Weather Prediction Using Machine Learning

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***Abstract*—Weather prediction refers to the use of scientific and technological methods to forecast weather conditions in a specific area. Despite being a highly complex and challenging task, this study aims to predict weather patterns by employing predictive analysis. To accomplish this objective, an extensive analysis of various data mining procedures is required before deployment. Specifically, this study proposes a classifier approach that utilizes artificial neural networks and logistic regression techniques to forecast the weather. The proposed system utilizes web datasets to carry out two essential tasks - classification (training) and prediction (testing). The outcomes of this study demonstrate the capability of these data mining approaches to accurately forecast weather conditions.**

Keywords—Weather Prediction, ANN, Logistic Regression, Linear Regression, Machine Learning

I. Introduction

Over the last century, weather forecasting has remained a challenging and technologically complex subject. With the unpredictable shifts in environmental conditions, climate change has been a significant worldwide discussion topic. Despite the in- creasing advancements in technology, accurately predicting the weather remains a difficult task due to several limitations. This makes weather forecasting a crucial area of meteorology. Accurate weather alerts are necessary for safeguarding lives and property. Farmers and traders in product markets rely heavily on weather forecasts to make informed decisions about temperature, humidity, wind, and rainfall. Given the critical relationship between agriculture and rainfall, accurate predictions of rainfall are crucial for the growth and production of food crops, both at the germination and fruit development stages.

As the earth's climate continues to change, it is expected that some regions will experience rising temperatures and heavier rainfall, while others will experience less rainfall. Coastal flooding and other related phenomena may also reduce the amount of land available for agriculture. These climatic changes make it challenging for farmers to adapt to evolving weather conditions, so accurate weather forecasting is increasingly important.

Learning weather representation from vast amounts of weather data is one of the most significant challenges in weather forecasting. This requires using various data mining techniques to analyze data from different dimensions or viewpoints, classify it, and condense the correlations discovered using data mining algorithms. The key terms in data mining are classification, learning, and prediction.

This study focuses on developing a classifier for weather forecasting, which integrates the Logistic Regression method with an artificial neural network. The proposed system performs two essential tasks, namely prediction, and classification (training and testing). The paper provides a comprehensive overview of the technical details, methodology, design architecture, and experimental findings. The related studies are discussed in section three, while sections five and six offer a detailed analysis of the experimental results. Finally, section seven summarizes the study's key findings and conclusions.

II. Problem Statement

The primary motivation for embarking on this project is to develop a comprehensive and reliable economic model that can be utilized by agriculturalists to forecast rainfall patterns over time. The significance of rainfall to ranchers and farmers cannot be overstated, as it can either make or break their crops and undo the laborious work put into the fields. In contemporary times, with global warming posing an increasingly serious problem, understanding rainfall patterns has become more crucial than ever before.

Sudden rainfalls, which are both common and frequent, have played a pivotal role in shaping the character of the earth's landmasses over millions of years. However, with the negative impact of climate change and the increasing frequency of extreme weather events, it has become imperative to study rainfall patterns to mitigate their adverse effects. The ability to accurately reproduce recent rainfall patterns and analyze the impacts and aftereffects of erroneous rainfall that leads to flooding will be a significant step towards achieving this goal.

Through this initiative, we aim to investigate how rainfall has impacted agriculture over time. By developing a robust economic model, we can forecast rainfall patterns, providing farmers with valuable insights into the best time to plant their crops, manage irrigation, and harvest their yields. This

study will enable us to understand how agricultural productivity has been affected by changes in rainfall patterns and how farmers can adapt their practices to cope with the evolving climate conditions.

To achieve our research objectives, we will employ sophisticated data analysis techniques, including machine learning algorithms and data mining methodologies. By leveraging these advanced analytical tools, we can examine historical rainfall data and identify trends and patterns that can inform our economic model. Moreover, we will analyze the impact of different variables on rainfall patterns, including geographical location, atmospheric pressure, and ocean currents, to develop a more comprehensive understanding of the complex interplay of factors that influence rainfall patterns.

In conclusion, this research project will provide valuable insights into the impacts of rainfall on agriculture and enable farmers to adapt their practices to cope with the evolving climate conditions.

III. Literature Review

In the past ten years, there have been a number of significant efforts to address problems with weather forecasting using statistical models, including machine learning systems, with encouraging results. The Weather Prediction System has employed a variety of techniques. The beginning of the twenty-first century has proven to be important in the history of machine learning because of the arrival of vast data, efficient supercomputers with Graphics Processing Units (GPU), and research interest in emerging new methodologies. Despite the fact that several techniques have been extensively researched since the 1960s, recent years are regarded as the pinnacle of artificial intelligence and machine learning due to the extraordinary growth in data volume and computing power.

