Chapter 4
Soil Moisture Prediction

4.1 Introduction

A crucial factor in governing the flow of water and energy between the ground and the atmosphere is soil moisture (Willmott et al., 1985). Additionally, it affects the biological and chemical processes in the soil (Moyano et al., 2013; Weitz et al., 2001). Weather and climate studies heavily depend on how soil moisture affects and is affected by meteorological or climatic factors like precipitation, temperature, and evapotranspiration (Berg et al., 2014; Koster et al., 2004; Seneviratne et al., 2010). The knowledge of soil moisture is essential for estimating precipitation, predicting the weather, and monitoring and forecasting natural disasters such as droughts, floods, and landslides (Bolten et al., 2009; Rahmani et al., 2016). For irrigation management in agriculture and crop yield prediction, soil moisture data is essential since it determines the amount of water available to the crops (Dai et al. 2011, Ines et al. 2013). Consequently, it is necessary for calculation as well as modelling of runoff and soil erosion (Raclot & Albergel, 2006; Zhang et al., 2011). Soil moisture content impacts the partitioning of rainfall into soil moisture storage and runoff (Koren et al., 2000). With respect to time and space, soil moisture is heterogeneous. Therefore, constant measurement of soil moisture is necessary regarding all its applications. Gravimetric methods, neutron scattering, gamma-ray attenuation, electromagnetic sensors including time-domain reflectometers, frequency-domain reflectometers, and electrical resistance blocks, tensiometers, fiber optic sensors, and others are among the traditional methods for determining soil moisture. Only point measurements are provided by these methods (Topp, 2003). Regional planning, however, necessitates the spatial and temporal characterization of soil moisture. It is difficult to use traditional as well as original measuring techniques over a vast area since it would be too difficult to measure time- and labor-intensive. It costs a lot of money to set up an extensive network of sensors for assessing soil moisture. Consistent intensive care of soil moisture conditions by the side of geographical and temporal scales can be done using remote sensing techniques (Ahmed et al., 2011). Using a variety of empirical and mechanical models, the remote sensing method uses electromagnetic radiations with wavelengths in the optical, infrared, and mostly microwave ranges to estimate soil moisture content. Through satellite remote sensing, a number of techniques are being employed to calculate soil moisture. Using either direct measurements or the creation of empirical spectral indices, optical remote sensing investigates the linear relationship amid land surface reflectance and soil moisture content (Jackson et al., 1976; Kogan, 1995; Liu et al., 2003). Through thermal inertia and temperature index, thermal remote sensing calculates soil moisture (Maltese et al., 2013; Minacapilli et al., 2009; Verhoef, 2004). By employing a direct relationship between soil dielectric constant and water content, microwave remote sensing offers surface soil moisture evaluations under year-round circumstances with respectable accuracy (Ahmed et al., 2011; Baghdadi et al., 2004). The microwave band is the best choice for measuring soil moisture since it is able to see through the atmosphere and vegetation to find soil moisture in the top layer (Ahmed et al., 2011). With the aim of determining the soil moisture content, radiometers, scatterometers, and Synthetic Aperture Radar (SAR) on airborne or spacecraft platforms are frequently used. Because of non-parametric behavior as well as the capacity to capture complex and non-linear relationships, machine learning (ML) algorithms such as linear regression, artificial neural networks (ANNs), deep learning, support vector machines (SVMs), classification and regression tree (CART), random forest (RF), and others have seen a significant increase in application over the past ten years in the field of soil moisture research. The development of pedotransfer functions (PTFs) is applicable to calculating soil hydraulic characteristics and prediction models for the forecasting of soil moisture could be accomplished using ML techniques. The application of ML techniques is essential for real-time soil moisture monitoring and need-based, site-specific watering to the plants in data-driven precision irrigation or Internet of Things (IoT)-based smart irrigation. The soil moisture products obtained from satellites, such as Soil Moisture Active Passive (SMAP), Soil Moisture and Ocean Salinity (SMOS), European Space Agency Climate Change Initiative (ESA CCI), Advanced Scatterometer (ASCAT), and others, have coarser spatial resolutions (> 9 km), which restricts their applicability at the watershed or regional scale because soil moisture is highly variable with space and time (Cui et al., 2018). In order to downscale these soil moisture products at a finer spatial resolution, deep learning for sustainable agriculture can be used to build models using machine learning that includes a variety of covariates, such as vegetation, slope, soil texture, etc. (Peng et al., 2017). The ML techniques have created new possibilities for assessing soil moisture. Since there are so many factors that can be calculated, it is challenging to develop an ideal mathematical model for soil moisture. The forecasting models that are currently being used have problems with prediction accuracy, generality, as well as other aspects including prediction performance and multi-feature processing capabilities. Considering all of these variables and using Gallipoli, Turkey as a reference site, a deep neural network model was created to forecast moisture with a high degree of accuracy and little error. From 2008 through 2021, entities are included in the dataset. By performing extensive mathematical analysis and determining the association between particular variables and the spearman coefficient, the right weather information can be used to forecast soil moisture with the appropriate amount of weight. The results of the suggested strategy demonstrate the effectiveness and realism of the deep learning approach for moisture prediction. Additionally, deep learning techniques may generalize models with superb accuracy and minimal errors, which is utilized to conserve irrigation water.

