursts effectively, even with a smaller dataset.

4. Collaborative Endeavors: Collaborating with fellow researchers or organizations focused on similar challenges can be a productive strategy. By pooling resources and expertise, collective efforts can effectively tackle data-related obstacles and work toward solutions.

The cloudburst prediction using the Indian dataset will be analyzed using different machine learning algorithms such as random forest, CatBoost, XGBoost and decision tree.

Random Forest is a robust ensemble learning method that offers substantial advantages for cloudburst weather prediction. It builds multiple decision trees, each trained on different subsets of the data, which is crucial in reducing overfitting. In the context of cloudburst prediction, where the relationship between weather variables can be intricate, Random Forest's ensemble approach helps capture the underlying patterns more effectively. By aggregating the results of these trees, Random Forest can provide a consensus prediction, which is especially valuable for assessing the likelihood of cloudburst events. It is essential to note that Random Forest's inherent randomness in the tree construction process also helps in creating diverse models, reducing the risk of bias in predictions.

Step-1: Select random K data points from the training set.
Step-2: Build the decision trees associated with the selected data points (Subsets).
Step-3: Choose the number N for decision trees that you want to build.
Step-4: Repeat Step 1 & 2.
Step-5: For new data points, find the predictions of each decision tree, and assign the new data points to the category that wins the majority votes.

Algorithm 1: Random Forest Model for Cloud Prediction

CatBoost is a powerful open-source gradient boosting library known for its robust performance in a variety of predictive tasks. When applied to cloudburst weather prediction, CatBoost's distinctive feature is its ability to handle both categorical and numerical features seamlessly without the need for explicit encoding. This is particularly advantageous for cloudburst forecasting because weather data often involves a wide range of variables, some of which may be categorical, like weather conditions, while others are numerical, such as temperature and humidity. In addition to its feature-handling capabilities, CatBoost employs the Symmetric Weighted Quantile Sketch (SWQS) algorithm to handle missing values efficiently. This feature is particularly relevant in weather data, where missing data points are not uncommon due to the unpredictability of certain weather phenomena. By addressing missing data, CatBoost contributes to more accurate and reliable predictions of cloudburst events. Moreover, it mitigates overfitting, a common concern when working with complex weather datasets.

Step-1: Select categorical variables are appropriately encoded by CatBoost.

Step-2: Initialize a CatBoost Classifier model for cloudburst prediction

Step-3: Evaluate the model's performance on the testing dataset.

Step-4: Analyze the decision boundaries and feature interactions generated by the model to gain insight.

Step-5: Deploy the trained CatBoost model to make real-time cloudburst predictions.

Step-6: optimize the model as needed by considering new features.

Algorithm 2: CatBoost Model for Cloud Prediction

The XGBoost Classifier, part of the XGBoost library, is a versatile gradient boosting algorithm that excels in classification tasks, making it well-suited for cloudburst weather forecasting. It effectively combines multiple decision trees, reducing overfitting and improving the accuracy of predictions. This is crucial in the context of cloudburst prediction, where accurate and timely forecasts are of utmost importance. The XGBoost algorithm's focus on boosting performance and accuracy contributes significantly to more reliable forecasts of cloudburst events. It employs regularization techniques and optimized tree building processes, resulting in improved model generalization and predictive power.

Step 1: Make an Initial Prediction and Calculate Residuals.
Step 2: Build an XGBoost Tree.
Step 3: Prune the Tree.
Step 4: Calculate the Output Values of Leaves.
Step 5: Make New Predictions.
Step 6: Calculate Residuals Using the New Predictions.

Algorithm 3: XGBoost Model for Cloud Prediction

Decision trees are versatile supervised learning tools that can be applied to cloudburst weather prediction. They determine the best attribute to split data based on criteria like entropy or Gini impurity. This is particularly valuable in weather analysis where understanding the contributing factors to cloudburst events is essential. Decision trees can handle both continuous and categorical variables, allowing for a comprehensive analysis of diverse weather-related features. Furthermore, the transparent decision-making insight provided by decision trees can aid meteorologists and researchers in gaining a deeper understanding of the complex relationships between various weather variables and cloudburst events.