P. Goswami [1] and Srividya conducted an analysis incorporating CN, RNN, and TDNN features, which led to the conclusion that composite models perform better than single models in terms of accuracy. C. Venkatesan et al. utilized multi-layer feed-forward neural networks to predict rainfall during the Indian summer monsoon (MLFNN), employing the Error Back Propagation (EBP) technique for rainfall forecasting. Three different network models were used, with two, three, and ten input parameters, and their outcomes were compared to statistical projections. Meanwhile, A. Sahai et al. employed an error back-propagation approach using monthly and seasonal time series to estimate summer monsoon rainfall in India. Information from monthly and seasonal mean rainfall values of the previous five years was used to predict rainfall. A CN neural network was used to predict annual rainfall in the Kerala area, which demonstrated superior performance compared to Fourier analysis.

In a study conducted by S. Nanda et al. [7], the authors proposed using a complex statistical model called ARIMA and three ANN models, namely MLP, LPE (Legendre Polynomial Equation), and FLANN (Functional-Link Artificial Neural Network), to forecast rainfall. FLANN demonstrated a higher degree of forecast ac- curacy than the ARIMA model. A. Naik and S. Pathan employed an artificial neural network (ANN) model for predicting rainfall but with a more durable method than the conventional backpropagation approach. Furthermore, Pinky Saikia Dutta and Hitesh Tahbilder utilized the conventional statistical technique of Multiple Linear Regression to predict monthly rainfall in Assam, incorporating parameters such as Min-Max temperature, Mean Sea Level Pressure, Wind Speed, and Rainfall, which yielded respectable levels of accuracy. These findings highlight the potential of machine learning approaches, such as artificial neural networks, for accurate and reliable weather forecasting. The use of composite models and the incorporation of various input parameters can lead to higher accuracy levels in weather prediction. Future research could focus on developing more sophisticated models that incorporate both statistical and machine-learning approaches for more precise predictions of weather patterns. Such research could provide valuable insights into climate change and help to mitigate its impacts.

According to M. Navon's paper [2], a comprehensive overview of various aspects of 4-D VAR and its development over the past two decades is presented. It also aims to present its evolution by highlighting its application and implementation. The 3-D VAR gives the optimal estimation of the true state of the atmosphere during the development of variational data assimilation at operational centers. Due to time and space limitations, no attempt has been made to cover the ensemble Kalman filter data assimilation. This paper however is not exhaustive because it does not address all problems related to 4-D VAR applications. It is abundantly clear that in the past 15 years, significant advancements in NWP have been largely attributed to the development of observational sources, and that 4-D VAR may utilize these sources due to significant research efforts at both operational and research centers. Data assimilation ideas will undoubtedly be used more frequently as more geoscience-related scientific fields have access to larger data sets through sensor networks and satellite remote sensing and as Earth system models get more accurate and sophisticated. It is intended that this study would draw attention to a number of aspects of 4-D VAR data assimilation and pique the curiosity of scientists and practitioners in both the atmospheric and variational optimization fields.

In a paper published by F. Olaiya [4] in 2012, the use of the C5 decision tree algorithm was proposed to classify weather parameters such as temperature, rainfall, wind speed, and evaporation by month and year. This approach allowed for the observation of how these parameters influenced weather patterns throughout the study period. Through sufficient data collection over time, significant shifts in climatic patterns can be detected. Artificial neural networks (ANNs) have emerged as a valuable tool for identifying the complex relationships between meteorological parameters and forecasting future weather conditions. In this study, predictive ANN models were constructed to forecast Wind speed, Evaporation, Radiation, Minimum Temperature, Maximum Temperature, and Rainfall based on Month and Year. Two types of neural network architectures, the TLFN and Recurrent networks, were utilized in the construction of these models. The study found that the recurrent TLFD network, equipped with the TDNN memory component,

produced superior training and testing outcomes compared to the TLFD network with the Gamma memory component. The effectiveness of the models was evaluated using training and test- ing data, with the analysis taking into consideration the limited size of the data available. It is important to note that collecting data over a more extended period is necessary to achieve better results. Nonetheless, the findings of this study demonstrate the efficacy of ANNs in weather prediction and suggest that they could play a vital role in improving our ability to forecast weather conditions. Future research will utilize neuro-fuzzy models to predict weather patterns. This study is vital for understanding climate change as data mining approaches can be used to investigate temperature, rainfall, and wind speed fluctuations.

