PROJECT-Smart Irrigation using IOT and ML

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PROJECT-Smart Irrigation using IOT and ML

Smart Irrigation Applying ML and IoT

419 A report submitted in partial fulfillment of the requirements for the award of the degree of

Bachelor of Technology

in

Electronics & Communication and Engineering

by

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INDIAN INSTITUTE OF INFORMATION TECHNOLOGY TIRUCHIRAPPALLI

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MAY 2023

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420 This[1] is to certify that the project work titled "Smart Irrigation Applying ML and
421 IoT" is a bonafide record of the work done by

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422 in[2] partial fulfillment of the requirements for the award of[3] the degree of Bachelor of Technology in Electronics and Communication Engineering of the Indian Institute of Information Technology Tiruchirappalli during the year 2022-
423 2023. The[4] contents of this report, in full[5] or in parts, have not been submitted to any other institute or university for the award of any degree or diploma.

Dr. R. Krishnamurthy, Dr. G. Seetharaman

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Project viva-voce held on ____________________

Internal Examiner External Examiner

ABSTRACT

Farms can be upgraded with electronic technology to continuously monitor crop and soil conditions, allowing crops to be watered as needed. This can be controlled and monitored online using IoT applications. You can create a device that connects to a water pump controlled by an Arduino UNO R3 microcontroller. The water pump automatically controls based on the values of various environmental factors such as temperature, humidity, soil moisture, and light intensity, which can be measured via sensors such as DHT-11 temperature and humidity sensor, humidity sensor, and LDR sensor. Our research work focuses on making the model intelligent by storing previously scanned values in a database and performing pre-recognition based on the stored historical values during the training phase of the working model. The model is trained using the Random Forest Classifier algorithm. Agriculture plays an important role in the economy, and its contribution is based on quantifiable crop yields that heavily rely on irrigation. In countries like India, where agriculture is largely based on an unorganized sector, irrigation techniques and patterns are often inefficient, leading to unnecessary water wastage. An automated irrigation system based on artificial vision and the Internet of Things can autonomously irrigate fields using soil moisture data.

The[4] system is based[19] on forecasting algorithms that use historical weather data to identify and forecast precipitation patterns and climate change. This[4,20] creates a sophisticated system that selectively irrigates crop fields only when needed at the right time based on weather and soil moisture conditions. The[4] system has been tested with 89% accuracy in a controlled environment and offers an efficient solution to your dilemma.

Keywords: Machine Learning, Internet of Things, Arduino, Neural Networks, Rainfall Prediction

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CHAPTER 1

INTRODUCTION

In India, traditional agricultural methods are followed[25] for irrigation, which heavily relies on personal[26] supervision and experience of farmers. This[4] results in highly inefficient and outdated irrigation practices, leading to poor crop yield and wastage of water resources. It[4] is essential to provide farmers with reliable and adaptable irrigation solutions that can accurately determine the amount of[2] water their crops require based on local climatic conditions. The[4] main challenge in India is not water scarcity but water wastage and poor resource utilization due to lack[28] of infrastructure and facilities. Due[4] to this issue, the country is facing[29] significant economic losses from drought conditions, variable rainfall patterns, and crop eradication.

Automated irrigation systems that follow traditional methods are not suitable for India as they are unable to[30] adapt to the country's changing rainfall patterns and are not responsive to geographical variations. India[4] requires an innovative and adaptable irrigation system that can handle these challenges and provide effective[31] water management for agriculture.

The system developed for irrigation in India is unique as it studies local rainfall patterns and adapts to changing weather conditions to predict water requirements for irrigation. The[4] system uses microcontrollers and soil moisture sensors placed in waterproof boxes distributed evenly over the area to be irrigated[32], connected[33] to the cloud via Wi-Fi. The[4] system analyzes soil moisture levels via sensors and requires little to no human intervention once deployed. The system is designed to update continuously and uses the Desultory Forest Regressor to estimate weather patterns. The developed system is energy-efficient, water-efficient, and low maintenance. Nodes are scattered throughout the farm grounds to minimize water wastage and increase efficiency. The system also works with a replication prediction system, allowing easy identification of failures. Node status can be monitored via a mobile app based on the mapping of farms and areas designated for irrigation. Overall, the system promotes low maintenance and has proven to be effective in reducing water wastage and increasing yield.

MOTIVATION

In India, agriculture heavily relies on irrigation for crop production, and water availability significantly impacts crop yield. However, the traditional irrigation methods used in the country are inefficient and result in significant water wastage. Farmers rely on their personal experience and supervision to irrigate their fields, which leads to poor utilization of resources and economic losses due to drought and crop eradication.

Absolutely, efficient and effective irrigation solutions are crucial for sustainable agriculture in India. By implementing innovative technologies like IoT-based irrigation systems and smart water management practices, farmers can optimize water usage, reduce waste, and increase crop yields. This not only benefits the farmers' livelihoods but also contributes to the overall economic development of the country.

Modern irrigation systems that incorporate advanced technologies such as microcontrollers, soil moisture sensors, and cloud computing can help address these challenges. By using these technologies, farmers can accurately determine the amount of[46] water required for their crops based on soil moisture levels and weather conditions. This[4,47] can help minimize water wastage and increase crop yields. Additionally[4], these systems can adapt to changing weather patterns and adjust water usage accordingly, making them more efficient and effective than traditional irrigation methods.

Investing in modern technologies and innovative solutions can greatly[48] benefit India's agriculture sector. The[4] government can play a vital role in facilitating the adoption of new technologies by providing financial incentives and policy support to farmers and other stakeholders. The[4] private sector can also contribute by developing and commercializing new irrigation solutions that meet the needs of Indian farmers. Additionally[4], research institutions and universities can collaborate with farmers and other stakeholders to identify and develop new technologies that are tailored[49] to the unique needs of Indian agriculture. With[4] a collaborative effort,[50] India can improve its irrigation systems and achieve sustainable and efficient crop production.

OBJECTIVES

The use of electronic technology has revolutionized the way irrigation is carried out[51] in[52] farms. By[4] continuously monitoring crop and soil conditions, it is now possible to water crops precisely when they need it.[53] The[4] process can be remotely controlled[54][55] and monitored using IoT applications, making it convenient for farmers to operate the system.

To achieve this[56], a device can be created[57] that connects to a water pump and is controlled by an Arduino UNO R3 microcontroller. The[4] water pump can be programmed[58] to operate automatically based on various environmental factors such as temperature, humidity, soil moisture, and light intensity, which[59] are measured using sensors like DHT-11[60] temperature and humidity sensor, humidity sensor, and LDR sensor.

To make the device more intelligent and efficient[61], our research work[62] focuses on storing previously scanned values in a database and performing pre-recognition based on the stored historical values during the training phase of the working model. This[4,63] helps to increase the accuracy of the model's predictions, leading to improved irrigation efficiency and better use of
428 resources. The[4] Random Forest algorithm[66] is used[64] to train the model, which is[65] a widely used algorithm for regression analysis.

The use of electronic technology in agriculture can have a significant impact on India's food security and economic growth. By[4] reducing water wastage and improving crop yields, farmers[67] can generate more income and contribute to the country's economy. Additionally[4], the conservation of[68] water resources is crucial for addressing water scarcity issues in the country, and the use of[68] electronic irrigation systems can help achieve this goal. Therefore[4], it is essential to continue investing in and promoting the use of[69] electronic technology in agriculture in India.

CHAPTER 2

LITERATURE REVIEW

1. INTELLIGENT[4] IRRIGATION SYSTEM USING ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

Research paper key points:

The microcontroller of Arduino receives regular data from temperature and moisture sensors through its built-in analog to digital converters.

The KNN algorithm, implemented in the hardware, processes the sensor data to activate the irrigation pump through Raspberry Pi3.

The system updates a database with sensor values and irrigation processes for future reference.

The proposed system aims to combine [70] ANN and KNN methods to provide farmers with data on [70] crop selection, growth, and yield.

Drawbacks or limitations:

The system lacks a rainfall prediction system, which can lead to over-irrigation. Over-irrigation due to rainfall immediately after the [71] irrigation process [71] can negatively impact crop yield.

2. PREDICTION [4] OF RAINFALL USING INTENSIFIED LSTM-BASED RECURRENT NEURAL NETWORK WITH WEIGHTED LINEAR UNITS

Research Paper Key points:

It is about using deep learning techniques, specifically an Intensified LSTM-based Recurrent Neural Network (ILSTM RNN) with Weighted Linear Units (WLUs), for predicting rainfall. The [4] authors note that accurate rainfall prediction is important[72] for a variety of[73] applications, including agriculture, hydrology, and disaster management.

429 The paper presents the ULSTERMEN-WLU model, which combines the strengths of both[74] LSTMs and WLUs. LSTMs are a type of recurrent neural network that are[75] particularly good at modeling sequences of data,[76] while[77] WLUs are a type of activation function that can help prevent the vanishing gradient problem that can occur in deep networks. The[4] authors argue that by[78] using these two techniques in combination, they[78] can achieve better performance in rainfall prediction.

Overall, the[79] paper presents a novel approach to rainfall prediction using deep learning techniques and demonstrates its effectiveness on a real-world dataset.

MACHINE LEARNING: APPLICATIONS IN INDIAN AGRICULTURE

Research paper key points:

It provides an overview of various applications of machine learning techniques in the field of agriculture in India[80]. The[4] paper highlights the need for modernization of agriculture and the role of technology[81] in achieving the same. It[4] discusses the potential of machine learning in solving various problems related to agriculture[82], such as crop yield prediction, disease detection, soil analysis, weather forecasting, and farm management.

430 The paper provides an in-depth analysis of different machine learning algorithms that can be used[83] for agriculture applications and their strengths and weaknesses. It[4] also discusses the challenges faced in implementing machine learning techniques in agriculture and suggests possible solutions to overcome these challenges.

Drawbacks or limitations:

The paper primarily focuses on the use of machine learning in predicting[84] pest attacks and disease outbreaks in crops like tomatoes, paddy, and grapes. However[4], the techniques used may not necessarily be applicable[85,86] to other crops, which limits the generalizability of the findings[86].

431 Machine learning models require large amounts of data to train and make accurate predictions. However[4], the availability of relevant and high-quality data in Indian agriculture can be limited, which may impact the effectiveness of the proposed methods.

The paper does not explicitly consider the social and economic factors that affect agricultural practices in India, such as farmer education and access to resources. These[4] factors may impact[87] the adoption and success of machine-learning applications in Indian agriculture.

MACHINE LEARNING CLASSIFICATION TECHNIQUE FOR FAMINE PREDICTION

Research paper key points:

The research suggests a machine learning-based categorization method for famine forecasting that combines meteorological and satellite imagery data. The suggested method uses the Random Forest (RF)[88] algorithm to categorize satellite imagery and meteorological data into several hunger severity levels. Only accuracy can be reported in the study, which may not[89] give a complete[89] picture of the model's performance.

5. AUTOMATED[4] IRRIGATION SYSTEM USING A WIRELESS SENSOR NETWORK AND GPRS MODULE

Research Paper Key Points:

A gateway device also manages sensor data, activates actuators, and sends data to the web application. The[4] system had a[90] dispersed wireless network of soil moisture and temperature sensors installed in the root zone of the plants. To regulate the amount of water used, a[91] microcontroller-based gateway was programmed with an algorithm based on temperature and soil moisture threshold values.

The system used photovoltaic panels for power and included a duplex communication link based on a cellular-Internet interface that allowed users to schedule irrigation and review data via a web page.

Drawbacks or Limitations:

The project's findings were published[92] in a study where the water motor's ability to turn on and off is controlled[93] by the temperature of the soil and a temperature sensor inserted into plant roots. Their lack of a method to inform the user of the status of the agricultural field is a flaw in their project.

6. AN OVERVIEW OF SMART IRRIGATION SYSTEMS USING IOT

Research Paper Key Points:

The Microcontroller Node MCU ESP8266 is used in the intelligent irrigation system.

Using the soil sensor, the irrigation system measures the soil's temperature and humidity before watering the plants accordingly.

Additionally, the system will email you whenever the plants are watered and include all the pertinent plant information, such as temperature and humidity.

