# Rainfall Prediction Using Machine Learning

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**ABSTRACT-** "Rainfall Prediction Using Machine Learning" is the project's name. The dataset for this project is kept in Microsoft Excel, and the project is written in Python. Manymachine learning algorithms are used in this prediction to see which method makes the best accurate predictions. Forecasting rainfall is crucial in many areas of a nation and can aid in averting catastrophic natural catastrophes. Logistic Regression, Random Forest Classifier, Gradient Boosting, KNN, Decision Tree, Adaboost Classifier, and Catboost Classifier were allutilised to make this prediction. This project uses a total ofseven modules. The Australian rainfall dataset was utilised. The project's primarygoal is to evaluate different algorithms and identify the top algorithmout of those algorithms. The farmers may greatly benefit from this prediction by planting the appropriate crops based on their requirement for water.

**KEYWORDS**: Machine Learning, Logistic Regression, KNN, Random forest classifier, Gradient Boosting, Adaboost, Decision tree, Catboost.

## 1. INTRODUCTION

How to predict when it will rain is a topic that interests governments, corporations, risk management organisations, and the scientific community all at the same time. Rainfall is a climatic factor that affects a variety of human endeavours, such as tourism, forestry, construction, and agricultural production.

This project is used to predict the rainfall in the 49 cities of Australia. The prediction uses various algorithms. Forecasting rainfall is crucial in many areas of the nation and can aid in averting catastrophic natural catastrophes.

The goal of this study is to offer complete machine learning life cycle models. Here, we'll look at several model descriptions in more depth. The models in question are listed as follows:

- 1. DATA COLLECTION
- 2. DATA VISUALIZATION
- 3. DATA PREPROCESSING

## 4. MODEL SELECTION

## 5. PERFORMANCE EVALUATION.

The structure of the essay is as follows. In section 2, we first explain the dataset. Section 3 presents the strategies and approaches that were employed. In section 4, the outcomes are finally discussed.

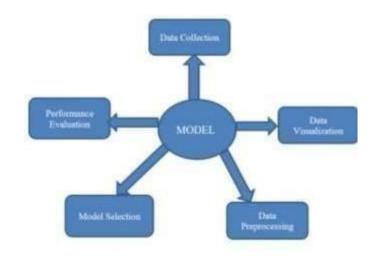


Fig.1(a) 5 steps involved in Model

## 2. DATASET

This section will cover every aspect of the dataset. We'll look at the location of the dataset, the properties it contains, and how each attribute is described in the dataset.

Several descriptions are provided for each characteristic.

The Attributes and datatype and no.of null values in each attribute of the dataset are described as shown below:

	9	Date	142193 non-null	object						
E.	1	Location	142193 non-null	object						
	2	MinTemp	141556 non-null	float64						
	3	MaxTemp	141871 non-null	float64						
	4	Rainfall	140787 non-null	float64						
	5	Evaporation	81350 non-null	float64						
	6	Sunshine	74377 non-null	float64						
	7	WindGustDir	132863 non-null	object						
	8	WindGustSpeed	132923 non-null	float64						
	9	WindDir9am	132180 non-null	object						
	18	WindDir3pm	138415 non-null	object						
	11	WindSpeed9am	140845 non-null	float64						
	12	WindSpeed3pm	139563 non-null	float64						
	13	Humidity9am	140419 non-null	float64						
	14	Humidity3pm	138583 mon-null	float64						
	15	Pressure9am	128179 non-null	float64						
	16	Pressure3pm	128212 non-null	float64						
	17	Cloud9am	88536 non-null	float64						
	18	Cloud3pm	85099 non-null	float64						
	19	Temp9am	141289 non-null	float64						
	28	Temp3pm	139467 non-null	float64						
	21	RainToday	140787 non-null	object						
	22	RISK_MM	142193 non-null	float64						
	23	RainTomorrow	142193 non-null	object						
	dtypes: float64(17), object(7)									
	memory usage: 26.0+ MB									

In the above dataset total we are having 23 attributes in the above metioned attributes our main aim is to predict wheather there will be rain tomorrow or not the main attribute is used for this prediction is "RAINTOMORROW".

In our dataset we are having the null values in each and every attribute so we have to remove those null values. In order to remove those null values we have the concept of data preprocessing. In this data preprocessing we will be using the

data cleaing technique. The description of the attributes are shown in the below picture.