4.2 GALLIPOLI WEATHER AND AGRICULTURE

The presence of the sea to the north, south, and west as well as the mountains that cover a large portion of the nation have a significant impact on Turkey's variable climate, which is often a dry semi-continental Mediterranean variety. Contrasts between the interior and the coastal fringes are produced by the sea and the mountains. The Mediterranean regime's maximum winter rainfall occurs in a few places, while summer dryness is common. However, due to the country's height, winters there are frequently much colder than in Mediterranean regions, and summer and winter temperatures differ significantly. With roughly a quarter of the population working in agriculture, Turkey has one of the top ten agricultural economies in the world. Half of the nation is made up of agricultural land. Turkey is one of the world's top producers of apricots, hazelnuts, wheat, sugar beets, milk, poultry, cotton, tomatoes, and other fruits and vegetables. Turkey's young and expanding population offers prospects for market expansion and the launch of new goods. For its rapidly expanding meat and poultry industries, Turkey imports grains, oilseeds, particularly soybean and meal, and grain products. Additionally, Turkey imports raw materials for its bakery and food processing industries as well as more cotton as a raw material for its sophisticated textile industry. Excessively high moisture and extremely low moisture content might result in ruined the seed and lint as well as a decline in the quality of seed of any plant. So proper level of moisture in land is significant for agriculture field. The month-wise climate survey for Gallipoli is shown in table 4.1.

Month	Climate data (Sea Temperature and Day Light)	Rain in mm	AVG. Temp. high and low in °C	Sun shine hours
January	Gallipoli, Turkey experiences an average sea temperature of 12°C (53.6°F) in January. The typical day at Gallipoli, Turkey, in January lasts 9 hours and 40 minutes. Sunrise occurs at 08:36 and sunset occurs at 17:57 on the first day of the month. Sunrise on January 31 occurs at 08:23 and sunset is at 18:29 +03.	97	10 & 3	5
February	In Gallipoli, Turkey, February is the month with the coldest seawater, with an average sea temperature of 11.3°C (52.3°F). February days typically last 10 hours and 41 minutes. Sunrise occurs at 08:22 and sunset occurs at 18:31 on the first day of the month. Gallipoli's final day of February sees sunrise at 07:48 and sunset at 19:03 +03.	66	10 & 4	7
March	The average ocean temperature in March in Gallipoli, Turkey, is 11.8°C (53.2°F). Swimming is dangerous at 11.8 °C (53.2 °F). Insecure immersion at temperatures below 10°C (50°F) immediately results in a cold shock with a maximal severity and hyperventilation. Gallipoli experiences dawn at 07:46 and sunset at 19:04 on March 1. The time of sunrise is 06:58 and the time of sunset is 19:36 +03.	61	12 & 5	7