The idea behind this project is to give landowners the ability to oversee and monitor the development of the plants in their farms. The idea we've employed is really straightforward and simple to put into practice. Both labor and time will be saved.

Drawbacks or limitations:

Their lack of a method to inform the user of the status of the agricultural field is a flaw in their project.

This project's disadvantage is that the system can't assess the worth of the plant's nutrients.

Measurement of soil moisture is the only aspect of the "Automatic Irrigation System on Sensing Soil Moisture Content." But in addition to the soil moisture sensor, our proposed system also includes a temperature sensor.

7.ARDUINO BASED MACHINE LEARNING AND IOT SMART IRRIGATION SYSTEM

Key Points:

The system is designed[111] to optimize irrigation by[112] using machine learning algorithms to predict soil moisture levels based on various factors such as temperature, humidity, and precipitation.

The system uses an Arduino board to collect data from sensors[113] and send it to the cloud for processing.

Machine learning algorithms are used[114] to analyze the data and make predictions about[115] soil moisture levels. The[4] system can then adjust irrigation levels accordingly.

The system is intended[116] to reduce water consumption and increase crop yields by ensuring that plants receive the optimal amount of water.

Limitations or Drawbacks:

432 The accuracy of the machine learning algorithms may depend on the quality
433 and quantity of the data collected. Inaccurate[4,117] or incomplete[117] data could lead to incorrect[117] predictions and ineffective[117] irrigation.

The system may require frequent calibration and adjustment to ensure optimal performance.

The cost of implementing[118] the system, including the cost of sensors and other hardware, may be prohibitive for some farmers or agricultural organizations.

The system may require a reliable internet connection and access to cloud services, which may not[119] be available in all[119] areas.

CHAPTER 3

PROPOSED METHODOLOGY:

3.1 COMPONENTS AND TECHNOLOGY USED

3.1.1 Arduino Uno R3:

One type of ATmega328P-based microcontroller board is the Arduino Uno R3. It[4] comes with everything needed to support the microcontroller; all you need to do is[120] use a USB cable to connect it to a computer and provide power using an AC-DC adapter or a battery to get things going. The[4] word "Uno" was chosen to signify the launch of the Arduino IDE 1.0 software since it is an "Italian" word that signifies[121] "one." The third and latest version of the Arduino Uno is called the R3. The[4] reference versions of the[123] Arduino board and IDE software are currently being updated.[122] The[4] first in a line of USB Arduino boards, the Uno-board serves as[124] the platform's reference design.

Arduino Uno R3 configuration

Fig. 3.1.1 Arduino Uno R3 configuration

The Arduino Uno R3 board includes the following specifications.

It is an ATmega328P based Microcontroller

The Operating Voltage of the Arduino is 5V

The recommended input voltage ranges from 7V to 12V

The i/p voltage (limit) is 6V to 20V

Digital input and output pins-14

Digital input & output pins (PWM)-6

Analog i/p pins are 6

DC Current for each I/O Pin is 20 mA

DC Current used for 3.3V Pin is 50 mA

Flash Memory -32 KB, and 0.5 KB memory is used by the boot loader

SRAM is 2 KB

EEPROM is 1 KB

The speed of the CLK is 16 MHz

In Built LED

The length and width of the Arduino are 68.6 mm X 53.4 mm

The weight of the Arduino board is 25 g

3.1.2 DHT11 Sensor

The DHT11 digital temperature and humidity sensor is a composite sensor that outputs temperature and humidity as calibrated digital signals. The device has great dependability and outstanding long-term stability thanks to the technology of a dedicated digital modules collection as well as the temperature and humidity sensor technology. The sensor is coupled to a high-performance 8-bit microprocessor and has an NTC temperature and a resistive sense of wetness measurement mechanism.

3.1.3 Soil moisture sensor

The volumetric water content of the soil is measured by soil moisture sensors. Soil moisture sensors measure the volumetric water content indirectly by using some other property of the soil, such as electrical resistance, dielectric constant, or interaction with neutrons as a proxy for the moisture content, because the direct gravimetric measurement of free soil moisture requires removing, drying, and weighing of a sample.

It is necessary to calibrate the relationship between the measured property and soil moisture since it can change based on the environment, including the soil type, temperature, and electric conductivity. The soil moisture has an impact on the reflected microwave radiation, which is employed for remote sensing in agriculture and hydrology. Farmers and gardeners can both employ portable probing tools. Sensors that assess the volumetric water content are commonly referred to as soil moisture sensors. Tensiometers and gypsum blocks are examples of another class of sensors that measure the water potential property of soil moisture. These sensors are also known as soil water potential sensors.

3.1.4 Relay Module

Relays are electrically powered machines. It has a controlled system that is also known as an output circuit or an output contactor, as well as a control system that is also known as an input circuit or an input contactor. Circuits for automatic control typically employ it. To put it simply, it is an automatic switch to a low-current signal regulating a high-current circuit . A relay's lower moment of inertia, stability, long-term dependability, and small volume are its advantages. It is widely used in power protection, automation, sports, remote control, intelligence gathering, and communication equipment, as well as electromechanical and power electronic ones. A relay typically has an induction component that can reflect inputs like current, voltage, power, resistance, frequency, temperature, pressure, speed, and light, among other things. Additionally, it has an actuator module (output) that has the ability to energize or de-energize a controlled circuit's connection. Between the input and output parts, there is an intermediary component that is utilized to couple and isolate input current as well as actuate the output. When the specified input parameters (voltage, current, temperature, etc.) are above the critical value, the controlled output circuit of the relay will be energized or de-energized.

3.1.5 Motor Pump (DC 12V)

441 A DC motor is any of[150] a class of rotary electrical motors that converts direct
current electrical energy into mechanical energy. The[4] most common types rely
on the forces produced by magnetic fields. Nearly[4] all types of DC[88] motors have
some internal mechanism, either electromechanical or electronic, to
442 periodically change the direction of current in part[151] of the motor. DC[4,88] motors
were the first form of motor widely used, as they could be powered[152] from[153]
existing direct-current lighting power distribution systems[154] . A[4] DC motor's
speed can be controlled over a wide range, using either a variable supply
voltage or by changing the strength of current[155,156] in its field windings. Small[4] DC
motors are used[157] in tools, toys, and appliances. The[4] universal motor can operate
on direct current but is a lightweight brushed motor used for portable power
tools and appliances.[158] Larger[4] DC motors are currently used in the[160] propulsion of
electric vehicles, elevators, and[160] hoists and in[159,160] drives for steel rolling mills.

3.1.6 Breadboard[161]

The Breadboard[161] serves as a foundation for serving[162] electronics. Due[4] to the
availability of solderless breadboards, also known as plugboards or terminal
array boards, the phrase "breadboard" is now frequently used to describe
these. The[4] solderless breadboard[161] is reusable because soldering is not
necessary. This[4,163] makes it simple to use[164] for developing temporary prototypes
and conducting circuit design experiments. Solderless[4] breadboards are,
therefore, common[165] among students and in technological education. Earlier[4]
443 breadboard models lacked this characteristic. A variety of electronic systems[4,166]
may be prototyped[167] by using breadboards, from small analog and digital circuits
to complete central processing units (CPUs). It[4] is difficult[168] to reuse[169] a stripboard
(Veroboard) or other prototyping printed circuit board used to create one-off or
semi-permanent soldered prototypes.

3.1.7 Connecting wires

444 An electrical wire, or group of them in a cable, with a connector or pin at each
end (or sometimes without them - simply[173] 'tinned') is known as a jump wire (also
445 known as jumper wire,[170] or jumper), and it[171] is typically used[172] to connect the parts
of a breadboard or other prototype or test circuit, internally or with other
machinery or components, without soldering. Jump[4] wires are installed
446 individually by placing their "end connections" into a breadboard's slots, a
circuit board's header connector, or a piece of[174] test equipment. Male-to-male[4],
male-to-female, and female-to-female jumper wires are the most common
447 types. The[4] wire's termination tip distinguishes each one from the other. Male[4]
ends have a pin protruding and can plug into things, while female ends[175] do not
and are used to plug things into. Male-to-male[4] jumper wires are the most
common and what you likely will use most often. When[4] connecting two ports on
a breadboard, a male-to-male wire is what you'll need.

3.2 RAINFALL PREDICTION USING ARTIFICIAL INTELLIGENCE

The rainfall presage[176] involved a one-phase solution:

3.2.1 PREDICTION OF PROBABILITY OF RAINFALL IN THE NEXT 30 MINUTES

The device continuously checks the status at regular intervals when it is turned on[177] periodically. The[4] first phase is to make the network available to determine whether there is a likelihood of rainfall to occur in the next 30 minutes or not. The average temperature, pressure[24], wind speed, and air humidity are only a few of the variables that affect rainfall. The[4] dataset utilized is reliable for local areas and regions since it includes parameters that can be used[178] to predict rainfall in general and because all of the parameters had low values. The[4] information used comes from local region-specific rainfall statistics on Weather Underground. The[4] data was split[179] into three sets: training, testing, and a percentage of 70 and 30, respectively.

3.2.2 FLOWCHART OF MODEL METHODOLOGY

Fig 3.2.2.1 Flow Chart of ML

3.2.3 DATA COLLECTION

3.2.3.1 Web Scraping:

Web scraping is a method for obtaining data from websites using computer programs or automated scripts. It[4] entails accessing, downloading, and processing website material and data in order to[180] extract pertinent information. Web[4] scraping is frequently employed[181] for data mining, market research, price monitoring, and other uses that require the collection and analysis of[182] vast amounts of data.

We initially looked for the pertinent data but were unable to find it. They[4], therefore, thought about two possibilities. Either[4] purchase the government's data or get it from a website. In[4] the end[183], we chose the web scraping option and learned how to perform web scraping with Python tools like Selenium and Beautiful Soup 4.

Writing code was required to scrape the webpage and obtain the data about the rainfall. The[4] website's design, however, required[184] that the code wait 15 seconds for the page to fully load before extracting the data. As[4] a result, data collection took longer than expected; it took us 7–10 days to collect the required data. Cleaning the data is the first stage in the data preparation process. This[4,185] entails eliminating any columns or data items that are superfluous[186] or not pertinent to the issue at hand.[187] For[4] instance, to ensure that a number column is entirely numerical, any letters in the column should be eliminated.[188]

Fig 3.2.3.1.1 Dataset

448 After that, it's crucial to delete any blank or missing values from the dataset. This[4,189] can be accomplished[190] in one of two ways: either by deleting the rows that contain[191] the missing information or by imputed values such as the mean or median. The[4] next stage is to look for any outliers in the dataset after the data has been cleaned[192,193] . It[4] is crucial to[194] find and eliminate outliers since they have a considerable negative impact on[195] the performance of machine learning models.

Fig a Fig b

Fig c Fig d

Fig 3.2.3.1.2 Histograms before outliers (a. Temperature, b. Pressure[24] (in atm), c Wind Speed(mph), d. Humidity)

Fig a Fig b

Fig c Fig d

Fig 3.2.3.1.3 Histograms after Outliers (a. Temperature, b. Pressure[24] (in atm), c. Wind Speed(mph), d. Humidity)

The red line indicates the 3[196] standard deviations from the mean. The[4] next step in data preparation is labeling the target variable, which in this case[197] is whether or not it will rain. This[4,198] is necessary for supervised learning algorithms to be trained[199] on the data.

Fig 3.2.3.1.4 Count of Rain and No Rain

The[200] data must now be divided[201] into training and testing sets after being cleaned and labeled.[200] In[4] order to[202] make sure that both the training and testing sets have a representative mix of data points, this is often done[203] using a stratified sampling technique. The[4] dataset needs to be balanced using oversampling techniques because it is unbalanced with regard to[204] the goal variable (rain[205] or no rain). To[4] balance out the distribution of data in the dataset, this entails producing fictitious data points.

3.2.4 Logistic Regression

449 It is used[206] for predicting the categorical dependent variable using a given set of independent variables. Logistic[4] regression predicts the[207] output of a categorical dependent variable. Therefore[4], the outcome must be a categorical[208] or discrete value. It[4] can be either Yes or No, 0 or 1, True or False, etc., but instead of giving

the exact value[209] as 0 and 1, it gives[210] the probabilistic values which lie[211] between 0 and 1. Then[4] we set a threshold value for the classification.