Feature	Description						
Date	The date of observation						
Location	The common name of the location of the weather station						
MinTemp	The minimum temperature in degrees celsius						
MaxTemp	The maximum temperature in degrees celsius						
Rainfall	The amount of rainfall recorded for the day in mm						
Evaporation	The so-called Class A pan evaporation (mm) in the 24 hours to 9am						
Sunshine	The number of hours of bright sunshine in the day.						
WindGustDir	The direction of the strongest wind gust in the 24 hours to midnight						
WindGustSpeed '	The speed (km/h) of the strongest wind gust in the 24 hours to midnight						
WindDir9am	Direction of the wind at 9am						
WindDir3pm	Direction of the wind at 3pm						
WindSpeed9am	Wind speed (km/hr) averaged over 10 minutes prior to 9am						
WindSpeed3pm	Wind speed (km/hr) averaged over 10 minutes prior to 3pm						
Humidity9am	Humidity (percent) at 9am						
Humidity3pm	n Humidity (percent) at 3pm						
Pressure9am	Atmospheric pressure (hpa) reduced to mean sea level at 9am						
Pressure3pm	Atmospheric pressure (hpa) reduced to mean sea level at 3pm						
Cloud9am	Fraction of sky obscured by cloud at 9am.						
Cloud3pm	pm Fraction of sky obscured by cloud at 3pm.						
Temp9am	Temperature (degrees C) at 9am						
Temp3pm	Temperature (degrees C) at 3pm						
RainToday	1 if precipitation exceeds 1mm, otherwise 0						
RISK_MM	The amount of next day rain in mm.						
RainTomorrow	The target variable. Did it rain tomorrow?						

Fig 2.1.weatherAUS.csv

The total no.of rows in the dataset is 42191 rows for 24 columns. Sample data in the dataset is shown in the below picture format.