In [3] this paper, Abhishek et al. (2012) proposed an artificial neural network model for weather forecasting. The study evaluated the performance of the model in predicting temperature and humidity in different seasons. The authors explain the limitations of traditional numerical weather prediction models and the potential of artificial neural network (ANN) models for weather forecasting. They then describe the architecture of their proposed model, which consists of three layers: input, hidden, and output. The input layer contains weather variables such as temperature, humidity, pressure, and wind direction. The hidden layer performs calculations on the input data, and the output layer produces a forecast of the weather variable of interest, such as temperature. The authors used data from the India Meteorological Department (IMD) for training and testing their model. They tested their model using statistical metrics like MAE or mean absolute error, mean bias error, and root mean square error for accuracy. The results showed that the ANN model had better accuracy than traditional numerical weather prediction models for predicting temperature and rainfall.

Moreover, various authors tried to predict wind power by using a nonlinear prediction method, Gaussian Process rather than using traditional historic data from SCADA for better accuracy. By using this method, they improved the performance of NWP and made it possible to accurately predict wind power and speed so it becomes easy for maintenance workers to work on wind turbines. This paper contributes to maintaining the popular eco-friendly energy source of our time, wind power. So we can expect longer up time for those turbines. Data has been gathered from two wind farms in China. One is in the Gansu province of windy western China (denoted as Farm-G) and another one is from Jiangsu province, a coastal area (Farm-J). Both of these wind farms are 2400 km apart. The methodology is where it gets interesting. Instead of using barebones numerical weather prediction, they added the Gaussian process as a correction tool to the model. In fact, they im- proved the Gaussian process by censoring it with factors only related to wind speed to make it more efficient. The following methods are used to measure accuracy; the root mean square error (RMSE), the normalized root mean square error (NRMSE), the mean absolute error (MAE), and the normalized mean absolute percentage error (NMAPE). The empirical evidence from the simulation demonstrates that the proposed GP-CSpeed model has substantially greater accuracy, ranging from 9% to 14%, compared to an MLP model when analyzing the voluminous datasets of Farm- G, and Farm-J. These results conclusively validate the efficiency and efficacy of the GP-CSpeed model. Additionally, the GP-CSpeed model's superiority is particularly remarkable when confronted with limited training data, as it attains a remarkable 16.67% enhancement for the recently established Farm-R dataset. There was no significant limitation to this model but we can gather data from different parts of the world to build an international model which can help without the hassle of collecting data in each area.

Here [9] by utilizing NWP ensemble wind power forecasts, writers attempt to anticipate sudden, forceful gusts of wind known as ramps. These ramps have the potential to cause wind farms to undergo significant fluctuations in production within a brief time frame. The aim is to provide an original and genuine interpretation of the sentence. This study holds significant relevance for contemporary wind farms, as the occurrence of ramps can lead to intricate fluctuations in power generation, resulting in an erratic supply of electricity. The word 'ramp' can have multiple interpretations, one of which pertains to fluctuations in wind power occurring at various temporal scales. It sometimes refers to intra-hourly variations, e.g. 10 minutes to an hour. A power system operator can use this to earn valuable intelligence to make management decisions. All the data for this research was gathered from an 8-megawatts wind farm in France. So they started off by mathematically defining a ramp using calculus power vs. time to find those quick changes in power signal. Clusters of ramps were used to detect ramps but it did not work out the way they expected. Then a probabilistic forecast was created to deal with that issue. Lastly, they used Nadarya–Watson estimator and logistic regression as well besides NWP ensembles. For testing purposes, a decomposed Brier score was used. This method provides much better accuracy in sharp turns in graphs which is necessary to predict ramps. This is a breakthrough finding rather than improving existing systems, so a lot can be improved both mathematically and technically. A wind power forecast for a limited time span may not provide adequate details to make crucial security management decisions regarding the possibility of ramp events. Ramps can have a correlation to many other factors. If we gather data on-ramps rather than manually defining it, we can achieve much higher accuracy. Subsequent research could involve assessing the methodology at additional locations to confirm the findings across varying weather patterns.