So, here[212] we generally try to separate the data points with the line or the plane.

The equation of the plane[213] is (here, consider M as the slope)

The sum of the product of the distance between the point & the plane and +ve and

-ve data points should be minimum. We[4] take such kind of line into consideration[214].

In the above equation, Y is either +1 or -1 based on the data points. If[4] a point[215] is from the left side of the plane[219], then the distance will be +ve, and the other side of the points[216] are[217] -ve[218] distance.

If there is any outlier[221] added to the dataset, then[221] the best line may be ignored[220] unknowingly. To[4] avoid that, we use a special[222] function after the product of the distance and[223] Y called the sigmoid function.

450 We will use the sigmoid function to optimize our equation. If[4] the distance of Xi

451 is increased[224] from the higher plane, then our sigmoid function squishes that distance into the value between 0 – 1. It[4] provides probabilistic interpretations. And, if the distance of point Xi from the plane is 0, then its probability will be 0.5.

So, this is our optimal sigmoid function which will help for preserving[225] the optimal equation from the outlier.

Fig 3.2.4.1 Linear Regression and Logistic Regression Graphs

Fig 3.2.4.2 Metrics of Logistic Regression Model

3.2.5 Artificial Neural Network (ANN)

Artificial Neural Networks (ANN) is a type of[226] machine learning algorithm that mimics the structure and functioning of the human brain. They[4] comprise interconnected nodes arranged in layers that process information, with each node executing a basic mathematical calculation based on the input received. When using an ANN, data is first inputted into the input layer, which then passes[227] through one or more hidden layers of nodes. Each[4] node in a hidden layer performs a mathematical operation on the input, and the[228] resulting output is then transferred to the next layer until it arrives at the output layer, which produces[228] the final result.

The learning process in ANNs involves modifying the weights assigned to each connection between nodes. These[4] weights govern the level of influence each node has on the output of the network[229] and are[230] adjusted[231] during the training process based on the difference between the predicted and actual output. ANNs are widely utilized[232] in diverse applications, including speech and image recognition, natural language processing, and prediction tasks such as weather prediction and stock market forecasting. In[4] agriculture, ANNs are used[233] to[235] predict crop yields,[234] and[235] soil moisture and detect pests.

One of the key[236] advantages of ANNs is their capacity to identify intricate patterns in data, even if these patterns are not explicitly defined. They[4] also possess strong generalization abilities, enabling them to perform well on prediction tasks with new data. However[4], ANNs can be computationally demanding and require substantial amounts of[237] training data to produce accurate results.

Fig 3.2.5.1 ANN Visualization

Fig 3.2.5.2 ANN Model Metrics

3.2.6 Random Forest Classifier

The Random Forest Classifier is a type of[238] ensemble learning algorithm that utilizes decision trees. It[4] operates by creating numerous decision trees during the training phase and then selecting the mode of the classes (for classification) or mean prediction (for regression) of the individual trees as the output. In[4] constructing each tree, a[239] random subset of the input features and training data is employed[240].

The algorithm works as follows:

Create a new dataset by randomly choosing a subset of the training data with replacement[241].

Randomly select a subset of features to be employed[242] in constructing[243] the decision tree.

Construct the decision tree using the chosen data and features.

To form a decision tree forest, repeat steps 1-3.

452 For classification[244] of[245] new data points, pass them through every decision tree in the forest and determine the majority vote of predicted[246] class (classification)[247] or average prediction (regression).

Fig 3.2.6.1 Different Decision Trees (Random Forest)

The Random Forest Classifier can be expressed[248] mathematically[249] as follows:

Assuming a dataset D = {(x1, y1), (x2, y2), ..., (xn, yn)}, where xi is the feature vector for the i-th[250] instance, and yi is the corresponding class label. The[4] goal of the algorithm is[251] to build a forest F of decision trees T that can forecast the class label of a new instance x.

To create each tree T in forest F

Randomly choose a subset of the training data D' (with replacement).

Randomly choose a subset of features F' to construct the decision tree T[252].

Build decision tree T using the chosen data and features.

To forecast the class label of a new instance x

Pass x through every decision tree T in the forest F.

Compute the predicted class label yi for each tree T.

Generate the majority vote of the predicted class labels (classification) or average prediction (regression) across all trees T.

Fig 3.2.6.2 Random Forest Model Metrics

3.2.7 Confusion Matrix

A confusion matrix is a table that assesses the effectiveness of a machine-learning model in classification problems. It's[4] a 2x2 matrix that contrasts the[253] predicted and actual values of a binary classifier.[253] The[4] matrix's four cells represent:[254]

True Positive (TP)[88]: The number of accurate positive[255] predictions made by the model[256][257].

False Positive (FP)[88]: The number of inaccurate positive[258] predictions made by the model[259].

True Negative (TN)[88]: The number of accurate negative[260] predictions made by the model[261][262].

False Negative (FN[88]): The number of inaccurate negative[263] predictions made by the model[264] [265].

The matrix's rows represent the actual values (positive or negative), and the columns represent the predicted values (positive or negative).

Fig 3.2.7.1 Confusion Matrix

453 To assess the performance of a machine learning model,[266] various[267] metrics such
454 as accuracy, precision, recall, and F1 score are used.[268] Accuracy[4] is the ratio of
455 correctly predicted instances to the total number of instances,[269] and it[270] can be
calculated[271] by dividing the sum of true positives (TP[88]) and true negatives (TN[88]) by
the total number of predictions.

456 Precision is the ratio of correctly predicted positive instances to the total
457 number of positive instances[272] predicted by the model, which can be calculated[27]
458 as TP[88] divided by the sum of TP[88] and false positives (FP[88]). Recall[4,274] is the ratio of
correctly predicted positive instances to the total number of actual[275] positive
instances[276], which can be calculated[277] as TP[88] divided by the sum of TP[88] and false
negatives (FN[88]).

459 F1 score is the harmonic mean of precision and recall, which can be calculated[2]
461 as 2[279] times the product of precision[280] and recall[281] divided by their sum. A[4] confusion
matrix is a 2x2 matrix that compares the[282] predicted and actual values of a
binary classifier[282] and provides information on TP[88], TN, FP[88], and FN[88]. It[4] can be used[2]
to evaluate the model's performance and identify[284] errors, and to[284] determine if
the model is overfitting or underfitting.

3.2.8 Optional Algorithms

Recurrent Neural Network (RNN):

462 A Recurrent Neural Network (RNN) is a neural network that is[285] specifically designed[286] to handle sequential data. Unlike[4] traditional neural networks, which process inputs and outputs independently, RNNs are able to[287] capture the temporal dependencies present in sequential data by incorporating loops that allow information to persist.

Consider the example of sentiment analysis on a sequence of words. Each[4] word in the input sequence of n words has a corresponding word embedding vector x t, and the objective is to predict the sentiment of the entire sentence. If[4] we were to use[288] a traditional neural network, we would simply[290] feed the word embedding vectors x t one[289] at a time into a feedforward network to obtain a final

463 prediction. However[4], this approach does not account for the temporal dependencies between words. By[4] contrast, an RNN can capture these dependencies by using its recurrent loops to process the entire sequence of word embeddings, thereby enabling it to make more accurate predictions about the sentiment of the sentence.

Fig 3.2.8.1 RNN LSTM GRU Working Block Diagrams

464 Recurrent[291] Neural Network (RNN) is a type of neural network that is[292] designed[293] to process sequential data by maintaining an internal state that depends on the current input and the previous state.[294] Unlike[4] traditional neural networks, RNNs can capture temporal dependencies between inputs.

For example, when analyzing the sentiment of a sentence, a traditional neural network processes each word independently. However[4], an RNN processes each word in sequence by updating its internal state with the current input[296] and the[296] previous state[295,296] . This[4,297] allows the network to capture the contextual information from previous[298] words[299] and make a prediction about[300] the sentiment of the whole sentence.

RNNs are trained[301] using a method called backpropagation through time (BPTT), which takes into account[302] the temporal dependencies between inputs. During[4] training, the internal state is updated[303] at each time step, and the error is propagated backward through time to update the weights of the network[304]. Overall, RNNs are useful for[305] processing sequential data and capturing temporal dependencies. They[4] are trained[306] using BPTT, which allows for efficient computation of gradients over long sequences.

Fig 3.2.8.2 RNN Model Confusion Matrix

Fig 3.2.8.3 RNN Model Metrics

3.2.9 Result of ML:

Fig 3.2.9.1 Logistic Regression Model Confusion Matrix

Fig 3.2.9.2 ANN Model Confusion Matrix

Fig 3.2.9.3 Random Forest Classifier Model Confusion Matrix

Performances of models (Accuracy):

Logistic Regression ---> 73.2%

Artificial Neural Network ---> 85.0%

Random Forest Classifier ---> 90%

Fig 3.2.9.4 Metrics of Logistic Regression Model

Fig 3.2.9.5 ANN Model Metrics

Fig 3.2.9.6 Random Forest Model Metrics

3.3 Platform Used

3.3.1 Anaconda Jupyter

465 Anaconda Navigator is a graphical user interface (GUI) tool that comes bundled with the Anaconda distribution.[4] It provides a convenient way to set up, manage, and launch various tools,[307] including Jupyter Notebook.[308] Meanwhile,[4] a Conda Python environment creates a separate and isolated environment for Python, which enables users to install packages without affecting their system's Python installation.

3.3.2 Google Colaboratory

Google Colaboratory is a cloud-based Jupyter notebook[309] environment that provides free access to powerful backend hardware such as GPUs and TPUs. This[310] allows users to perform all the tasks that can be done[311] in a locally hosted Jupyter notebook[312] without the need for local installations or setups. Since[4]

Google Colaboratory is hosted on cloud servers, users can easily share their notebooks with others and collaborate in real-time.

3.3.3 PyCharm CE

PyCharm is an Integrated Development Environment (IDE) specifically designed for Python development, offering a comprehensive set of tools and features that facilitate productive Python, web, and data science development in a convenient and tightly integrated environment.

3.4 FLOWCHART OF MODEL METHODOLOGY:

Fig 3.4.1 PROCESS FLOW

3.5 FLOWCHART OF THE PROCESS

Fig 3.5.1 FLOWCHART OF THE PROCESS

3.6 ARCHITECTURE OF THE MODEL:

Fig 3.6.1 ARCHITECTURE OF THE MODEL

3.7 BLYNK WEB USER INTERFACE:

Fig 3.7.1 BLYNK WEB USER INTERFACE:

3.8 ANDROID APP INTERFACE

Fig 3.8.1 ANDROID APP INTERFACE

3.9 USER WEB INTERFACE

Fig 3.9.1 Irrigation Status

Fig 3.9.2 Sensor Data Visualization

CHAPTER 4

4. RESULTS[4]

The proposed system is an intelligent irrigation solution based on artificial intelligence that utilizes the soil moisture content and crop moisture requirements to automate the irrigation process. The[4] main advantage of the system is its efficiency and economic feasibility. The[4] main idea behind the proposed rainfall estimation is to obtain accurate rainfall estimates for a specific local region and annual rainfall data to aid in future[317] estimation of[318] rainfall[319] in different states.

When the soil moisture level falls below the required threshold value, and there is no rainfall[320] predicted by the machine learning algorithm, the model activates the motor pump for crop irrigation.[321]

Fig 4.1 Blynk Web User Interface

When irrigation is needed, the circuit is on, as[322] we can see[323] the LED is on.

CHAPTER 5

5. CONCLUSION[4]

Our team has created an autonomous irrigation system that incorporates Artificial Intelligence learning and predictive algorithms to enhance the capabilities of existing automatic irrigation systems. By[4] leveraging these technologies, our system is capable of making informed decisions and adjusting[324] its operations based on changing environmental conditions.

The methods outlined in this paper have the potential to significantly improve irrigation efficiency while reducing the amount of effort required and conserving water resources compared to traditional irrigation methods. Our[4] system is currently reliant on weather station data to make its calculations. However[4], we recognize that weather stations may not be readily available in certain regions, particularly in rural areas of the Indian subcontinent and arid regions where water resources are scarce.

To address this issue, we propose the deployment of[325] on-premise sensors that can provide accurate and timely information to the irrigation system. This[4] approach would enable the system to make informed decisions and adjust its operations based on localized conditions, even in areas where weather station data is not available.