	HinTenp	<b>HaxTenp</b>		Evaporation	Sunshine	WindGustDir	MindGustSpeed	WindDir9am	MindOir3pm	MindSpeedNan	id.ndSpeed3pn	Humidity9an	Humidity3pm
Albury	13.4	22.9	0.6	NaN	NaN	W	44.0	w	WWW	20.0	24.0	71.0	22.0
Albury	7.4	25.1	0.0	NaN	Nati	WNW	44.0	NEW	WSW	4.0	22.0	44.0	25.0
Albury	12.9	25.7	0.0	NaN	NaN	WSW	46.0	W	WSW	19.0	26.0	38.0	30.0
Albury	9.2	28.0	0.0	NaN	NaN	NE	24.0	SE	Ε	11.0	9.0	45.0	16.0
Albury	17.5	32.3	1.0	NaN	Net	W	41.0	ENE	NW	7.0	20.0	82.0	33.0
Wollongong	13.6	19.2	0.0	NaN	NaN	WSW	17.0	SW	NaN	11.0	0.0	75.0	69.0
Wollongong	14.7	18.7	0.4	NaN	NaN	SSW	52.0	SW	SSW	9.0	30.0	88.0	68.0
Wollangong	14.6	193	0.0	NaN	NaN	SSW	39.0	SSW	SSE	26.0	22.0	66.0	63.0
Wollongong	13.3	17.3	0.0	NaN	NaN	s	56.0	SSW	s	22.0	33.0	57.0	60.0
Wollangang	11.7	17.6	0.0	NaN	NaN	SE	33.0	SW	SE	17.0	24.0	56.0	57.0
	Albury Albury Albury Albury Wollongong Wollongong Wollongong	Albury 7.4 Albury 12.9 Albury 9.2 Albury 17.5 Wolfengeng 13.6 Wolfengeng 14.7 Wolfengeng 13.3 Wolfengeng 13.3 Wolfengeng 13.3	Albury 7.4 25.1 Albury 12.9 25.7 Albury 9.2 26.0 Albury 17.5 32.3 Violengung 13.6 19.2 Violengung 14.7 18.7 Violengung 14.6 19.3 Violengung 14.6 19.3 Violengung 14.7 17.6	Abuy 7.4 25.1 0.0 Abuy 12.9 25.7 0.0 Abuy 92. 26.0 0.0 Abuy 17.5 32.3 1.0 Wildorgong 13.6 19.2 0.0 Wildorgong 14.7 18.7 0.4 Wildorgong 14.6 19.3 0.0 Wildorgong 11.3 17.3 0.6 Wildorgong 11.7 17.6 0.0	Abury 7.4 25.1 0.0 NaN Abury 12.9 25.7 0.0 NaN Abury 92.2 28.0 0.0 NaN Abury 17.5 32.3 1.0 NaN Wildorgong 13.6 19.2 0.0 NaN Wildorgong 14.7 18.7 0.4 NaN Wildorgong 14.6 19.3 0.0 NaN Wildorgong 14.6 19.3 0.0 NaN Wildorgong 11.3 17.3 0.0 NaN Wildorgong 11.7 17.6 0.0 NaN	Aftury 7.4 251 0.0 NaN NaN Adviv 12.9 257 0.0 NaN NaN Adviv 12.9 257 0.0 NaN NaN NaN Adviv 17.5 32.2 1.0 NaN NaN NaN NaN NaN NaN NaN NaN NaN Na	Aftury 7.4 251 00 NaN NaN 1945 19500 Aftury 12.9 25.7 0.0 NaN NaN 1945 1950 Aftury 17.5 12.3 1.0 NaN NaN 1945 1950 1950 1950 1950 1950 1950 1950 195	Aftury 7.4 251 0.0 NaM NaM VMOV 44.0 Aftury 12.9 25.7 0.0 NaM NaM VMOV 46.0 Aftury 17.5 12.3 1.0 NaM NaM ME 24.0 Aftury 17.5 12.3 1.0 NaM NaM W 41.0 Villdungsing 14.7 18.7 0.4 NaM NaM SSW 52.0 Villdungsing 14.6 19.3 0.0 NaM NaM SSW 52.0 Villdungsing 14.6 19.3 0.0 NaM NaM SSW 53.0 Villdungsing 14.6 19.3 0.0 NaM NaM SSW 53.0 Villdungsing 14.6 19.3 0.0 NaM NaM SSW 55.0 Villdungsing 14.6 19.3 0.0 NaM NaM SSW 55.0	Abury         7.4         25 1         0.0         NaN         VMAV         VMOV         44 0         NAM           Abury         12.9         25.7         0.0         NaN         NaN         VMOV         44,0         W           Abury         9.2         28.0         0.0         NaN         NaN         VM         41.0         EME           Abury         17.5         32.3         1.0         NaN         NaN         W         41.0         EME           Wildrageng         13.6         19.2         0.0         NaN         NaN         WWW         17.0         60           Wildrageng         14.7         13.7         0.4         NaN         NaN         SSW         32.0         SSW           Wildrageng         13.3         17.3         0.0         NaN         NaN         SSW         35.0         SSW           Wildrageng         13.3         17.3         0.0         NaN         NaN         SSW         35.0         SSW           Wildrageng         11.7         17.6         0.0         NaM         NaN         SE         33.0         SSW	Aftury         7.4         25 1         0.0         NaM         NaM         VMOV         44.0         NaM         VMOW           Adbury         12.9         25 7         0.0         NaM         NaM         VMOW         46.0         VM         VMOW           Adbury         17.5         32.3         0.0         NaM         NaM         NE         24.0         SE         E           Adbury         17.5         32.3         1.0         NaM         NaM         VW         41.0         EME         NW           Wildrugung         13.6         19.2         0.0         NaM         NaM         V99Y         17.0         SW         NaM           Wildrugung         14.6         19.2         0.0         NaM         NaM         SSW         52.0         SW         SSW           Wildrugung         14.6         19.7         0.4         NaM         NaM         SSW         32.0         SW         SSW           Wildrugung         14.6         19.3         0.0         NaM         NaM         SSW         39.0         SSW         SSW           Wildrugung         13.3         17.5         0.0         NaM         NaM <t< td=""><td>Aftury 7.4 251 0.0 NaN NaN VOW 440 NAW VOW 100 100 Aftury 12.9 25.7 0.0 NaN NaN VOW 440 W VOW 150 0 150 Aftury 17.5 32.3 1.0 NaN NaN W 44.0 EME NAW 7.6 NAW 7.6 NAW NAW NAW 17.0 EME NAW 7.6 NAW NAW NAW 17.0 EME NAW 7.6 NAW NAW NAW 17.0 EME NAW 17.0 NAW NAW 17.0 EME NAW 17.0 EME NAW 17.0 NAW NAW NAW 17.0 EME NAW 17.0 EME NAW 17.0 NAW NAW 17.0 EME NAW 17.0 E</td><td>Aftury 7.4 251 0.0 NaN NaN V90V 440 22.0 Aftury 12.9 25.7 0.0 NaN NaN V90V 480 W90V 490 25.0 Aftury 12.9 25.7 0.0 NaN NaN V90V 48.0 W90V 19.0 26.0 Aftury 17.5 32.3 1.0 NaN NaN W90V 41.0 EME NNV 7.0 25.0 Wildergang 13.6 19.2 0.0 NaN NaN W90V 17.0 SW NaN 11.0 0.0 Wildergang 14.7 18.7 0.4 NaN NaN SSW 32.0 SW SSW 9.0 30.0 Wildergang 14.6 19.3 0.0 NaN NaN SSW 32.0 SSW SSW 9.0 22.0 Wildergang 14.6 19.3 0.0 NaN NaN SSW 35.0 SSW SSW 55.0 26.0 22.0 Wildergang 13.1 17.3 0.0 NaN NaN SSW 35.0 SSW SSW 55.0 22.0 Wildergang 14.6 19.3 0.0 NaN NaN SSW 35.0 SSW SSW 55.0 22.0 Wildergang 15.7 17.6 0.0 NaN NaN SSW 35.0 SSW 55.0 SSW 55.0 22.0</td><td>  Adary   7.4   25.1   0.0   NaM   NaM   VNNIT   44.0   NAM   VNSW   4.0   2.2   44.0   Adary   12.9   25.7   0.0   NaM   NaM   VNSW   44.0   W   VNSW   13.0   25.0   38.0   38.0   Adary   9.2   28.0   0.0   NaM   NaM   NE   24.0   SE   E   11.0   9.0   45.0   Adary   NaM   NaM   NaM   W   41.0   ENE   NW   7.0   26.0   22.0   22.0   Adary   NaM   NaM   W   41.0   ENE   NW   7.0   26.0   22.0   22.0   Adary   NaM   NaM   NAM   WSW   17.0   SW   NaM   11.0   0.0   75.0   NaM   NaM   NAM   NAM   SSW   32.0   SW   SSW   9.0   30.0   61.0   NaM   NaM   NaM   SSW   32.0   SSW   55.0   22.0   22.0   64.0   NaM   NaM   NaM   NAM   NAM   SSW   SSW   SSE   26.0   22.0   64.0   NaM   NaM   NAM   NAM   SSW   SSW   SSW   SSW   3.0   33.0   57.0   NAM   NAM   NAM   SSW   SSW   SSW   SSW   3.0   33.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0  </td></t<>	Aftury 7.4 251 0.0 NaN NaN VOW 440 NAW VOW 100 100 Aftury 12.9 25.7 0.0 NaN NaN VOW 440 W VOW 150 0 150 Aftury 17.5 32.3 1.0 NaN NaN W 44.0 EME NAW 7.6 NAW 7.6 NAW NAW NAW 17.0 EME NAW 7.6 NAW NAW NAW 17.0 EME NAW 7.6 NAW NAW 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11.0   9.0   45.0   Adary   NaM   NaM   NaM   W   41.0   ENE   NW   7.0   26.0   22.0   22.0   Adary   NaM   NaM   W   41.0   ENE   NW   7.0   26.0   22.0   22.0   Adary   NaM   NaM   NAM   WSW   17.0   SW   NaM   11.0   0.0   75.0   NaM   NaM   NAM   NAM   SSW   32.0   SW   SSW   9.0   30.0   61.0   NaM   NaM   NaM   SSW   32.0   SSW   55.0   22.0   22.0   64.0   NaM   NaM   NaM   NAM   NAM   SSW   SSW   SSE   26.0   22.0   64.0   NaM   NaM   NAM   NAM   SSW   SSW   SSW   SSW   3.0   33.0   57.0   NAM   NAM   NAM   SSW   SSW   SSW   SSW   3.0   33.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0   35.0