April	Turkey's Gallipoli has an average sea temperature of 13.2°C (55.8°F) in April. Gallipoli's typical day lasts 13 hours and 18 minutes in April. Sunrise occurs at 06:56 and sunset occurs at 19:37 on the first day of the month.	47	17 & 8	9
May	The typical water temperature in May in Gallipoli, Turkey, is 17.4°C (63.3°F). May days typically last 14 hours and 26 minutes. Sunrise is at 06:12 and sunset is at 20:08 on the first day of the month. Gallipoli has a dawn at 05:45 and a sunset at 20:36 +03.	32	22 & 12	11
June	The average sea water temperature in June in Gallipoli, Turkey, is 22.1°C (71.8°F). June has days that are on average 15 hours and 1 minute long, making it the month with the longest days. The sun rises at 05:45 and sets at 20:37 on the first of the month. The sun rises at 05:46 and sets at 20:47 (+03) on the last day of June.	21	28&16	12
July	The typical water temperature in July at Gallipoli, Turkey, is 24.9°C (76.8°F). The typical day in July at Gallipoli lasts 14 hours and 44 minutes. The sun rises at 05:46 and sets at 20:47 on the first of the month. Gallipoli experiences a dawn at 06:09 and a sunset at 20:29 +03.	17	30 & 19	13
August	August is the finest month for swimming and other water activities in Gallipoli, Turkey due to the optimum sea water temperature of 25.2°C (77.4°F). August	9	26 & 16	12

	days in Gallipoli last an average of 13 hours and 44 minutes. Sunrise occurs at 06:10 and sunset occurs at 20:28 on the first day of the month.			
September	The average seawater temperature in September in Gallipoli, Turkey, is 23.3°C (73.9°F). September days in Gallipoli, Turkey, last an average of 12 hours and 28 minutes. Gallipoli's dawn and sunset times for the first day of September are 06:40 and 19:46, respectively. The sunrise occurs 07:08 and the time of sunset is at 18:57 +03.	29	20 & 12	11
October	The typical sea temperature in October in Gallipoli, Turkey, is 19.8°C (67.6°F). In Gallipoli, a typical October day lasts 11 hours and 8 minutes. The sun rises at 07:09 and sets at 18:56 on the first of the month.	48	16 & 8	9
November	In Gallipoli, Turkey, the ocean typically reaches a temperature of 16°C (60.8°F) in November. The average day in November lasts 9 hours and 58 minutes. Sunrise occurs at 07:43 and sunset at 18:10 on the first day of the month.	89	12 & 5	7
December	The typical water temperature in Gallipoli, Turkey, in December is 13.4°C (56.1°F). December in Gallipoli has days that are on average 9 hours and 21 minutes long. Sunrise occurs at 08:16 and sunset occurs at 17:47.	118		5

Table 4.1 Month wise Sea Temperature and Day Light analysis for Gallipoli-Turkey

4.3 MATERIALS AND METHODS

4.3.1 Dataset Summary

Gallipoli, Turkey is the location of the sight map (40.3333° N, 26.5000° E). From November to April, the water is at a low temperature, and from May to October, it is at a moderate temperature. In Gallipoli, January is the coldest month, July is the warmest, August is the driest month, and December is the wettest month. Gallipoli Turkey's metrological agency offers a meteorological dataset from 2008 to 2021.

The dataset has over 1, 20, 000 entities for the various parameters listed in table 4.2. This study builds a solid theoretical analysis framework for Gallipoli-Turkey. Taking this all data into consideration to predict soil moisture which effectively reduces the bias of the model. In this manner, the developed model performs excellently when it is test against tested data.

DateTime	Date time in "dd.mm.yyyy hh:mm" arrangement
Temperature	Temperature at 2 m in °C
Sunshine Duration	Sunshine duration in min
Shortwave Radiation	Shortwave radiation in W/m^2
Relative Humidity	Relative Humidity at 2 m in %
Mean Sea Level Pressure	Mean Sea Level Pressure (MSL) in hPa
Soil Temperature	Soil temperature at 0-10 cm down in °C
Soil Moisture	Soil moisture at 0-10 cm down in m^3/m^3
Wind Speed	Wind speed at 10 m in km/h
Wind Direction	Wind direction at 10 m in degrees

Table 4.2 Gallipoli Weather data entities

4.3.2 Dataset Preprocessing and Performance Estimation

The total number of entries for all parameters in the CSV file is 1, 22,732. They can be divided into training and testing using a normal 80% to 20% ratio. In this instance, training uses 80% of the data, whereas testing uses 20%. The model is trained on 98,185 items, and 24,547 entries are utilized to test the model. With these many entries, a deep neural network-based model using the transfer learning idea is created. Figure 4.1 displays a visualization of the various features. It is clear from the graphic that the wind direction and the amount of sunshine along the entire plane indicate that both parameters are nearly constant. The remaining characteristics are diverse in kind.