Step-1: Begin the tree with the root node, says S, which contains the complete dataset.
Step-2: Find the best attribute in the dataset using Attribute Selection Measure (ASM).
Step-3: Divide the S into subsets that contains possible values for the best attributes.
Step-4: Generate the decision tree node, which contains the best attribute.
Step-5: Recursively make new decision trees using the subsets of the dataset created in step -3. Continue this process until a stage is reached where you cannot further classify the nodes and called the final node as a leaf node.

Algorithm 4: Decision Tree Model for Cloud Prediction

TABLE I – DATASET CONSIDERED FOR EXPERIMENTATION

AUSTRILIA DATASET:

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Date	Location	MinTemp	MaxTemp	WindGust	WindGust	Humidity9	Pressure9	Pressure3	Temp9am	Temp3pm	CloudBurs	CloudBurstTomorrow	
2	########	Albury	13.4	22.9	W	44	71	1007.7	1007.1	16.9	21.8	No	No	
3	########	Albury	7.4	25.1	WNW	44	44	1010.6	1007.8	17.2	24.3	No	No	
4	########	Albury	12.9	25.7	WSW	46	38	1007.6	1008.7	21	23.2	No	No	
5	########	Albury	9.2	28	NE	24	45	1017.6	1012.8	18.1	26.5	No	No	
6	########	Albury	17.5	32.3	W	41	82	1010.8	1006	17.8	29.7	No	No	
7	########	Albury	14.6	29.7	WNW	56	55	1009.2	1005.4	20.6	28.9	No	No	
8	########	Albury	14.3	25	W	50	49	1009.6	1008.2	18.1	24.6	No	No	
9	########	Albury	7.7	26.7	W	35	48	1013.4	1010.1	16.3	25.5	No	No	
10	########	Albury	9.7	31.9	NNW	80	42	1008.9	1003.6	18.3	30.2	No	Yes	
11	########	Albury	13.1	30.1	W	28	58	1007	1005.7	20.1	28.2	Yes	No	
12	########	Albury	13.4	30.4	N	30	48	1011.8	1008.7	20.4	28.8	No	Yes	
13	########	Albury	15.9	21.7	NNE	31	89	1010.5	1004.2	15.9	17	Yes	Yes	
14	########	Albury	15.9	18.6	W	61	76	994.3	993	17.4	15.8	Yes	Yes	
15	########	Albury	12.6	21	SW	44	65	1001.2	1001.8	15.8	19.8	Yes	No	
16	########	Albury	8.4	24.6	NA	NA	57	1009.7	1008.7	15.9	23.5	No	NA	
17	########	Albury	9.8	27.7	WNW	50	50	1013.4	1010.3	17.3	26.2	NA	No	
18	########	Albury	14.1	20.9	ENE	22	69	1012.2	1010.4	17.2	18.1	No	Yes	
19	########	Albury	13.5	22.9	W	63	80	1005.8	1002.2	18	21.5	Yes	Yes	
20	########	Albury	11.2	22.5	SSE	43	47	1009.4	1009.7	15.5	21	Yes	No	

INDIA DATASET:

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Date	Location	MinTemp	MaxTemp	WindGust	WindGust	Humidity9	Pressure9	Pressure3	Temp9am	Temp3pm	CloudBurs	CloudBurstTomorrow	
2	########	Musi river										Yes	No	
3	########	uttarakhai	10	18.9			96			10	20	Yes	No	
4	########	shimla	9.1	19.1			95			9	23	Yes	No	
5	########	shilagarh										Yes	No	
6	########	badrinath shrine										Yes	No	
7	########	bhavi										Yes	No	
8	########	munsiyari										Yes	No	
9	########	leh town	25	27	SE	11	88	1004	1007	23	25	Yes	No	
10	########	almora	21	27	SW	3	84	1002	1001	21	25	Yes	No	
11	########	khadakwa	23	32	ESE	4	53	1005	1003	23	26	Yes	No	
12	########	pashan,pu	23	31	E	7	60	1006	1004	23	28	Yes	No	
13	########	jammu	26	38	SE	7	30	992	995	26	35	Yes	No	
14	########	upper mai	25	34	N	6	88	1009	1003	25	26	Yes	No	
15	########	delhi	26	33	SSE	5	78	1002	1005	26	24	Yes	No	
16	########	ukhimath	24	27	SE	2	96	1002	1006	24	24	Yes	No	
17	########	kedarnath	20	26	E	4	87	1000	1004	20	27	Yes	No	
18	########	malin,pun	23	25	W	11	91	1003	1007	23	25	Yes	No	
19	########	tehri garh	26	30	E	2	89	1002	1008	26	23	Yes	No	
20	########	kashmir va	22	28	NE	6	72	1002	1007	22	28	Yes	No	
21	########	Tharali an	22	34	NW	3	39	1004	1005	22	27	Yes	No	