Overall, our autonomous irrigation system represents a significant advancement in the field of[326] irrigation technology. By[4] leveraging the power of

Artificial Intelligence and predictive algorithms, we have developed a highly effective solution that has the potential to improve crop yields and conserve water resources. We are confident that this technology will prove to be a valuable asset in supporting sustainable agricultural practices in regions where water is scarce, and traditional irrigation methods are no longer sufficient.

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7. Source[4] Code:

Arduino code:

```
#include <DHT.h>
/* Fill in your Template ID (only if using Blynk.Cloud)[338] */
#define BLYNK_TEMPLATE_ID "TMPLYXtOg0jT"
#define BLYNK_DEVICE_NAME "BTPPROJECT"[339]
#define BLYNK_AUTH_TOKEN
"lIBPUqiLkEt3R0kDt0cMn3p5X5suse_k"
493 // You could use a spare Hardware Serial on boards that have it
(like Mega)
#include <SoftwareSerial.h>
//SoftwareSerial DebugSerial(2, 3); // RX, TX
#include <BlynkSimpleStream.h>
#define PUMP 11
#define SENSOR V1
494 // You should get Auth Token in the Blynk App.
// Go to the Project Settings (nut icon).
char auth[] = BLYNK_AUTH_TOKEN;
float soilMoisture;[340]
float temperature;
float humidity;
int var;
int cnt=0;
// Blynk Timer timer;
void syncValues[341]()
{
humidity=80+random(6)-3;
```

```
temperature=27+random(6)-3;
}
BLYNK_WRITE(V0){
var=param.asInt();
if(var==0)
{
digitalWrite(PUMP,LOW);
}
else
{
digitalWrite(PUMP,HIGH);
}
}
void myTimer()
{
Serial.println(soilMoisture);
Blynk.virtualWrite(V1, soilMoisture);
}
```

495

```
#define DHTPIN 8 // Digital pin connected to the DHT sensor
#define DHTTYPE DHT22
DHT dht(DHTPIN, DHTTYPE);
void setup()
{
cnt=0;
analogReference(DEFAULT);
//DebugSerial.begin(9600);
pinMode(PUMP,OUTPUT);
```

```
Serial.begin(9600);
Blynk.begin(Serial, auth);
dht.begin();
//timer.setInterval(1000L, myTimer);
}
void loop() {
soilMoisture[342] = analogRead(A0);
humidity = dht.readHumidity[343]();
temperature = dht.readTemperature[344]();
Blynk.run();
// Serial.println[345](soilMoisture[346]);
// Serial.println[347](temperature);
// Serial.println[348](humidity);
syncValues[349]();
Blynk.virtualWrite(V1, soilMoisture[350]);
//Blynk.virtualWrite(V2, temperature);
// Blynk.virtualWrite(V3, humidity);
cnt++;
delay(1000);
//timer.run(); }
```

Backend code:

```
# importing the requests library
import requests
import time
import pickle;
token="lIBPUqiLkEt3R0kDt0cMn3p5X5suse_k"
pumpPin="v0";
```

soilPin="v1"

temperaturePin="v2"

humidityPin="v3";

weather_api="http://api.weatherbit.io/v2.0/forecast/agweather?lat=23.27

56&lon=77.4560&key=c0cebec5f6594632acdfc4b8347014f9";

loaded_model=pickle.load(open("finalized_model.sav", 'rb'[351]));

def

required_soilMoisture(temperature,humidity,avg_pres,evapotranspiration

):

return

loaded_model.predict([[temperature,humidity,avg_pres,evapotranspiration

n]])[0][0]+50;

def isThePumpNeedsToBeOn(curSoilMoisture,requiredSoilMoisture[352]):

if(curSoilMoisture/10>requiredSoilMoisture):

return False

else[353]:

return True

while[354] True:

URL =

"https://blynk.cloud/external/api/get?token="+token+"&"+pumpPin+

"&"+soilPin+"&"+temperaturePin+"&"+humidityPin;

URLupdate="https://blynk.cloud/external/api/update?token="+toke

n+"&"

sending get request and saving the response as response[355] object

r = requests.get(url[356] = URL)

u=requests.get(url=weather_api);

extracting data in JSON format

data = r.json()

data2=u.json();

evapotranspiration=data2['data'][0]['evapotranspiration'];

avg_pres=data2['data'][0]['pres_avg'];

print(avg_pres);

requests.get(url=URLupdate+"V4="+str(avg_pres));

requests[357].get(url=URLupdate+"V5="+str(evapotranspiration));

print(data);

print(required_soilMoisture(data['v2'], data['v3'], avg_pres,

evapotranspiration))

time.sleep(10);

For Web Scraping:

from datetime import date, timedelta

from selenium import webdriver[358]

from selenium.webdriver[359].common.by import By

from selenium.webdriver[360].support.ui import WebDriverWait

from[361] selenium.webdriver[362,363].support import expected_conditions as EC

from bs4 import BeautifulSoup

import csv

Initialize the Chrome driver

driver = webdriver[364].Chrome()

Define the start and end date range

start_date = date(2023, 1, 14)

end_date = date(2023, 1, 14)

Define the location and URL template

location = "secunderabad"

url_template =

"https://www.wunderground.com/history/daily/in/{location}/VOHY/date/{year}-{month}-{day}"

bool_ = True

while start_date <= end_date:

k, n = 1, 1

try[365]:

Create an empty list to store the table data

data = []

Loop through the dates

delta = timedelta(days=1)

while start_date <= end_date:

Format the date in the required format

date_str = start_date.strftime[366]("%Y-%m-%d")

year_str = start_date.strftime[367]("%Y")

month_str = start_date.strftime[368]("%m")

day_str = start_date.strftime[369]("%d")

Construct the URL

url = url_template.format(location=location, year=year_str, month=month_str, day=day_str)

Navigate to the URL

driver.get(URL)

Wait for the table to load

wait = WebDriverWait(driver, 15)

table = wait.until(

EC.presence_of_element_located((By.CSS_SELECTOR, ".mat-table.cdk[370]-table.mat-sort.ng-star-inserted")))

```
# Parse the web page content as HTML using BeautifulSoup
soup = BeautifulSoup(driver.page_source, "html.parser")

# Find the table element by its tag and class
table = soup.find("table", class_="mat-table cdk-table mat-sort ng-star-
inserted")
# Loop through the table rows
for row in table.find_all("tr"):
# Create an empty list to store the row data
row_data = []
# Loop through the row cells
for cell in row.find_all("td"):
# Append the cell text to the row data list
row_data.append(cell.text.strip())
# Append the row data list to the table data list
if len(row_data) > 0:
# Add the date to the row data list
row_data.insert(0, date_str)
data.append(row_data)
# Increment the date by 1   day
start_date += delta
except:
# Save the data to a CSV file
with open("data_web_scrap.csv", "a", newline="") as CSV file:
writer = csv.writer(csvfile)
# Write the header row
if bool_:
```

```
writer.writerow(
["Date," "Time," "Temperature," "Dew Point," "Humidity," "Wind," "Wind Speed,"
"Wind Gust," "Pressure,"
"Precipitation", "Condition"])
bool_ = False
# Write the data rows
writer.writerows(data)
k += 1
if k == n:
# Save the data to a CSV file
with open("data_web_scrap.csv", "a", newline="") as CSV file:
writer = csv.writer(CSV file)
# Write the header row
if bool_:
writer.writerow(
["Date," "Time," "Temperature," "Dew Point," "Humidity," "Wind," "Wind Speed,"
"Wind Gust,"
"Pressure",
"Precipitation", "Condition"])
bool_ = False
# Write the data rows
writer.writerows(data)
start_date += delta
# Close the Chrome driver
driver.quit()
```

For ML Part:

RAINFALL PREDICTION

```
# ** Importing all Required Libraries**


import[387] pandas as pd
import matplotlib.pyplot[388] as[389,390] pt
import matplotlib[391]
import seaborn as sb
import numpy[392] as np
import tensorflow[393] as tf
import pickle
from imblearn[394].over_sampling import RandomOverSampler
from collections import Counter
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import Normalizer
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics[395] import confusion_matrix
from sklearn.metrics import classification_report
get_ipython().run_line_magic('matplotlib'[396] [397], 'inline')


df = pd.read_csv('/content/data_web_scrap_hyderabad_12_23_new2.csv')
df.head()
df.shape[398]
df[399].Temperature.unique()


df[df.Temperature == 'Temperature']
```

```
df1 = df[df.Date != 'Date']

df1['Temperature1'] = df1['Temperature'].apply(lambda x: float(x[0:-2]))
df1.head()
**Changing Fahrenheit (°F) to Celsius (°C)**
df1['Temperature 1'] = 5/9*(df1['Temperature 1'] - 32)
df1.head()

# For wind check link
# https://www.weather.gov/pqr/wind

df1.isnull().sum()

sb.heatmap(df1.isnull(), yticklabels 400 = False, cbar = False, cmap 401 = 'viridis')
null_rows = df1[df1.isna().any(axis = 1)]
def wind(x):
try:
return float(x[0:-4])
except 402:
a = x[0:-4].replace(',', '')
return float(a)

df1['Wind Speed1'] = df1['Wind Speed'].apply(wind)

Wind_Speed1 = df1['Wind Speed1'].tolist()

l = []
```

```
for i in Wind_Speed1:
if i < 30:
l.append(i)

sb.histplot(x = l, kde = True)
sb.boxplot(Wind_Speed1)

df1['Pressure1'] = df1['Pressure'].apply(lambda x: float(x[0:-3]))
df1.head()

df1['Humidity1'] = df1['Humidity'].apply(lambda x: int(x[0:-2]))

df1.corr()

df1.groupby('Condition')['Condition'].agg('count')

df2 = df1.copy()

df2.reset_index(level = 0, inplace = True)

df2.rename(columns = {'index':'Index'}, inplace = True)

Cond_df = df2.groupby('Condition')['Index'].agg('count').reset_index()
Cond_df
# Rain ---> 1
# Not Rain ---> 0
```

```
condi = Cond_df.Condition.to_list()
condi

df2['Rain_01'] = df2['Condition'].replace(['Cloudy,' 'Cloudy / Windy,' 'Fair,' 'Fair /
Windy,' 'Fog,' 'Fog / Windy,'
'Haze,' 'Haze / Windy,' 'Mist,' 'Mostly Cloudy,' 'Mostly Cloudy / Windy,'
'Partly Cloudy,' 'Partly Cloudy / Windy,' 'Smoke,' 'Widespread Dust,'
'Widespread Dust / Windy'], 0)

df2['Rain_01'] = df2['Rain_01'].replace(['Light Drizzle,' 'Thunder,' 'Light Rain
with Thunder,' 'Rain,'
'Light Rain,' 'Showers in the Vicinity,' 'T-Storm,' 'Drizzle,'
'Thunder / Windy',[404] 'Rain / Windy',[405] 'T-Storm / Windy',[406]
'Heavy T-Storm,' 'Light Rain Shower,' 'Heavy Rain,' 'Rain Shower,'
'Drizzle / Windy,' 'Drizzle and Fog,' 'Light Rain / Windy,'
'Light Drizzle / Windy'], 1)

df2.Rain_01.unique()
# **inHg to atm**
# 1 atm = 29.92 inHg ----> inHg is inches in Hg(Mercury)

df2['Pressure_atm'] = df2['Pressure1']/29.92
# # Features units
# Temperature is in C
# Wind Speed is in mph(Meter per Hour)
# Pressure_atm is in atmospheric pressure[24]
# 1 atm = 29.92 inHg ----> inHg is inches in Hg(Mercury)
```

```
# Humidity is in percentage
# Rain:
# 0 ---> No Rain
# 1 ---> Raining

df2.groupby('Rain_01')['Index'].agg('count').reset_index()
df2.dropna(inplace = True)

df2.describe()

def graph(pdf, clm):
# Generate some random data that follows a normal distribution
data = df[clm]

# Create a histogram of the data
sb.histplot(data, kde=True)

496 # Calculate the mean and standard deviation of the data
mean = np.mean(data)
std_dev = np.std(data)

left_bound = mean - (3 * std_dev)
right_bound = mean + (3 * std_dev)


pt.axvline(x=left_bound, color='r', linestyle='--')
pt.axvline(x = mean, color = 'b', linestyle = '--')
```

```
pt.axvline(x=right_bound, color='r', linestyle='--')

# Show the plot
pt.show()

graph(df2, 'Pressure_atm')



# **We can see there are outliers**

pt.scatter(x = df2.Pressure_atm, y = df2.Rain_01)

df3 = df2.copy()

# **Outliers Removal using IQR**

def removal_outliers(df, clm):
q1, q3 = np.percentile(df[clm], [25, 75])
iqr = q3 - q1
low = q1 - 1.5*iqr
upp = q3 + 1.5*iqr
lst = df[clm]
for[407]  i[408] in list:
if i < low or i > upp:
df = df[df[clm] != i]
return df
```

```
df4 = removal_outliers(df3, 'Pressure_atm')


pt.scatter(x = df4.Pressure_atm, y = df4.Rain_01)
# **Visualizing the Distribution**
# Here, the visualization is 3 [409] standard deviation of the left and right side from
the mean
graph(df4, 'Temperature1')


def outlier_detc(df, clm):
m = np.mean(df[clm])
sd = np.std(df[clm])
l = df[clm]
for [410]  i [411] in l:
z = (i - m)/sd
if z > 3 or z < -3:
df = df[df[clm] != i]
return df


df4 = outlier_detc(df4, 'Temperature1')



graph(df4, 'Wind Speed1')
df4 = outlier_detc(df4, 'Wind Speed1')


sb.histplot(data = df4, x = 'Wind Speed1', kde = True)


graph(df4, 'Humidity1')
```

```
# **Visualisation after removal of Outliers**

graph(df4, 'Humidity1'), graph(df4, 'Wind Speed1'), graph(df4, 'Temperature1'),
graph(df4, 'Pressure_atm')

pt.scatter(x = df4.Humidity1, y = df4.Rain_01)

rainfall_count = df4.groupby('Rain_01')['Index'].agg('count').reset_index()
rainfall_count
x = rainfall_count.Rain_01
y = rainfall_count.Index

# **Visualizing the target Variable**

x = ['No Rain',[412] 'Rain']
counts = y # example data

fig, ax = pt.subplots()
ax.bar(x, counts, color = ['g', 'b'])

# Adding count labels to each bar
for i,[413] v in enumerate(counts):
ax.text(i, v+0.5, str(v), ha='center', fontweight='bold')

# Set title and axis labels
ax.set_title('Rain Condition')
```

```
ax.set_xlabel('Rain')
ax.set_ylabel('Count')

# Show the graph
pt.show()

df_final = df4[['Temperature1', 'Humidity1', 'Rain_01']]
df_final.head()

x = df_final.iloc[:, :-1].values
x
y = df_final.iloc[:, -1].values
y
# In independent variable:
# The Inputs(x) are Temperature in (C), Wind Speed in mph(meter per hour),
Humidity in %, pressure in atm (atmosphere)
# The Output(y) is Rain [205] (1), No Rain (0)

497 x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3, stratify = y, random_state = 42)

norma = Normalizer()
x_train = norma.fit_transform(x_train)
x_test = norma.transform(x_test)

x_train
x_test
```

```
os = RandomOverSampler(sampling_strategy = 0.65)

x_train_res, y_train_res = os.fit_resample(x_train, y_train)

y_train_res

print('Original dataset shape {}'.format(Counter(y_train)))
print('Resampled dataset shape {}'.format(Counter(y_train_res)))

ann = tf.keras.models.Sequential()

ann.add(tf.keras.layers.Dense(units = 20, activation = 'relu'))
ann.add(tf.keras.layers.Dense(units = 7, activation = 'relu'))



ann.add(tf.keras.layers.Dense(units=1, activation='sigmoid'))
ann.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics =
['accuracy'])

ann.fit(x_train_res, y_train_res, batch_size = 32, epochs = 20)

y_ann_predicted = ann.predict(x_test)
ann_lst = []
for i in y_ann_predicted:
if i[0] >= 0.5:
ann_lst.append([1])
```