The graphical analysis for all the parameters listed in Table 4.2 from 2008 to 2021 is shown in Figure 4.1. The statistical analysis of each parameter that aids in the creation of a prediction model is shown in Table 4.3. We only create a heat map between all of the factors to examine the data's nature. In order to adequately explain a relationship between two variables, it is used to identify the most distinct clusters or the most effective combination of attributes. In our data set, drawing some simple linear divisions or basic lines also aids in the development of some simple categorization models. A simple heat map displays a direct graphical analysis of information. More detailed heat maps allow the user to comprehend complex data sets. It is clear from the heat map that the data are diverse in character.

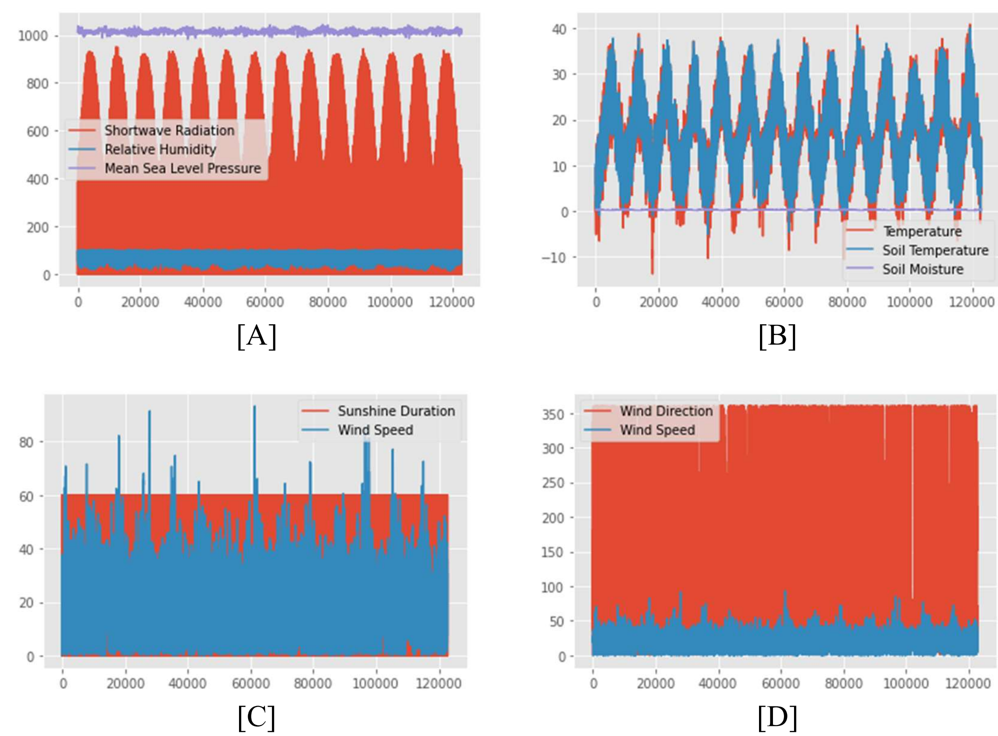


Figure 4. 1 [A] to [D]: Plots of different weather parameter for Gallipoli-Turkey

	Wind Direction	Wind Speed	Soil Moisture	Soil Temperature	Mean Sea Level Pressure	Relative Humidity	Shortwave Radiation	Sunshine Duration	Temperature
Total Entry	122733.0	122733.0	122733.0	122733.0	122733.0	122733.0	122733.0	122733.0	122733.0
Average Value	108.071393	19.391254	0.210705	16.336311	1015.073141	69.683924	202.333411	21.084680	15.670196
Standard Deviation	91.270893	11.141315	0.067094	8.054375	6.795215	19.079325	272.710423	27.030718	8.192027
Smallest Value	0.310	0.000	0.102	-5.200	981.300	13.000	0.000	0.000	-13.800
25%	44.090	10.400	0.153	10.100	1010.600	55.000	0.000	0.000	9.700
50%	60.360	18.300	0.214	15.900	1014.400	72.000	16.020	0.000	15.500
75%	195.020	26.800	0.263	22.400	1019.200	86.000	379.140	56.000	21.400
Biggest Value	360.000	93.300	0.433	40.100	1043.600	100.000	950.520	60.000	40.800