Culclasure et al. [5] used neural networks to provide local weather forecasts. The thesis explores various machine learning techniques and evaluates their performance in predicting weather conditions. [6] Litta et al. put forth a proposition for an artificial neural network (ANN) model, which aims to predict meteorological parameters preceding pre-monsoon thunderstorms. The study focused on forecasting thunderstorms, which are critical weather phenomena in India. Rasp et al. [11] introduced WeatherBench, a benchmark data set for data-driven weather forecasting. The dataset includes high-resolution global atmospheric simulations and provides a standardized way to compare different forecasting models. Kumar et al. [10] proposed a method for verifying uncertainty calibration in weather forecasting. The study aimed to provide a way to better estimate and communicate uncertainties in weather

predictions, which can help decision-makers take appropriate actions. Fo ̈ll et al. [8] proposed a deep recurrent Gaussian process model with a variational sparse spectrum approximation. The model is capable of learning long-term dependencies and can capture uncertainties in its predictions. Trebing et al. [12] introduced Smaat-UNet, a precipitation nowcasting model based on a small attention-UNet architecture. The model outperforms several existing methods in predicting short-term precipitation and can be used for real-time applications.

Weather forecasting is an essential aspect of human activity as it helps us plan our daily routines and make informed decisions. The early humans predicted the weather based on their observations of nature, such as cloud patterns, wind direction, and animal behavior. However, with the advancements in science and technology, the process of weather forecasting has become more sophisticated. At present, weather forecasting is accomplished through computerized models that employ intricate algorithms to forecast the atmospheric conditions of a specific region and moment. These predictive models collect comprehensive data on prevailing atmospheric conditions, encompassing crucial parameters such as temperature, barometric pressure, moisture content, wind velocity, and directional shifts. Based on this information, they forecast the future trajectory of weather patterns, enabling proactive measures to mitigate any potential impacts. While the use of computers in weather forecasting has improved the accuracy of predictions, it still requires human input to select the best predictive model for establishing the forecast. This involves various skills like pattern recognition, communication through different manners, accessing performance data of the model, and considering model bias data. The benefits of using computers in weather forecasting are evident, as it allows for the analysis of large amounts of data and the use of sophisticated algorithms to make predictions. Moreover, computer-based models can identify patterns that humans may not detect, making it easier to predict weather patterns accurately.

Accurate daily weather prediction is crucial for making efficient decisions. However, traditional linear weather prediction models fail to account for non-linearity in input data, thereby necessitating the development of more advanced nonlinear models. In general, weather forecasting models can be categorized into three groups: data classification, data clustering, and data prediction. Data classification entails forecasting weather conditions based on input parameters, while data clustering involves grouping input data into clusters that each have a cluster centroid. Regression analysis, also known as data prediction, involves predicting the output variable's value using linear or nonlinear prediction models. To classify weather data, this study proposes a fully connected neural network (FCNN) model. Unlike conventional weather classification models, the FCNN model accounts for the nonlinear association between input features and output conditions [10]. The model has demonstrated exceptional learning and generalization abilities, allowing it to capture the intricate nonlinear relationships present within the input features of the dataset. Outperforming similar models in terms of overall accuracy, user accuracy, producer's accuracy, and kappa coefficient. The model achieved an OA of 87.83% as tested with the IMD dataset. Additionally, the model's flexibility makes it potentially useful for higher dimensional dataset classification.

The scientific application of technology and knowledge to forecast atmospheric conditions for a specific place and time is known as meteorological forecasting. Though attempts at weather forecasting have been made ad hoc since the 19th century, it has only been possible due to the collection of data about the prevailing state of the atmosphere in a particular location, which is then used to make predictions regarding its future state. The selection of the most accurate predictive model requires human input, while the use of computer-based models that take into account numerous celestial objects is crucial to forecasting weather, climate, and cloud cover changes, which, in turn, are integral to various human activities. The selection of the most suitable predictive model still heavily depends on human involvement, such as pattern recognition, model bias assessment, etc. The application of computers in information management has been prevalent for quite some time, and their integration into weather forecasting has become well-established. This amalgamation of human expertise and technological advancements has resulted in more precise and reliable weather predictions.

1) Availability: The manual system did not provide us with this information.
2) Time: Provides specifics (output) rapidly.
3) Accuracy: Leveraging the power of computing can result in significantly enhanced precision in data acquisition compared to manual documentation.
4) The Ideal: We were never given insufficient information by the computer. On a computer, we will always find comprehensive and exhaustive data.
5) Effective and purposeful behavior: No matter what task we assign to a computer, it will only perform that one.

It indicates that the computer always performs a useful and user-friendly function. This system facilitates more accurate forecasting of the report. There are fewer in- stances of failure. The plan has reached a stable stage, but additional advancements are still necessary. It was created in response to a need. This system will be designed in the shape of a cross so that it can be utilized globally in the future. Every user can easily operate it due to its intuitive design. This application has been modified to consume less RAM and phone storage space.