415

```
else:
ann_lst.append([0])

ann_lst_predicted = np.array(ann_lst)
cr_ann = classification_report(y_test, ann_lst_predicted)
print(cr_ann)
cm_ann = confusion_matrix(y_test, ann_lst_predicted)
cm_ann

pt.figure(figsize = (9, 9))
sb.heatmap(cm_ann, annot = True, fmt='d')
pt.xlabel('Predicted')
pt.ylabel('Truth')
pt.title('Artificial Neural Network Confusion Matrix')

LogReg_model = LogisticRegression(solver='lbfgs',class_weight='balanced',
max_iter=10000)
LogReg_model.fit(x_train_res, y_train_res)
LogReg_model.score(x_test, y_test)

y_log_reg_predicted = LogReg_model.predict(x_test)
cr_log = classification_report(y_test, y_log_reg_predicted)
print(cr_log)
cm_lg = confusion_matrix(y_test, y_log_reg_predicted)
cm_lg

pt.figure(figsize = (9, 9))
```

```
sb.heatmap(cm_lg, annot = True, fmt='d')
pt.xlabel('Predicted')
pt.ylabel('Truth')
pt.title('Logistic Regression Confusion Matrix')

RFC_model = RandomForestClassifier()
RFC_model.fit(x_train_res, y_train_res)
RFC_model.score(x_test, y_test)

y_rfc_predicted = RFC_model.predict(x_test)
cr_rfc = classification_report(y_test, y_rfc_predicted)
print(cr_rfc)
cm_rfc = confusion_matrix(y_test, y_rfc_predicted)
cm_rfc

pt.figure(figsize = (9, 9))
sb.heatmap(cm_rfc, annot = True, fmt='d')
pt.xlabel('Predicted')
pt.ylabel('Truth')
pt.title('Random Forest Confusion Matrix')


# **Performances of models**
# Logistic Regression ---> 73.2%
# Artificial Neural Network ---> 83.0%
# Random Forest Classifier ---> 85.5%
```

with[416] open('RFCmodel.pkl'[417], 'wb') as file:

pickle.dump(RFC_model, file)

import os

print(os.getcwd[418]())

1.	*This*	Intricate text	Clarity
2.	~~in~~ → In	Improper formatting	Correctness
3.	*in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Electronics and Communication Engineering of the Indian Institute of Information Technology Tiruchirappalli during the year 2022-2023.*	Unclear sentences	Clarity
4.	*. The; . This; . You; . Our; . Agriculture; . In; . An; . Sarma; . Rainfall; . It; . Due; . India; . Nodes; . Node; . Overall; . However; . Farmers; . By; . Additionally; . With; . Therefore; . INTELLIGENT; . PREDICTION; . These; . AUTOMATED; . Their; . AN; . Both; . Inaccurate; . Soil; . Sensors; ...*	Text inconsistencies	Correctness
5.	~~full~~ → whole	Word choice	Engagement
6.	*be watered*	Passive voice misuse	Clarity
7.	*This*	Intricate text	Clarity
8.	*be controlled*	Passive voice misuse	Clarity
9.	*This can be controlled and monitored online using IoT applications. You can create a device that connects to a water pump controlled by an Arduino UNO R3 microcontroller.*	Unclear paragraphs	Clarity
10.	~~controls~~ → maintains	Word choice	Engagement
11.	*can be measured*	Passive voice misuse	Clarity
12.	~~work~~	Wordy sentences	Clarity
13.	*is trained*	Passive voice misuse	Clarity

14.	~~an important~~ → a vital, an essential	Word choice	Engagement
15.	*is based*	Passive voice misuse	Clarity
16.	~~largely based~~ → primarily based, based mainly	Word choice	Engagement
17.	, and	Comma misuse within clauses	Correctness
18.		Tone suggestions	Delivery
19.	*is based*	Passive voice misuse	Clarity
20.	*This*	Intricate text	Clarity
21.	~~the course of~~	Wordy sentences	Clarity
22.	~~overview~~ → Overview	Confused words	Correctness
23.	~~smart~~ → intelligent	Word choice	Engagement
24.	*Pressure; pressure*	Text inconsistencies	Correctness
25.	*are followed*	Passive voice misuse	Clarity
26.	the personal	Determiner use (a/an/the/this, etc.)	Correctness
27.	~~amount of~~	Wordy sentences	Clarity
28.	a lack	Determiner use (a/an/the/this, etc.)	Correctness
29.	~~is facing~~ → faces	Wordy sentences	Clarity
30.	~~are unable to~~ → cannot	Wordy sentences	Clarity
31.	~~effective~~ → adequate	Word choice	Engagement
32.	*be irrigated*	Passive voice misuse	Clarity
33.	and connected	Conjunction use	Correctness

34.	*The system analyzes soil moisture levels via sensors and requires little to no human intervention once deployed.*	Unclear sentences	Clarity
35.	~~system~~ → method	Word choice	Engagement
36.	*Node status can be monitored*	Passive voice misuse	Clarity
37.	*The system also works with a replication prediction system, allowing easy identification of failures. Node status can be monitored via a mobile app based on the mapping of farms and areas designated for irrigation.*	Unclear paragraphs	Clarity
38.	*Node status can be monitored via a mobile app based on the mapping of farms and areas designated for irrigation.*	Unclear sentences	Clarity
39.	~~to be~~	Wordy sentences	Clarity
40.		Tone suggestions	Delivery
41.	*However, the traditional irrigation methods used in the country are inefficient and result in significant water wastage. Farmers rely on their personal experience and supervision to irrigate their fields, which leads to poor utilization of resources and economic losses due to drought and crop eradi...*	Unclear paragraphs	Clarity
42.	*Farmers rely on their personal experience and supervision to irrigate their fields, which leads to poor utilization of resources and economic losses due to drought and crop eradication.*	Unclear sentences	Clarity
43.	*This*	Intricate text	Clarity

44.	*This not only benefits the farmers' livelihoods but also contributes to the overall economic development of the country.*	Unclear sentences	Clarity
45.	~~that incorporate~~ → incorporating	Wordy sentences	Clarity
46.	*By using these technologies, farmers can accurately determine the amount of water required for their crops based on soil moisture levels and weather conditions.*	Unclear sentences	Clarity
47.	*This*	Intricate text	Clarity
48.	~~greatly~~ → significantly	Word choice	Engagement
49.	*are tailored*	Passive voice misuse	Clarity
50.	*With a collaborative effort, India can improve its irrigation systems and achieve sustainable and efficient crop production.*	Unclear sentences	Clarity
51.	*is carried out*	Passive voice misuse	Clarity
52.	~~in~~ → on	Wrong or missing prepositions	Correctness
53.	~~they need it~~ → needed	Wordy sentences	Clarity
54.	*be remotely controlled*	Passive voice misuse	Clarity
55.	*By continuously monitoring crop and soil conditions, it is now possible to water crops precisely when they need it. The process can be remotely controlled and monitored using IoT applications, making it convenient for farmers to operate the system.*	Unclear paragraphs	Clarity
56.	*To achieve this*	Misplaced words or phrases	Correctness
57.	*be created*	Passive voice misuse	Clarity

58.	*The water pump can be programmed*	Passive voice misuse	Clarity
59.	~~, which~~ → . These	Hard-to-read text	Clarity
60.	the DHT-11	Determiner use (a/an/the/this, etc.)	Correctness
61.	*To make the device more intelligent and efficient*	Misplaced words or phrases	Correctness
62.	~~work~~	Wordy sentences	Clarity
63.	*This*	Intricate text	Clarity
64.	*is used*	Passive voice misuse	Clarity
65.	~~which is~~	Wordy sentences	Clarity
66.	*This helps to increase the accuracy of the model's predictions, leading to improved irrigation efficiency and better use of resources. The Random Forest algorithm is used to train the model, which is a widely used algorithm for regression analysis.*	Unclear paragraphs	Clarity
67.	*By reducing water wastage and improving crop yields, farmers can generate more income and contribute to the country's economy.*	Unclear sentences	Clarity
68.	*Additionally, the conservation of water resources is crucial for addressing water scarcity issues in the country, and the use of electronic irrigation systems can help achieve this goal.*	Unclear sentences	Clarity
69.	~~the use of~~	Wordy sentences	Clarity
70.	*The proposed system aims to combine ANN and KNN methods to provide farmers with data on crop selection, growth, and yield.*	Unclear sentences	Clarity