IV. EXPERIMENTATION AND RESULT ANALYSIS

In experimentation, we employed a unique approach to address the scarcity of Indian cloudburst prediction datasets. We initially obtained a reference dataset from Kaggle, which was originally Australian based. Subsequently, we adapted this Australian dataset to create an Indian counterpart with matching attributes.

Our model's training process leveraged the Australian dataset, while the Indian dataset served as the testing dataset. We ensured that both datasets shared common attributes, which were categorized into numerical, discrete, continuous, and categorical features. We employed various supervised machine learning algorithms, including CatBoost, Random Forest, Decision Tree, Logistic Regression, and XGBoost Classifier. These techniques were integrated into our proposed self-organized structure for prediction.

Table I in our study illustrates the datasets used for training and testing. By aligning the attributes between the Australian and Indian datasets, we aimed to build a robust model for cloudburst prediction, despite the limited availability of dedicated Indian data. Cloudburst datasets typically consist of tabular weather data, where each column represents a specific variable, and each row corresponds to a data point relevant to cloudburst prediction.

TABLE II – EXPERIMENT RESULTS BASED ON F1-SCORE, PRECISION, RECALL, SUPPORT

Algorithm	Value	Precision	Recall	F1-score	support
Cat boost	0	0.88	0.95	0.91	22717
	1	0.75	0.56	0.64	6375
Random forest	0	0.89	0.91	0.90	22717
	1	0.66	0.61	0.63	6375
Logistic regression	0	0.92	0.77	0.84	22717
	1	0.48	0.76	0.59	6375
K nearest neighbour	0	0.90	0.77	0.83	22717
	1	0.46	0.71	0.56	6375
XGB classifier	0	0.88	0.94	0.91	22717
	1	0.72	0.55	0.62	6375
Decision tree	0	0.87	0.83	0.85	22717
	1	0.48	0.55	0.51	6375

TABLE III – ACCURACY OF DIFFERENT ALGORITHMS

Accuracy of catboost	86.18
Accuracy of randomforest	84.45
Accuracy of logistic regression	76.90
Accuracy of Knearestneighbour	75.53
Accuracy of XGBclassifier	85.49
Accuracy of decisiontree	76.97

In Table 2 and 3, the algorithm performance metrics are presented. The CatBoost algorithm achieved the highest accuracy at 86.18%. For value 0, it had a precision of 0.88, recall of 0.95, and an F1 score of 0.91. For value 1, it showed a precision of 0.75, recall of 0.56, and an F1 score of 0.64. The Random Forest algorithm attained an accuracy of 84.14%. For value 0, it had a precision of 0.89, recall of 0.91, and an F1 score of 0.90. For value 1, it exhibited a precision of 0.66, recall of 0.61, and an F1 score of 0.63.

Logistic Regression yielded an accuracy of 76.90%. For value 0, it resulted in a precision of 0.92, recall of 0.77, and an F1 score of 0.84, while for value 1, it had a precision of 0.48, recall of 0.76, and an F1 score of 0.59. The XGBclassifier algorithm achieved an accuracy of 85.49%, with precision, recall, and F1 scores of 0.88, 0.94, and 0.91 for value 0, and 0.72, 0.55, and 0.62 for value 1. The Decisiontree algorithm showed an accuracy of 76.97%, with precision, recall, and F1 scores of 0.87, 0.83, and 0.85 for value 0, and 0.48, 0.55, and 0.51 for value 1. K-nearest Neighbours had an accuracy of 75.53%, with precision, recall, and F1 scores of 0.90, 0.77, and 0.83 for value 0, and 0.46, 0.71, and 0.56 for value 1.