IV. Research Methodology

This study utilizes data mining techniques, specifically Artificial Neural Network and Logistic Regression, to extract valuable information from a dataset and make weather predictions based on recent weather information. By using these techniques, the system is able to analyze and identify patterns in the data, allowing it to make accurate predictions about future weather conditions. The use of these advanced techniques ensures that the system is able to process and interpret complex data sets and produce reliable weather forecasts.

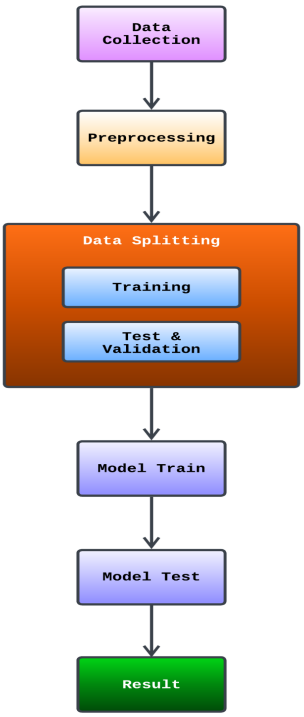


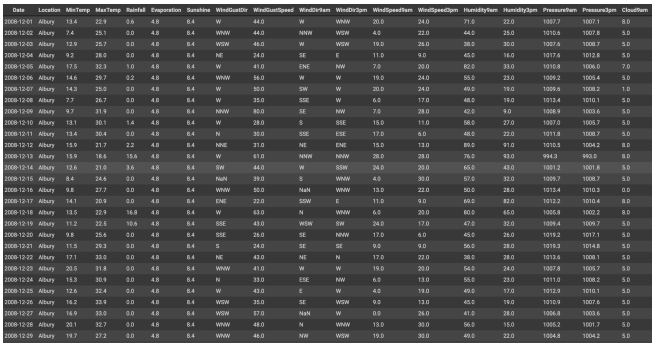
Fig. 1. Workflow of Weather Prediction

V. Model and Description

Artificial Neural Network (ANN) is a type of machine learning model that is inspired by the structure and function of the human brain. It is a digitized version of the human brain that can process information in a similar way to how the human brain works. Like humans, ANNs are trained with examples and data, rather than being programmed with specific instructions. By analyzing large datasets and using complex algorithms, ANNs can identify patterns and relationships in data that are difficult or impossible for humans to detect. This makes ANNs ideal for tasks such as image recognition, natural language processing, and weather prediction.

Logistic regression is a statistical analysis approach that leverages historical observations from a dataset to forecast a binary outcome, such as a positive or negative result. It is a robust technique for data analysis that derives predictions from the patterns and interrelationships among variables. A logistic regression model anticipates a dependent variable by examining the correlation among one or more independent variables. In various fields such as finance, healthcare, and marketing, accurate predictions based on logistic regression models are critical for decision-making. In the domain of weather prediction, logistic regression can be used to scrutinize patterns in past weather data and make predictions about the probability of particular weather phenomena transpiring in the future.