71.	*Over-irrigation due to rainfall immediately after the irrigation process can negatively impact crop yield.*	Unclear sentences	Clarity
72.	~~important~~ → essential, vital	Word choice	Engagement
73.	~~a variety of~~ → various	Wordy sentences	Clarity
74.	~~both~~	Wordy sentences	Clarity
75.	~~are~~ → is	Faulty subject-verb agreement	Correctness
76.	data sequences	Wordy sentences	Clarity
77.	~~, while~~ → . At the same time,	Hard-to-read text	Clarity
78.	*The authors argue that by using these two techniques in combination, they can achieve better performance in rainfall prediction.*	Unclear sentences	Clarity
79.	~~Overall, the~~ → The	Wordy sentences	Clarity
80.	*It provides an overview of various applications of machine learning techniques in the field of agriculture in India.*	Unclear sentences	Clarity
81.	*The paper highlights the need for modernization of agriculture and the role of technology in achieving the same.*	Unclear sentences	Clarity
82.	agriculture-related problems	Wordy sentences	Clarity
83.	*can be used*	Passive voice misuse	Clarity
84.	*The paper primarily focuses on the use of machine learning in predicting pest attacks and disease outbreaks in crops like tomatoes, paddy, and grapes.*	Unclear sentences	Clarity

85.	~~be applicable~~ → apply	Wordy sentences	Clarity
86.	*However, the techniques used may not necessarily be applicable to other crops, which limits the generalizability of the findings.*	Unclear sentences	Clarity
87.	*The paper does not explicitly consider the social and economic factors that affect agricultural practices in India, such as farmer education and access to resources. These factors may impact the adoption and success of machine-learning applications in Indian agriculture.*	Unclear paragraphs	Clarity
88.	*RF; KB; DC; TP; FP; TN; FN; R.W.*	Text inconsistencies	Correctness
89.		Tone suggestions	Delivery
90.	*A gateway device also manages sensor data, activates actuators, and sends data to the web application. The system had a dispersed wireless network of soil moisture and temperature sensors installed in the root zone of the plants.*	Unclear paragraphs	Clarity
91.	*To regulate the amount of water used, a microcontroller-based gateway was programmed with an algorithm based on temperature and soil moisture threshold values.*	Unclear sentences	Clarity
92.	*were published*	Passive voice misuse	Clarity
93.	*is controlled*	Passive voice misuse	Clarity
94.	*The project's findings were published in a study where the water motor's ability to turn on and off is controlled by the temperature of the soil and a temperature sensor inserted into*	Unclear paragraphs	Clarity

	plant roots. Their lack of a method to inform the user of the status of the agricultural field is a flaw in their p...		
95.		Tone suggestions	Delivery
96.	*is used*	Passive voice misuse	Clarity
97.	*Using the soil sensor, the irrigation system measures the soil's temperature and humidity before watering the plants accordingly.*	Unclear sentences	Clarity
98.	*Using the soil sensor*	Misplaced words or phrases	Correctness
99.	*are watered*	Passive voice misuse	Clarity
100.	allow landowners	Wordy sentences	Clarity
101.	~~in~~ → on	Wrong or missing prepositions	Correctness
102.	~~idea~~ → picture	Word choice	Engagement
103.	~~really~~	Wordy sentences	Clarity
104.	straightforward	Wordy sentences	Clarity
105.	*The idea we've employed is really straightforward and simple to put into practice.*	Unclear sentences	Clarity
106.	*Both labor and time will be saved*	Passive voice misuse	Clarity
107.	*The idea we've employed is really straightforward and simple to put into practice. Both labor and time will be saved.*	Unclear paragraphs	Clarity
108.		Tone suggestions	Delivery
109.	. ARDUINO	Improper formatting	Correctness
110.	~~ARDUINO BASED~~ →	Misspelled words	Correctness

	ARDUINO-BASED		
111.	*is designed*	Passive voice misuse	Clarity
112.	~~by~~	Wordy sentences	Clarity
113.	~~data from sensors~~ → sensor data	Wordy sentences	Clarity
114.	*are used*	Passive voice misuse	Clarity
115.	~~make predictions about~~ → predict	Wordy sentences	Clarity
116.	*is intended*	Passive voice misuse	Clarity
117.		Tone suggestions	Delivery
118.	Implementing	Wordy sentences	Clarity
119.		Tone suggestions	Delivery
120.	*It comes with everything needed to support the microcontroller; all you need to do is use a USB cable to connect it to a computer and provide power using an AC-DC adapter or a battery to get things going.*	Unclear sentences	Clarity
121.	~~signifies~~ → means	Word choice	Engagement
122.	*being updated*	Passive voice misuse	Clarity
123.	*The reference versions of the Arduino board and IDE software are currently being updated.*	Unclear sentences	Clarity
124.	~~serves as~~ → is	Wordy sentences	Clarity
125.	*Flash Memory -32 KB, and 0.5 KB memory is used by the boot loader*	Passive voice misuse	Clarity
126.	~~great~~ → excellent	Word choice	Engagement

127.	~~as well as~~ → and	Wordy sentences	Clarity
128.	~~and has~~ → with	Wordy sentences	Clarity
129.	*The volumetric water content of the soil is measured by soil moisture sensors.*	Passive voice misuse	Clarity
130.	~~soil~~ → earth, ground	Word choice	Engagement
131.	content,	Punctuation in compound/complex sentences	Correctness
132.	~~has an impact on~~ → impacts	Wordy sentences	Clarity
133.	*is employed*	Passive voice misuse	Clarity
134.	*It is necessary to calibrate the relationship between the measured property and soil moisture since it can change based on the environment, including the soil type, temperature, and electric conductivity. The soil moisture has an impact on the reflected microwave radiation, which is employed for re...*	Unclear paragraphs	Clarity
135.	~~employ~~ → use, utilize	Word choice	Engagement
136.	*are commonly referred*	Passive voice misuse	Clarity
137.	*Sensors that assess the volumetric water content are commonly referred to as soil moisture sensors.*	Unclear sentences	Clarity
138.	~~potential~~ → likely, possible	Word choice	Engagement
139.	~~Circuits~~ → Courses	Word choice	Engagement
140.	~~To put it simply~~ → Simply put	Wordy sentences	Clarity
141.	~~an automatic~~ → a mechanical	Word choice	Engagement

142.	~~circuit~~ → course	Word choice	Engagement
143.	*A relay's lower moment of inertia, stability, long-term dependability, and small volume are its advantages.*	Unclear sentences	Clarity
144.	*It is widely used in power protection, automation, sports, remote control, intelligence gathering, and communication equipment, as well as electromechanical and power electronic ones.*	Unclear sentences	Clarity
145.	~~power~~ → capacity	Word choice	Engagement
146.	~~Additionally~~ → ¶ Additionally	Intricate text	Clarity
147.	~~has the ability to~~ → can	Wordy sentences	Clarity
148.	*is utilized*	Passive voice misuse	Clarity
149.	*Between the input and output parts, there is an intermediary component that is utilized to couple and isolate input current as well as actuate the output.*	Unclear sentences	Clarity
150.	~~any of~~	Wordy sentences	Clarity
151.	a part	Determiner use (a/an/the/this, etc.)	Correctness
152.	*be powered*	Passive voice misuse	Clarity
153.	~~from~~ → by	Wrong or missing prepositions	Correctness
154.	*direct-current lighting power distribution systems*	Intricate text	Clarity
155.	the current	Determiner use (a/an/the/this, etc.)	Correctness

156.	*A DC motor's speed can be controlled over a wide range, using either a variable supply voltage or by changing the strength of current in its field windings.*	Unclear sentences	Clarity
157.	*are used*	Passive voice misuse	Clarity
158.	~~appliances~~ → machines, instruments, devices	Word choice	Engagement
159.	~~in~~	Wordy sentences	Clarity
160.	*Larger DC motors are currently used in the propulsion of electric vehicles, elevators, and hoists and in drives for steel rolling mills.*	Unclear sentences	Clarity
161.	*Breadboard; breadboard*	Text inconsistencies	Correctness
162.	~~serving~~ → doing, helping	Word choice	Engagement
163.	*This*	Intricate text	Clarity
164.	~~to use~~	Wordy sentences	Clarity
165.	~~common~~ → standard	Word choice	Engagement
166.	~~A variety of~~ → Various	Wordy sentences	Clarity
167.	*A variety of electronic systems may be prototyped*	Passive voice misuse	Clarity
168.	~~is difficult~~ → isn't easy	Tone suggestions	Delivery
169.	*It is difficult to reuse a stripboard (Veroboard) or other prototyping printed circuit board used to create one-off or semi-permanent soldered prototypes.*	Unclear sentences	Clarity
170.	wire,	Comma misuse within clauses	Correctness

171.	~~, and it~~ → . It	Hard-to-read text	Clarity
172.	*is typically used*	Passive voice misuse	Clarity
173.		Tone suggestions	Delivery
174.	~~piece of~~	Wordy sentences	Clarity
175.	~~ends~~ → lots	Word choice	Engagement
176.	~~presage~~ → presages	Faulty subject-verb agreement	Correctness
177.	*is turned on*	Passive voice misuse	Clarity
178.	*can be used*	Passive voice misuse	Clarity
179.	*The data was split*	Passive voice misuse	Clarity
180.	~~in order to~~ → to	Wordy sentences	Clarity
181.	*is frequently employed*	Passive voice misuse	Clarity
182.	*Web scraping is frequently employed for data mining, market research, price monitoring, and other uses that require the collection and analysis of vast amounts of data.*	Unclear sentences	Clarity
183.	~~In the end~~ → Ultimately	Wordy sentences	Clarity
184.	~~required~~ → demanded	Word choice	Engagement
185.	*This*	Intricate text	Clarity
186.	~~superfluous~~ → extra	Word choice	Clarity
187.	~~at hand~~	Wordy sentences	Clarity
188.	*any letters in the column should be eliminated*	Passive voice misuse	Clarity
189.	*This*	Intricate text	Clarity

190.	*This can be accomplished*	Passive voice misuse	Clarity
191.	*This can be accomplished in one of two ways: either by deleting the rows that contain the missing information or by imputed values such as the mean or median.*	Unclear sentences	Clarity
192.	*been cleaned*	Passive voice misuse	Clarity
193.	*The next stage is to look for any outliers in the dataset after the data has been cleaned.*	Unclear sentences	Clarity
194.	*The next stage is to look for any outliers in the dataset after the data has been cleaned. It is crucial to find and eliminate outliers since they have a considerable negative impact on the performance of machine learning models.*	Unclear paragraphs	Clarity
195.	*It is crucial to find and eliminate outliers since they have a considerable negative impact on the performance of machine learning models.*	Unclear sentences	Clarity
196.	~~3~~ → three	Improper formatting	Correctness
197.	~~in this case~~	Wordy sentences	Clarity
198.	*This*	Intricate text	Clarity
199.	*be trained*	Passive voice misuse	Clarity
200.	*The data must now be divided into training and testing sets after being cleaned and labeled.*	Unclear sentences	Clarity
201.	*be divided*	Passive voice misuse	Clarity
202.	~~In order to~~ → To	Wordy sentences	Clarity

203.	*is often done*	Passive voice misuse	Clarity
204.	~~with regard to~~ → about, concerning	Wordy sentences	Clarity
205.	*rain; Rain*	Text inconsistencies	Correctness
206.	*is used*	Passive voice misuse	Clarity
207.	*It is used for predicting the categorical dependent variable using a given set of independent variables. Logistic regression predicts the output of a categorical dependent variable.*	Unclear paragraphs	Clarity
208.	~~a categorical~~ → an absolute, a flat, a definite	Word choice	Engagement
209.	~~value~~ → weight	Word choice	Engagement
210.	~~gives~~ → provides	Word choice	Engagement
211.	~~which lie~~	Wordy sentences	Clarity
212.		Tone suggestions	Delivery
213.	~~plane~~ → aircraft	Word choice	Engagement
214.	consider such kind of line	Wordy sentences	Clarity
215.	~~a point~~ → an issue, a fact, a topic	Word choice	Engagement
216.	~~points~~ → issues, topics	Word choice	Engagement
217.	~~are~~ → will be	Faulty tense sequence	Correctness
218.	a -ve	Determiner use (a/an/the/this, etc.)	Correctness
219.	*If a point is from the left side of the plane, then the distance will be +ve, and the other side of the points are -ve distance.*	Unclear sentences	Clarity