Table 4.3 Analysis of weather parameters for Gallipoli-Turkey

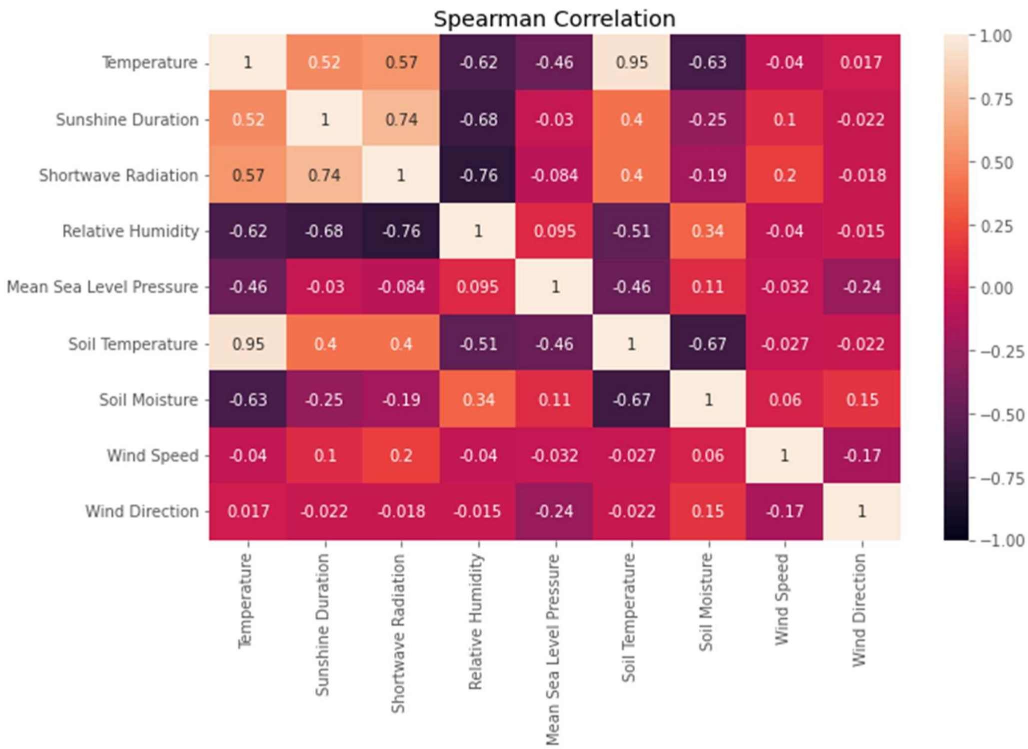


Figure 4.2 Heatmap of all parameters for Gallipoli-Turkey Weather Dataset

	Temperature	Sunshine Duration	Shortwave Radiation	Relative Humidity
Soil Moisture Correlation	-0.63	-0.25	-0.19	0.34

Table 4.4 Soil moisture's Correlation with Temperature, Sunshine Duration, Shortwave Radiation and Relative Humidity for Gallipoli-Turkey weather Dataset

	Mean Sea Level Pressure	Soil Temperature	Wind Speed	Wind Direction
Soil Moisture Correlation	0.11	-0.67	0.06	0.15

Table 4.5 Soil moisture's Correlation with Mean Sea Level Pressure, Soil Temperature, Wind Speed and Wind Direction for Gallipoli-Turkey weather Dataset

Figure 4.3 Pair plot of all parameters for Gallipoli-Turkey Weather Dataset

4.3.3 Heatmap and Pair plot for Gallipoli weather Dataset

A heat map is a two-dimensional visualization of data in which colors stand in for values. A straightforward heat map offers a quick visual representation of the data. The user can comprehend complex data sets with the help of more intricate heat maps. Pair plots are used to determine the most distinct clusters or the best combination of features to describe a connection between two variables. The heatmap and pair plot for Gallipoli weather dataset is shown in figure 4.2 and figure 4.3.

Creating some straightforward linear separations or basic lines in our data set, also helps to create some straightforward classification models. According to the heat map and pair plot, soil moisture is positively correlated with humidity levels, average sea level pressures, wind speed, and prevailing winds, but negatively correlated with temperature, sunshine duration, shortwave radio radiation, and soil temperature.

Table 4.4 and Table 4.5 displays the relationship between various factors and soil moisture. From there, it may be able to take some initiative in determining the weight that should follow for constructing a model with high accuracy and few errors. The model's global potential is enhanced by the many characteristics used here.