Fig 2.2.dataset

The irrelevant features in the above dataset is mentioned below:

- 1. Sunshine with 43% of null values.
- 2.Evaporation with 48% of null values.
- 3.cloud 3pm with 43% of null values.
- 4.cloud 9am with 38% of null values.

# 3. Methodology

Methodology is nothing but used methods and AI algorithms in our project here we are discussing the algorithms used in our project brefily. The algorithms used in our project are discussed below. Here we used the seven algorithms in order to predict the best one based on the accuracy percentage they got. the algorithms are:

- 1.KNN
- 2. Random Forest classifier
- 3.Logistic Regression
- 4. Gradient Boosting classifier
- 5.Adaboost
- 6.Decision Tree
- 7.Catboost

Now we will see about these algorithms one by one in detail brefily.

## **1.KNN**:

The full form of KNN is K-Nearest Neighbour .This algorithm is one of the simplest Machine Learning algorithm.This comes under the Supervised Machine Learning Technique.This Algorithm can be used for both regression and classification.Among those two mostly this is used for classification problems.This algorithm can also be called as the LAZY LEARNING Algorithm.

## 2. Random Forest Classifier:

This is one of the popular Machine Learning Algorithm which comes under the Supervised Machine Learning Technique.In this Random Forest Classifier these will produce the more no.of tress among those trees we have to take the best tree that gives the more accuracy.