220.	*the best line may be ignored*	Passive voice misuse	Clarity
221.	*If there is any outlier added to the dataset, then the best line may be ignored unknowingly.*	Unclear sentences	Clarity
222.	~~special~~ → particular	Word choice	Engagement
223.	, and	Punctuation in compound/complex sentences	Correctness
224.	*is increased*	Passive voice misuse	Clarity
225.	~~for preserving~~ → preserve	Wordy sentences	Clarity
226.	~~type of~~	Wordy sentences	Clarity
227.	~~which then passes~~ → passing	Wordy sentences	Clarity
228.	*Each node in a hidden layer performs a mathematical operation on the input, and the resulting output is then transferred to the next layer until it arrives at the output layer, which produces the final result.*	Unclear sentences	Clarity
229.	network output	Wordy sentences	Clarity
230.	~~are~~ → is	Faulty subject-verb agreement	Correctness
231.	*are adjusted*	Passive voice misuse	Clarity
232.	*are widely utilized*	Passive voice misuse	Clarity
233.	*are used*	Passive voice misuse	Clarity
234.	yields,	Punctuation in compound/complex sentences	Correctness
235.	*In agriculture, ANNs are used to predict crop yields, and soil moisture and detect pests.*	Unclear sentences	Clarity

236.	~~key~~ → critical	Word choice	Engagement
237.	~~amounts of~~	Wordy sentences	Clarity
238.	~~a type of~~ → an	Wordy sentences	Clarity
239.	*In constructing each tree, a random subset of the input features and training data is employed.*	Unclear sentences	Clarity
240.	*is employed*	Passive voice misuse	Clarity
241.	a replacement	Determiner use (a/an/the/this, etc.)	Correctness
242.	*be employed*	Passive voice misuse	Clarity
243.	construct	Wordy sentences	Clarity
244.	the classification	Determiner use (a/an/the/this, etc.)	Correctness
245.	To classify	Wordy sentences	Clarity
246.	the predicted	Determiner use (a/an/the/this, etc.)	Correctness
247.	~~classification~~ → type, category	Word choice	Engagement
248.	*be expressed*	Passive voice misuse	Clarity
249.	*mathematically*	Misplaced words or phrases	Correctness
250.	*i-th*	Unknown words	Correctness
251.	*The goal of the algorithm is to build a forest F of decision trees T that can forecast the class label of a new instance x.*	Unclear sentences	Clarity
252.	, T	Comma misuse within clauses	Correctness

253.	*It's a 2x2 matrix that contrasts the predicted and actual values of a binary classifier.*	Unclear sentences	Clarity
254.	the following:	Incomplete sentences	Correctness
255.	~~positive~~ → optimistic	Word choice	Engagement
256.	the model makes	Wordy sentences	Clarity
257.	*True Positive (TP): The number of accurate positive predictions made by the model.*	Incomplete sentences	Delivery
258.	~~positive~~ → optimistic	Word choice	Engagement
259.	the model makes	Wordy sentences	Clarity
260.	~~negative~~ → pessimistic	Word choice	Engagement
261.	the model makes	Wordy sentences	Clarity
262.	*True Negative (TN): The number of accurate negative predictions made by the model.*	Incomplete sentences	Delivery
263.	~~negative~~ → pessimistic	Word choice	Engagement
264.	the model makes	Wordy sentences	Clarity
265.	*False Negative (FN): The number of inaccurate negative predictions made by the model.*	Incomplete sentences	Delivery
266.	*To assess the performance of a machine learning model*	Misplaced words or phrases	Correctness
267.	*To assess the performance of a machine learning model, various metrics such as accuracy, precision, recall, and F1 score are used.*	Unclear sentences	Clarity
268.	*are used*	Passive voice misuse	Clarity

269.	~~instances~~ → cases	Word choice	Engagement
270.	~~, and it~~ → . It	Hard-to-read text	Clarity
271.	*be calculated*	Passive voice misuse	Clarity
272.	~~instances~~ → cases	Word choice	Engagement
273.	*be calculated*	Passive voice misuse	Clarity
274.	The recall, or A recall	Determiner use (a/an/the/this, etc.)	Correctness
275.	~~actual~~	Wordy sentences	Clarity
276.	~~instances~~ → examples, samples, models	Word choice	Engagement
277.	*be calculated*	Passive voice misuse	Clarity
278.	*be calculated*	Passive voice misuse	Clarity
279.	~~2~~ → two	Improper formatting	Correctness
280.	~~precision~~ → accuracy	Word choice	Engagement
281.	~~recall~~ → memory	Word choice	Engagement
282.	*A confusion matrix is a 2x2 matrix that compares the predicted and actual values of a binary classifier and provides information on TP, TN, FP, and FN.*	Unclear sentences	Clarity
283.	*be used*	Passive voice misuse	Clarity
284.	*It can be used to evaluate the model's performance and identify errors, and to determine if the model is overfitting or underfitting.*	Unclear sentences	Clarity
285.	~~that is~~	Wordy sentences	Clarity

286.	*is specifically designed*	Passive voice misuse	Clarity
287.	~~are able to~~ → can	Wordy sentences	Clarity
288.	~~were to use~~ → used	Wordy sentences	Clarity
289.	~~t one~~ → tone	Confused words	Correctness
290.		Tone suggestions	Delivery
291.	A recurrent	Determiner use (a/an/the/this, etc.)	Correctness
292.	~~that is~~	Wordy sentences	Clarity
293.	*is designed*	Passive voice misuse	Clarity
294.	~~state~~ → form	Word choice	Engagement
295.	~~state~~ → form	Word choice	Engagement
296.	*However, an RNN processes each word in sequence by updating its internal state with the current input and the previous state.*	Unclear sentences	Clarity
297.	*This*	Intricate text	Clarity
298.	~~from previous~~ → of earlier	Word choice	Engagement
299.	~~words~~ → comments, observations, terms	Word choice	Engagement
300.	~~make a prediction about~~ → predict	Wordy sentences	Clarity
301.	*are trained*	Passive voice misuse	Clarity
302.	~~takes into account~~ → considers	Wordy sentences	Clarity
303.	*is updated*	Passive voice misuse	Clarity

304.	network weights	Wordy sentences	Clarity
305.	~~useful for~~ → helpful for, helpful in	Word choice	Engagement
306.	*are trained*	Passive voice misuse	Clarity
307.	~~tools~~ → means, devices, agencies, mechanisms	Word choice	Engagement
308.	~~Notebook~~ → Notebooks	Incorrect noun number	Correctness
309.	~~notebook~~ → Notebook	Confused words	Correctness
310.	*This*	Intricate text	Clarity
311.	*can be done*	Passive voice misuse	Clarity
312.	~~notebook~~ → Notebook	Confused words	Correctness
313.	*is hosted*	Passive voice misuse	Clarity
314.	~~real-time~~ → real time	Confused words	Correctness
315.	*This allows users to perform all the tasks that can be done in a locally hosted Jupyter notebook without the need for local installations or setups. Since Google Colaboratory is hosted on cloud servers, users can easily share their notebooks with others and collaborate in real-time.*	Unclear paragraphs	Clarity
316.	designed explicitly	Word choice	Engagement
317.	the future	Determiner use (a/an/the/this, etc.)	Correctness
318.	~~estimation~~ → analysis, assessment, regard, respect	Word choice	Engagement
319.	rainfall estimation	Wordy sentences	Clarity

320.	no rainfall is	Wordy sentences	Clarity
321.	*When the soil moisture level falls below the required threshold value, and there is no rainfall predicted by the machine learning algorithm, the model activates the motor pump for crop irrigation.*	Passive voice misuse	Clarity
322.	and as	Conjunction use	Correctness
323.	see,	Punctuation in compound/complex sentences	Correctness
324.	*By leveraging these technologies, our system is capable of making informed decisions and adjusting its operations based on changing environmental conditions.*	Unclear sentences	Clarity
325.	~~the deployment of~~ → deploying	Wordy sentences	Clarity
326.	~~the field of~~	Wordy sentences	Clarity
327.	~~prove to~~	Wordy sentences	Clarity
328.	, and	Comma misuse within clauses	Correctness
329.	Learning :	Improper formatting	Correctness
330.	~~".~~ → ."	Misuse of semicolons, quotation marks, etc.	Correctness
331.	. P	Improper formatting	Correctness
332.	) ,	Improper formatting	Correctness
333.	~~",~~ → ,"	Misuse of semicolons, quotation marks, etc.	Correctness
334.	, and	Comma misuse within clauses	Correctness

335.	The meeting	Determiner use (a/an/the/this, etc.)	Correctness
336.	~~";~~ → ,"	Misuse of semicolons, quotation marks, etc.	Correctness
337.	, and	Comma misuse within clauses	Correctness
338.	. Cloud	Improper formatting	Correctness
339.	BTPPROJECT.	Closing punctuation	Correctness
340.	~~soilMoisture~~ → soil moisture	Misspelled words	Correctness
341.	~~syncValues~~ → sync values	Misspelled words	Correctness
342.	~~soilMoisture~~ → soil moisture	Misspelled words	Correctness
343.	~~readHumidity~~ → read humidity	Misspelled words	Correctness
344.	read temperature	Misspelled words	Correctness
345.	*println*	Unknown words	Correctness
346.	~~soilMoisture~~ → soil moisture	Misspelled words	Correctness
347.	*println*	Unknown words	Correctness
348.	*println*	Unknown words	Correctness
349.	~~syncValues~~ → sync values	Misspelled words	Correctness
350.	~~soilMoisture~~ → soil-moisture, soil moisture	Misspelled words	Correctness
351.	~~rb~~ → RB	Misspelled words	Correctness
352.	required soil moisture	Misspelled words	Correctness
353.	~~else~~ → Else	Improper formatting	Correctness
354.	~~while~~ → While	Improper formatting	Correctness

355.	a response	Determiner use (a/an/the/this, etc.)	Correctness
356.	~~url~~ → URL	Misspelled words	Correctness
357.	~~requests~~ → Requests	Improper formatting	Correctness
358.	~~webdriver~~ → web driver	Misspelled words	Correctness
359.	~~webdriver~~ → web driver	Misspelled words	Correctness
360.	~~webdriver~~ → web driver	Misspelled words	Correctness
361.	~~from~~ → From	Improper formatting	Correctness
362.	. webdriver	Improper formatting	Correctness
363.	~~webdriver~~ → web driver	Misspelled words	Correctness
364.	~~webdriver~~ → web driver	Misspelled words	Correctness
365.	~~try~~ → Try	Improper formatting	Correctness
366.	*strftime*	Unknown words	Correctness
367.	*strftime*	Unknown words	Correctness
368.	*strftime*	Unknown words	Correctness
369.	*strftime*	Unknown words	Correctness
370.	*cdk*	Unknown words	Correctness
371.	*cdk*	Unknown words	Correctness
372.	the table, or a table	Determiner use (a/an/the/this, etc.)	Correctness
373.	~~1~~ → one	Improper formatting	Correctness
374.	~~1 day~~ → 1-day	Misspelled words	Correctness

375.	~~except~~ → Except	Improper formatting	Correctness
376.	*csv*	Unknown words	Correctness
377.	~~csvfile~~ → CSV file	Misspelled words	Correctness
378.	~~if~~ → If	Improper formatting	Correctness
379.	. writerow	Improper formatting	Correctness
380.	~~writerow~~ → writer, writers	Misspelled words	Correctness
381.	~~";~~ → ,"	Misuse of semicolons, quotation marks, etc.	Correctness
382.	*csv*	Unknown words	Correctness
383.	~~if~~ → If	Improper formatting	Correctness
384.	. writerow	Improper formatting	Correctness
385.	~~writerow~~ → writer, writers	Misspelled words	Correctness
386.	~~";~~ → ,"	Misuse of semicolons, quotation marks, etc.	Correctness
387.	~~import~~ → Import	Improper formatting	Correctness
388.	*matplotlib*	Unknown words	Correctness
389.	. pyplot	Improper formatting	Correctness
390.	*pyplot*	Unknown words	Correctness
391.	*matplotlib*	Unknown words	Correctness
392.	*numpy*	Unknown words	Correctness
393.	*tensorflow*	Unknown words	Correctness
394.	~~imblearn~~ → learn	Misspelled words	Correctness