VI. Dataset



Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGustSpeed	WindDir9am	WindDir3pm	WindSpeed9am	WindSpeed3pm	Humidity9am	Humidity3pm	Pressure9am	Pressure3pm	Cloud9am
2008-12-01	Albury	13.4	22.9	0.6	4.8	8.4	W	44.0	W	WNW	20.0	24.0	71.0	22.0	1007.7	1007.1	8.0
2008-12-02	Albury	7.4	25.1	0.0	4.8	8.4	WNW	44.0	NNW	WSW	4.0	22.0	44.0	25.0	1010.6	1007.8	5.0
2008-12-03	Albury	12.9	25.7	0.0	4.8	8.4	WSW	46.0	W	WSW	19.0	26.0	38.0	30.0	1007.6	1008.7	5.0
2008-12-04	Albury	9.2	28.0	0.0	4.8	8.4	NE	24.0	SE	E	11.0	9.0	45.0	16.0	1017.6	1012.8	5.0
2008-12-05	Albury	17.5	32.3	1.0	4.8	8.4	W	41.0	ENE	NW	7.0	20.0	82.0	33.0	1010.8	1006.0	7.0
2008-12-06	Albury	14.6	29.7	0.2	4.8	8.4	WNW	56.0	W	W	19.0	24.0	55.0	23.0	1009.2	1005.4	5.0
2008-12-07	Albury	14.3	25.0	0.0	4.8	8.4	W	50.0	SW	W	20.0	24.0	49.0	19.0	1009.6	1008.2	1.0
2008-12-08	Albury	7.7	26.7	0.0	4.8	8.4	W	35.0	SSE	W	6.0	17.0	48.0	19.0	1013.4	1010.1	5.0
2008-12-09	Albury	9.7	31.9	0.0	4.8	8.4	NNW	80.0	SE	NW	7.0	28.0	42.0	9.0	1008.9	1003.6	5.0
2008-12-10	Albury	13.1	30.1	1.4	4.8	8.4	W	28.0	S	SSE	15.0	11.0	58.0	27.0	1007.0	1005.7	5.0
2008-12-11	Albury	13.4	30.4	0.0	4.8	8.4	N	30.0	SSE	ESE	17.0	6.0	48.0	22.0	1011.8	1008.7	5.0
2008-12-12	Albury	15.9	21.7	2.2	4.8	8.4	NNE	31.0	NE	ENE	15.0	13.0	89.0	91.0	1010.5	1004.2	8.0
2008-12-13	Albury	15.9	18.6	15.6	4.8	8.4	W	61.0	NNW	NNW	28.0	28.0	76.0	93.0	994.3	993.0	8.0
2008-12-14	Albury	12.6	21.0	3.6	4.8	8.4	SW	44.0	W	SSW	24.0	20.0	65.0	43.0	1001.2	1001.8	5.0
2008-12-15	Albury	8.4	24.6	0.0	4.8	8.4	NaN	39.0	S	WNW	4.0	30.0	57.0	32.0	1009.7	1008.7	5.0
2008-12-16	Albury	9.8	27.7	0.0	4.8	8.4	WNW	50.0	NaN	WNW	13.0	22.0	50.0	28.0	1013.4	1010.3	0.0
2008-12-17	Albury	14.1	20.9	0.0	4.8	8.4	ENE	22.0	SSW	E	11.0	9.0	69.0	82.0	1012.2	1010.4	8.0
2008-12-18	Albury	13.5	22.9	16.8	4.8	8.4	W	63.0	N	WNW	6.0	20.0	80.0	65.0	1005.8	1002.2	8.0
2008-12-19	Albury	11.2	22.5	10.6	4.8	8.4	SSE	43.0	WSW	SW	24.0	17.0	47.0	32.0	1009.4	1009.7	5.0
2008-12-20	Albury	9.8	25.6	0.0	4.8	8.4	SSE	24.0	SE	NNW	17.0	6.0	45.0	28.0	1019.2	1017.1	5.0
2008-12-21	Albury	11.5	29.3	0.0	4.8	8.4	S	24.0	SE	SE	9.0	9.0	56.0	28.0	1019.3	1014.8	5.0
2008-12-22	Albury	17.1	33.0	0.0	4.8	8.4	NE	43.0	NE	N	17.0	22.0	38.0	28.0	1013.6	1008.1	5.0
2008-12-23	Albury	20.5	31.8	0.0	4.8	8.4	WNW	41.0	W	W	19.0	20.0	54.0	24.0	1007.8	1005.7	5.0
2008-12-24	Albury	15.3	30.9	0.0	4.8	8.4	N	33.0	ESE	NW	6.0	13.0	55.0	23.0	1011.0	1008.2	5.0
2008-12-25	Albury	12.6	32.4	0.0	4.8	8.4	W	43.0	E	W	4.0	19.0	49.0	17.0	1012.9	1010.1	5.0
2008-12-26	Albury	16.2	33.9	0.0	4.8	8.4	WSW	35.0	SE	WSW	9.0	13.0	45.0	19.0	1010.9	1007.6	5.0
2008-12-27	Albury	16.9	33.0	0.0	4.8	8.4	WSW	57.0	NaN	W	0.0	26.0	41.0	28.0	1006.8	1003.6	5.0
2008-12-28	Albury	20.1	32.7	0.0	4.8	8.4	WNW	48.0	N	WNW	13.0	30.0	56.0	15.0	1005.2	1001.7	5.0
2008-12-29	Albury	19.7	27.2	0.0	4.8	8.4	WNW	46.0	NW	WSW	19.0	30.0	49.0	22.0	1004.8	1004.2	5.0

Fig. 2. Sample Dataset

The initial stages of the data mining process include gathering and preparing the data. The dataset used in this project was obtained from the Kaggle website. Since the accuracy of the outcomes is dependent on the reliability of the data, data preparation is a crucial step. The project utilizes user data. Even though the dataset had a large number of attributes, only the most important ones were focused on during the data preparation stage, while the rest were disregarded. After modifying the data, a format suitable for data mining was created. The weather forecasting was identified based on four specific characteristics.