## 3. Logistic Regression:

This Logistic Regression is an example for the Supervised Machine Learning. This Algorithm mostly use to predict the probability for the occurring of binary event. There are three types of Logistic Regression. These are mentioned below:

1.Binary Logistic Regression
2.Multinomial Logistic Regression
3.Ordinal Logistic Regression

These are the three types of LOGISTIC REGRESSION.

## 4. Gradient Boosting Classifier:

This algorithm is a machine learning technique which is used in classification and regression. This Classifier is present in the ensemble model. This gives the outcome as the binary tree. Based on those we need to take the best part which we will get the less accuracy. In this Algorithm we will use the important parameter named **shrinkage**.

This Gradient Boosting Classifier is the Supervised Machine Learning Algorithm.

## 5. Adaboost Classifier:

This Adaboost Algorithm is a Boosting Technique this can be find in the Ensemble Method in Machine Learning. This Adaboost can be called as the Adaptive Boosting Algorithm. This Algorithm is First Successful boosting algorithm. This algorithm is developed for binary classification purpose. This is very important boosting technique. this converts the multiple "weak classifiers" into single "strong classifier".

## 6. Decision Tree Classifier:

This Decision Tree Algorithm is a Supervised Machine Learning Algorithm. This can be used for both Classification and Regression. Mostly we use this for Classification problems. The format for this is tree-structured format. There will be two kinds of nodes. These are:

## 1.Decision Node

## 2.Leaf Node

In the Decision Node ther will be extention of tree, where as for the Leaf Node there will be no extention. This will consider as the final output.

## 7. Catboost Classifier:

This catboost Classifier is an open-source library. This Algorithm comes under the gradient Boosting classifer. where we can use the decision tree. this algorithm is developed by **YANDEX RESEARCHERS AND ENGINEERS**. This catboost classifier algorithm can be used easily.

## **DATA PREPROCESSING**

The data preprocessing is nothing but which is used to convert the raw data into the clean dataset. For example rawdata is nothing but having the null values. The machine Lerning Algorithm can not understand those null values our aim is to remove those null values. For this process of removing null values we will use the data cleaning step in the data preprocessing steps. The data preprocessing can be applied to the dataset before we use this dataset in our algorithm.Like wise also the Ranforest Algorithm can not perform analysis if the dataset contains the null values. The data preprocessing can also be used in order to format our dataset in particular way. The steps involved in the data preprocessing are mentioned as shown below.

- 1. Having Dataset
- 2. Import Required Libraries
- 3.Loading Dataset
- 4. Identifying Missing Data
- 5. Encoding Categorical Data
- 6. Splitting Dataset into Train and Test Datasets.
- 7. Feature Scaling.

These are seven steps involved in the **data preprocessing** process. After completion of these seven steps we call this dataset as the clean dataset. Now this dataset can used inour required Machine Learning Algorithms.

# **4.Experiments And Results**

In this final step we are going to evaluate the accuracy for the Australian Dataset by using the different machine learning algorithms. The Algorithms we used are KNN, Random forest, Decision Tree, Catboost, Adaboost, Gradient Boosting, Logistic Regression.

Before this we need to do the Data Preprocessing step.we need to train and test our dataset set to get the accurate results. In this step we will find which algorithm is best to use in our project based upon the accuracy score we get for different machine learning algorithms.

Now,we will observe code for the Catboost algorithm and the same code is used for all the algorithms but,we need to change the importing statements. The sample code is provided below:

From sklearn.ensemble import CatBoostClassifier
model = CatBoostClassifier(iterations=2000, eval\_metric =
"AUC")
model.fit(x\_train, y\_train)

y\_pred= model.predict(x\_test)

from sklearn.metrics import accuracy\_score ac = accuracy\_score(y\_pred, y\_test) #output - 0.86

Now, we will observe Accuracy for all the algorithms.

ALGORITHM	ACCURACY				
Logistic Regression	79%				
Decision Tree	73%				
Random Forest	81%				
KNN	80%				
Gradient Boosting	81%				
AdaBoost	80%				
CatBoost	86%				

By observing above table comparing algorithms we observe that catBoost classifier has highest accuracy and Decision tree has least accuracy. So for our project we took CatBoost classifier Algorithm.

## **CONCLUSION**

In this work, we explored and applied many preprocessing techniques to find out how they impacted the overall performance of our classifiers. We also compared every classifier using different inputs, making note of how the entering data can affect the predictions made by the model.

We can infer that Australian weather is erratic and that there is no connection between rainfall and a certain location or time. We found a number of links and trends in the data, allowing us to pinpoint important traits.

Because of the large quantity of data we have, we may employ Deep Learning models like Multilayer Perceptrons, Convolutional Neural Networks (CNN), and others. It would be great to compare Deep Learning models and Machine Learning classifiers.

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