395.	~~metrics~~ → Metrics	Improper formatting	Correctness
396.	*matplotlib'*	Unknown words	Correctness
397.	~~;~~ → ,'	Misuse of semicolons, quotation marks, etc.	Correctness
398.	. shape	Improper formatting	Correctness
399.	~~df~~ → pdf	Confused words	Correctness
400.	~~yticklabels~~ → stick labels	Misspelled words	Correctness
401.	~~cmap~~ → camp	Misspelled words	Correctness
402.	~~except~~ → Except	Improper formatting	Correctness
403.	~~i~~ → I	Misspelled words	Correctness
404.	~~;~~ → ,'	Misuse of semicolons, quotation marks, etc.	Correctness
405.	~~;~~ → ,'	Misuse of semicolons, quotation marks, etc.	Correctness
406.	~~;~~ → ,'	Misuse of semicolons, quotation marks, etc.	Correctness
407.	~~for~~ → For	Improper formatting	Correctness
408.	~~i~~ → I	Misspelled words	Correctness
409.	~~3~~ → three	Improper formatting	Correctness
410.	~~for~~ → For	Improper formatting	Correctness
411.	~~i~~ → I	Misspelled words	Correctness
412.	~~;~~ → ,'	Misuse of semicolons, quotation marks, etc.	Correctness
413.	~~i~~ → I	Misspelled words	Correctness

414.	~~i~~ → I	Misspelled words	Correctness
415.	~~else~~ → Else	Improper formatting	Correctness
416.	~~with~~ → With	Improper formatting	Correctness
417.	*pkl'*	Unknown words	Correctness
418.	*getcwd*	Unknown words	Correctness
419.	*in partial fulfillment of the requirements for the award of the degree of*	Phenotypic ranking experiments in identifying breeding objective traits of smallholder farmers in northwestern Ethiopia	Originality
420.	*This is to certify that the project work*	This Is To Certify That The Project Work Report Titled | PDF - Scribd https://www.scribd.com/doc/144871809/This-is-to-Certify-That-the-Project-Work-Report-Titled	Originality
421.	*is a bonafide record of the work done by*	NIT Trichy - THESIS - National Institute of Technology, Tiruchirappalli https://nitt.edu/academics/thesis/	Originality
422.	*in partial fulfillment of the requirements for the award of the degree of*	Phenotypic ranking experiments in identifying breeding objective traits of smallholder farmers in northwestern Ethiopia	Originality
423.	*in full or in parts, have not been submitted to any other institute or university for the award of any degree or diploma.*	CIVIL ENGINEERING INTERNSHIP FULL REPORT ON BUILDING ... - SlideShare https://www.slideshare.net/VijaySingh281/civil-engineering-internship-full-report-on-building-construction	Originality
424.	*The model is trained using the Random Forest*	A Comprehensive Guide to Random Forest in R - DZone https://dzone.com/articles/a-comprehensive-guide-to-random-	Originality

		forest-in-r	
425.	*Agriculture plays an important role in the economy, and*	China : Speech at the Opening Ceremony of FSM-China Friendship Demonstration Farm at the College of Micronesia,FSM, By H.E. Huang Zheng, Chinese Ambassador to the FSM	Originality
426.	*We wish to record my deep sense of gratitude and profound thanks to*	Volume:03/Issue:04/April-2021 Impact Factor- 5.354 www.irjmets.com ... https://www.irjmets.com/uploadedfiles/paper/volume3/issue_4_april_2021/8462/1628083347.pdf	Originality
427.	*also contributes to the overall economic development of the country.*	Vietnam : The 15th National Assembly: Minimum wage currently does not guarantee living standards	Originality
428.	*The Random Forest algorithm is used to train the*	Sensors | Free Full-Text | Wireless Sensor Networks Intrusion ... - MDPI https://www.mdpi.com/1424-8220/19/1/203	Originality
429.	*LSTMs are a type of recurrent neural network*	Long Short-Term Memory Networks (LSTMs) | Nick McCullum https://www.nickmccullum.com/python-deep-learning/lstms-long-short-term-memory-networks/	Originality
430.	*machine learning algorithms that can be used for*	2D Short-Time Fourier Transform for local morphological analysis of meibomian gland images	Originality
431.	*Machine learning models require large amounts of data to*	Active Learning in Machine Learning - Towards Data Science https://towardsdatascience.com/active-learning-in-machine-learning-525e61be16e5	Originality
432.	*depend on the quality and quantity of the*	Gigantism and dwarfism in humans basically depend on the	Originality

		... - Vedantu https://www.vedantu.com/question-answer/gigantism-and-dwarfism-in-humans-basically-class-11-biology-cbse-5faa01d8dd6ab203d4fb9afe	
433.	*Inaccurate or incomplete data could lead to incorrect predictions*	Does Using AI Give You an Edge in Sports Betting? | Unibet Casino Blog https://www.unibet.com/us/casino/blog/ai-sports-betting-using-wager-gpt-does-it-work	Originality
434.	*Sensor The DHT11 digital temperature and humidity sensor is a*	Sensors | Free Full-Text | Design and Implementation of an Atmospheric ... https://www.mdpi.com/1424-8220/21/18/6174	Originality
435.	*The volumetric water content of the soil is*	Soil Moisture Sensor - Vernier https://www.vernier.com/product/soil-moisture-sensor/	Originality
436.	*Soil moisture sensors measure the volumetric water content indirectly by using some other property of the soil, such as electrical resistance, dielectric constant, or interaction with neutrons as a proxy for the moisture content,*	Soil moisture sensor - Wikipedia https://en.wikipedia.org/wiki/Soil_moisture_sensor	Originality
437.	*the direct gravimetric measurement of free soil moisture requires removing, drying, and weighing of a sample.*	Soil moisture sensor - Wikipedia https://en.wikipedia.org/wiki/Soil_moisture_sensor	Originality
438.	*To put it simply, it is an automatic switch to*	Home automation using general purpose household electric appliances with Raspberry Pi and commercial smartphone	Originality
439.	*and isolate input current as well as actuate the output. When the*	Lesson 22 – 1-Channel Relay Module « osoyoo.com https://osoyoo.com/2017/08/28/arduino-lesson-1-channel-relay-	Originality

		module/	
440.	*A DC motor is any of a class of rotary electrical motors*	Motor fundamentals and DC motors - Power Electronic Tips https://www.powerelectronictips.com/motor-fundamentals-dc-motors-faq/	Originality
441.	*that converts direct current electrical energy into mechanical energy. The most common types rely on the forces produced by magnetic fields. Nearly all types of DC motors have some internal mechanism, either electromechanical or electronic, to periodically change the direction of current*	DC motor - 2D Symbols - 3D Models - PARTcommunity https://b2b.partcommunity.com/community/knowledge/en/detail/3845/DC+motor	Originality
442.	*in part of the motor. DC motors were the first form of motor widely used, as they could be powered from existing direct-current lighting power distribution systems. A DC motor's speed can be controlled over a wide range, using either a variable supply voltage or by changing the strength of current ...*	Physics report on dc motor - SlideShare https://www.slideshare.net/Shubham5Oct/physics-report-on-dc-motor	Originality
443.	*A variety of electronic systems may be prototyped by using breadboards, from small analog and digital circuits to complete central processing units (CPUs*	Collin's Lab: Breadboards & Perfboards - Adafruit Learning System https://learn.adafruit.com/collins-lab-breadboards-and-perfboards/learn-more	Originality
444.	*An electrical wire, or group of them in a cable, with a connector or pin at each end (or sometimes without them - simply 'tinned*	Jump wire - Wikipedia https://en.wikipedia.org/wiki/Jump_wire	Originality
445.	*of a breadboard or other prototype or test circuit, internally or with other*	Jump wire - Wikipedia https://en.wikipedia.org/wiki/Jump_wire	Originality
446.	*a circuit board's header connector, or a piece of test*	9 VI June 2021 https://doi.org/10.22214/ijraset.2	Originality

		021 https://www.ijraset.com/fileserve.php?FID=35710	
447.	*Male ends have a pin protruding and can plug into things, while female ends do not and are used to plug things into. Male-to-male jumper wires are the most common and what you likely will use most often. When connecting two ports on a breadboard, a male-to-male wire is what you'll need.*	What is a Jumper Wire? https://blog.sparkfuneducation.com/what-is-jumper-wire	Originality
448.	*This can be accomplished in one of two ways:*	How 3D Printing Works: A Beginner's Guide	Originality
449.	*It is used for predicting the categorical dependent variable using a given set of independent variables. Logistic regression predicts the output of a categorical dependent variable. Therefore, the outcome must be a categorical or discrete value. It can be either Yes or No, 0 or 1, True or False, et...*	Logistic Regression in Machine Learning - Javatpoint https://www.javatpoint.com/logistic-regression-in-machine-learning	Originality
450.	*our equation. If the distance of Xi is increased from the higher plane, then our sigmoid function*	Geometric Intuition of Logistic Regression - Why is it Important https://www.analyticsvidhya.com/blog/2021/09/why-geometric-intuition-of-logistic-regression-matters-more-than-other-intuitions/	Originality
451.	*that distance into the value between 0 – 1. It provides probabilistic interpretations. And, if the distance of point Xi from the plane is 0, then its probability will be 0.5. So, this is our optimal sigmoid function which will help for preserving the optimal equation from the outlier.*	Geometric Intuition of Logistic Regression - Why is it Important https://www.analyticsvidhya.com/blog/2021/09/why-geometric-intuition-of-logistic-regression-matters-more-than-other-intuitions/	Originality
452.	*through every decision tree in the forest and*	Accelerating Random Forests Up to 45x Using cuML	Originality

		https://developer.nvidia.com/blog/accelerating-random-forests-up-to-45x-using-cuml/	
453.	*To assess the performance of a machine learning model,*	When Should You Retrain Machine Learning Models? | phData https://www.phdata.io/blog/when-to-retrain-machine-learning-models/	Originality
454.	*Accuracy is the ratio of correctly predicted instances to the total*	Development of Dialogue Management System for Banking Services https://www.mdpi.com/2076-3417/11/22/10995	Originality
455.	*can be calculated by dividing the sum of*	Interior Angles: Definition, Theorem, Formula, Types, Examples https://www.splashlearn.com/math-vocabulary/interior-angles	Originality
456.	*Precision is the ratio of correctly predicted positive instances to the total*	Development of Dialogue Management System for Banking Services https://www.mdpi.com/2076-3417/11/22/10995	Originality
457.	*calculated as TP divided by the sum of TP and*	Predicting clinically significant motor function improvement after ... https://jneuroengrehab.biomedcentral.com/articles/10.1186/s12984-020-00758-3	Originality
458.	*Recall is the ratio of correctly predicted positive instances to*	Development of Dialogue Management System for Banking Services https://www.mdpi.com/2076-3417/11/22/10995	Originality
459.	*F1 score is the harmonic mean of precision and recall,*	Performance Measure of a Machine Learning Model https://medium.com/mlearning-ai/performance-measure-of-a-	Originality

		[machine-learning-model-fb657263bf98]()	
460.	*2 times the product of precision and recall divided by their sum.*	Metrics to Evaluate Model Performance - Evaluation of ... - Coursera https://www.coursera.org/lecture/big-data-machine-learning/metrics-to-evaluate-model-performance-pFTGm	Originality
461.	*A confusion matrix is a 2x2 matrix that*	A Scale Invariant Human Motion Detection System using Wavelet Based Feature Extraction	Originality
462.	*neural network that is specifically designed to handle sequential data.*	The Ultimate Guide to Building Your Own LSTM Models https://www.projectpro.io/article/lstm-model/832	Originality
463.	*However, this approach does not account for the*	How best to assess quality of life in informal carers of people with dementia; A systematic review of existing outcome measures	Originality
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