VII. Model Creation

The study employs two data mining techniques, namely Artificial Neural Network (ANN) and Logistic Regression, to categorize and analyze the weather data. The data used for the analysis is collected from a training dataset, which is integrated with test data to predict the weather. Both ANN and Logistic Regression algorithms search for correlations between the predictor values and the goal values and then use this information to make predictions on test data.

ANN is a type of computer system that imitates the structure and functioning of animal brains' neural networks. It is composed of nodes or connected units that simulate the behavior of biological neurons. In an ANN, the input is processed by a hidden layer, which then communicates the output. The computation in an ANN involves the weighted sum of the inputs, which is then modified by a bias. This computation is represented mathematically as a transfer function.

Logistic Regression, on the other hand, is a popular algorithm used in Machine Learning and falls under the category of Supervised Learning. It is used to predict a categorical dependent variable using a predetermined set of independent factors. In binary logistic regression, there is a single binary dependent variable, indicated by values 0 or 1. The independent variables can either be binary or continuous. Lo- logistic Regression identifies the relationship between the dependent and independent variables and uses this information to make predictions.

VIII. Implementation and Result

We had to create appropriate libraries needed for neural networks, such as TensorFlow, Keras, etc. for the construction of ANN and Logistic Regression. The dataset was loaded in the second step using the Pandas library. About ten years' worth of daily weather measurements from various points across Australia are included in the dataset. Several weather stations were used to gather observations. Correlation between numerical properties, date-time parsing, and encoding of days and months as continuous cyclic features were all used in the implementation.

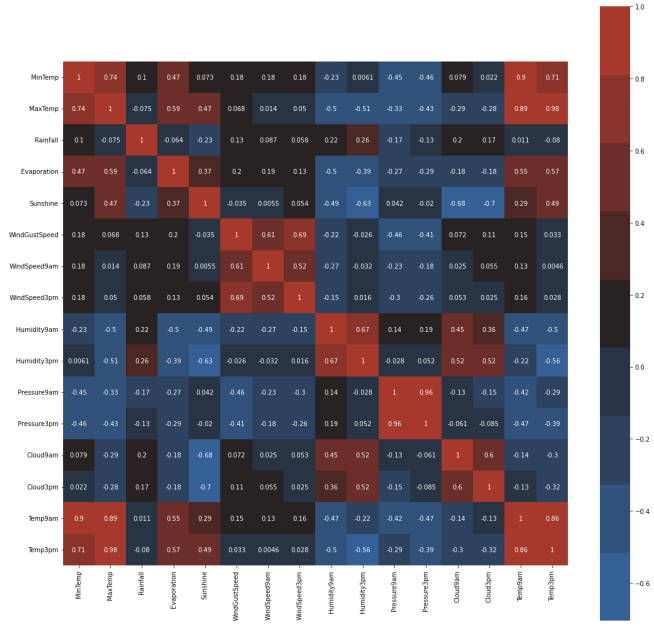


Fig. 3. Correlation Matrix

In order to test the accuracy of the data mining algorithms, several steps were taken to prepare the dataset. First, preprocessing techniques were applied to the data, which involved cleaning and organizing the data to remove any errors or inconsistencies. Next, scaling was performed to standardize the range of values in the dataset, which makes it easier for the algorithms to process the data. Outliers, which are values that are significantly different from the rest of the dataset, were also eliminated to improve the accuracy of the algorithms.

After preprocessing, the feature and goal variables were included in the dataset, and the modeling process began. This involved separating the data into train and test sets, which are used to train and validate the accuracy of the algorithms. The train set is used to train the ANN and Logistic Regression models, while the test set is used to evaluate the accuracy of the models.

Finally, the train and test sets were input into the ANN and Logistic Regression algorithms for output. The algorithms use the data to identify patterns and correlations between the independent and dependent variables, which they use to make predictions about the target variable, in this case, weather forecasting. The output of the algorithms provides insight into the accuracy and reliability of the predictions made by the models.