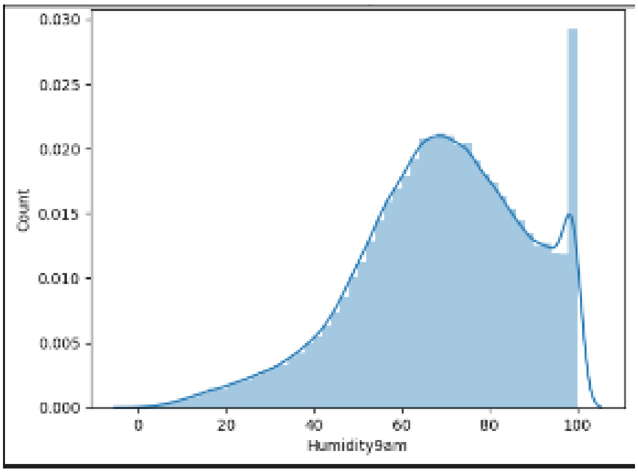

Fig 1: humidity vs count graph.

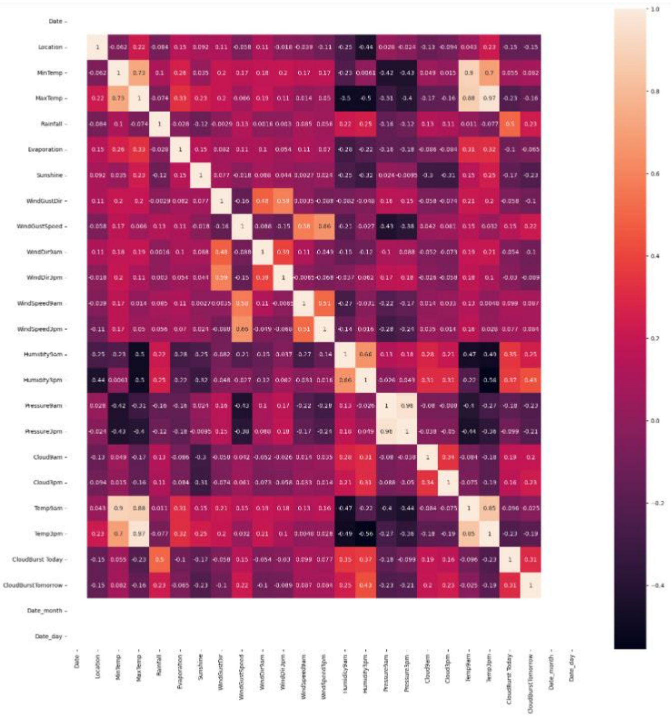

Fig. 2. Co-relation matrix of the attributes.

In Figure 1, we depicted a graph illustrating the relationship between humidity and count. Relative humidity, which quantifies the moisture content in the air relative to its capacity, plays a pivotal role in weather analysis. You can measure humidity using a hygrometer or calculate it based on air temperature, dew point, and established equations. Alternatively, a DIY approach involves constructing a sling psychrometer using readily available materials and basic tools.

specific humidity = 6.11 x 10^{7.5 x dew point} / {237.3 + dew point}

In Figure 2, we presented a correlation matrix, a tabular representation of correlation coefficients between variables. Each cell within the table reflects the correlation between two specific variables. This matrix serves to summarize data, act as input for advanced analyses, and diagnose more complex analytical processes. Typically, a correlation matrix is square, featuring identical variables in both rows and columns. The main diagonal, displaying a line of 1.00s from the top-left to the bottom-right, signifies perfect self-correlation for each variable. This symmetrical matrix exhibits mirrored correlations above and below the main diagonal.

V. CONCLUSION

Our study demonstrates the feasibility of leveraging diverse data sources and advanced machine learning algorithms to address data limitations in cloudburst prediction We employed several machines learning algorithms, including CatBoost, Random Forest, XGBoost, Decision Tree, and Logistic Regression, in our experimentation. The results revealed that CatBoost outperformed other algorithms with an accuracy of 86.18%. This highlights the algorithm's ability to handle both categorical and numerical features effectively, a critical aspect of cloudburst prediction. Random Forest also demonstrated promising results with an accuracy of 84.14%, emphasizing its ensemble approach's advantage in capturing complex weather patterns.

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