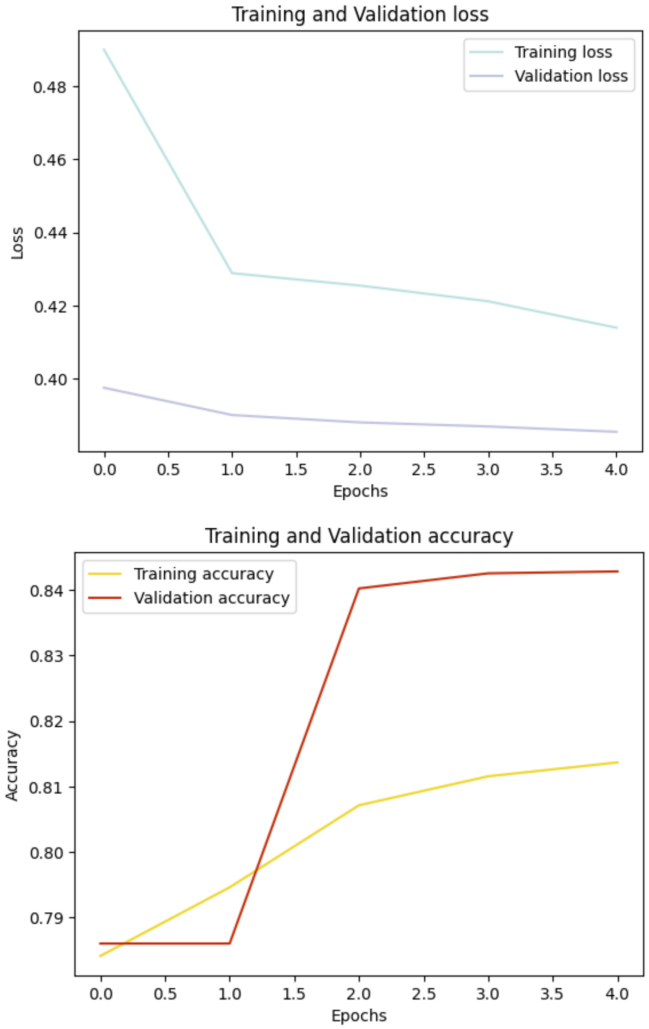


Fig. 4. Training and Validation Loss and Accuracy

	precision	recall	f1-score	support
0	0.87	0.95	0.91	20110
1	0.70	0.47	0.56	5398
accuracy			0.85	25508
macro avg	0.78	0.71	0.73	25508
weighted avg	0.83	0.85	0.83	25508

	precision	recall	f1-score	support
0	0.85	0.95	0.90	22726
1	0.71	0.41	0.52	6366
accuracy			0.83	29092
macro avg	0.78	0.68	0.71	29092
weighted avg	0.82	0.83	0.82	29092

Fig. 5. Test Results of ANN and Logistic Regression

IX. Challenges

Implementing a project for the first time can be challenging, and our project had several obstacles and hurdles to overcome. One of the primary challenges was identifying the appropriate dataset that would be suitable for our project. This was a difficult task, as we had to search through multiple sources before finding a good dataset that fit our needs.

Another challenge we faced was working with a large amount of data, which can slow down the processing time. To address this issue, we divided the larger dataset into smaller pieces and processed it in stages to make the project go more quickly and smoothly.

We also encountered hardware dependency issues, as the ANN technique we used required high-configuration hardware to compute. This added an extra layer of complexity to the project, as we had to ensure that our hardware was up to the task.

Finally, we had to overcome overfitting issues with the logistic regression model. This required us to carefully fit the model to ensure that it was not overfitting the data.

Despite these challenges, we were able to overcome them and successfully complete the project. Through our hard work and perseverance, we were able to implement an effective weather prediction system using data mining techniques.

X. Future Works

Feature scaling is indeed a critical step in ML models, as it helps to ensure that all input variables are on a similar scale. This is important because some models may give higher weightage to variables that have larger values, even if they are not necessarily more important. By scaling the features, we can avoid this issue and make sure that the model is not biased toward certain variables. Outliers can also be problematic for ML models as they can skew the results and lead to inaccurate predictions.

It is true that weather forecasting is a complex and nonlinear system, and traditional linear regression models may not be the most accurate for predicting weather patterns. However, as you mentioned, with the help of AI and machine learning, we can improve the accuracy of weather forecasting models by analyzing large amounts of data and identifying patterns that humans may not be able to discern on their own.

The use of IoT sensors to gather weather data is also an interesting approach, as it can help to increase the amount of data available for analysis and improve the accuracy of predictions. As technology continues to advance, we may see even more sophisticated AI systems being developed to analyze weather data and make predictions with even greater accuracy.

XI. Conclusion

To summarize, we employed Artificial Neural Network (ANN) and Logistic Regres- sion techniques to classify rainfall and compared their accuracy scores to determine the suitable method for developing a weather forecasting model. Our results showed that the ANN model outperformed the logistic regression model, achieving an 84% accuracy score. Moreover, we proposed a methodology for creating weather forecasts using machine learning algorithms that are more efficient than traditional physical models. These intelligent models require minimal resources and can operate on various platforms, including mobile devices.

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