The research demonstrates that the dataset is suitable for building a trustworthy model. Mean Absolute Error, Mean Squared Error, and Root Mean Square Error can all be calculated to gauge a model's performance. In Table 4.6, they are mentioned with particular mathematical equation.

Parameter	**Initial**	**Equation**
Mean Absolute Error	MAE	$\mathrm{MAE} \quad = 1/\mathrm{n}(\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{Y}' - \mathrm{Y}'')$
Mean Squared Error	MSE	$\mathrm{MSE} \quad = 1/\mathrm{n}(\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{Y}' - \mathrm{Y}'')^2$
Root Mean Squared Error	RMSE	$\mathrm{RMSE} = \mathrm{Sqrt}[1/\mathrm{n}(\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{Y}' - \mathrm{Y}'')]$

Table 4.6 Performance Evaluation Parameters for soil moisture prediction

4.4 Model Development

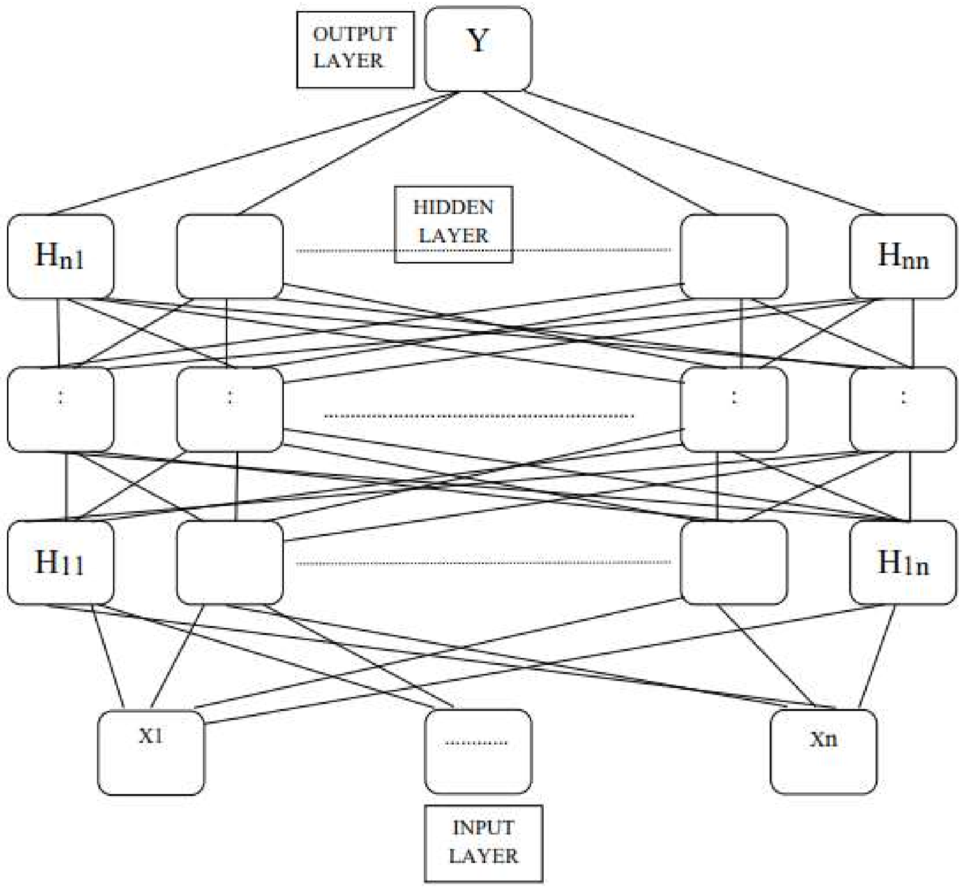


Figure 4.4 Basic architecture of Deep Neural Network

The fundamental design of a deep neural network regression is shown in Figure 4.4. It has a single input layer, a single output layer, and numerous hidden layers—at least two. The multi-hidden layer technique displays good performance by lowering the nodes in each hidden layer when compared to a single hidden layer perceptron for the same input data. Neural networks also referred to as artificial neural networks (ANNs) or simulated neural networks (SNNs), are the foundation of deep learning techniques. Their organization and terminology are based on the human brain, replicating how real neurons communicate. It starts with an input layer and then has hidden layers and an output layer. Every neuron is coupled to every other neuron at a specific threshold and weight. Any node whose output rises above the specified threshold value is activated and starts sending information to the top layer of the network. If not, there is nothing to transmit to the next tier of the network. A deep neural network can be described numerically as follows:

- Total no. of nodes in input layer = Total no. of parameters
- To remove problems of overfitting and underfitting it requires proper selection of no. of hidden layers.
- Neurons comprise the hidden layers. Both rectifier activation and aggregation tasks are performed by the neurons.
- ReLU is by the default activation function
- With ReLU the neurons exhibit sparse characteristics and also remove the problem of overfitting. It also increases the depth of the architecture and hence the speed of the training model. It is defined as

$$G(x) = \text{Maximum}\ (0, x) \tag{4.1}$$

- The output layer of both Regression and classification are dissimilar. The regression model's output layer is a distinct node. To produce the regression prediction assessment, the result of the preceding hidden layer is multiplied by the weight, which is then added to the bias on the output node. Equation 4.2 explains the procedure where bias is denoted with C and j is no. nodes in the preceding layer.

$$F[Y; Z, C] = \sum_j [\, Z_j^T Y_j + C] \tag{4.2}$$

- The result of the preceding layer becomes the input feed for the subsequent layer. Here Y is the input parameter, and Z represents the weight for a particular layer. Here C as well as C' are biases of the node.

$$F\ [Y; Z, C, z, b'] = Z^T \sum_j [\, Z_j^T Y_j + C] + C' \tag{4.3}$$

- The different optimization techniques like AdaGrade, ADAM, etc. are used which automatically adjust the learning rate which is decreased with regularly occurring parameters to evade fluctuation of parameters.

Based on comparisons of expected values outcomes and labels for both the training and test set features, model parameters (weights and biases) are changed to reduce error.

This is referred to as supervised learning for the more sophisticated neural network regression model. When the targeted objective or the maximum number of training directions have been completed, training is considered complete. The number of veiled layers and unseen layer nodes can have a direct impact on the model's training time and prediction accuracy.

- Draw an estimated decision boundary to divide the classes based on the data. Create a set of lines to represent the decision boundary.
- Keep in mind that these lines must surrender to the decision boundary when combined.
- The number of lines that have been chosen is a representation of the first hidden layer's hidden neurons.
- A new hidden layer is added to join the lines that the preceding layer generated. Keep in mind that every time you need to link the lines in the previous hidden layer, a new hidden layer is added.
- Each hidden layer has an equal number of hidden neurons as connections to be established.

This study examines eight meteorological data items and one variable associated with soil moisture to forecast soil moisture. Based on the regression features, the output layer has a maximum node count of 1, while the number of nodes in the input layer is 8, the same as the number of features. According to the data set, the hidden layer structure's 4 hidden layers are sufficient to meet the requirements. Iterative testing is required to evaluate and select the number of concealed nodes for each layer.

Architecture	**MSE**
8-128-128-256-256-1	0.0031
8-128-256-128-256-1	0.0029
8-256-128-256-128-1	0.0027
8-256-128-128-256-1	0.0022

Table 4.7 Results of different hidden layer combination for Proposed ANN model for soil moisture prediction

Four hidden layers' various node configurations were put into practice. Table 4.7 lists a few effective combinations that give the model good outcomes. The 8-256-128-128-256-1architecture, the final combination, is chosen to create the model. The model weights are uniformly initialized with a mean of 0 and a variance of 1.

4.5STEPS BY STEP PROCEDURE FOR PREPARING A MODEL

Input	:	Gallipoli Weather Dataset.
Output	:	Prediction of soil moisture with minimum errors.
STEP 1	:	Input the dataset.
STEP 2	:	Plot the features for graphical analysis.
STEP 3	:	Plot the heat map and pair plot for correlation using spearman coefficient.
STEP 4	:	Find the statistical analysis by data frame.describe().Transpose method for mathematical summary.
STEP 5	:	Split the dataset in to the ratio of 80%: 20% for training and testing.
STEP 6	:	Find the shape of train data and taste data.
STEP 7	:	Initially create sequential model and add dense layer with input shape = length of input columns.
STEP 8	:	Add normalize layer with BatchNormalization().
STEP 9	:	Add dense layer contains 256 units with activation function is ReLU.
STEP 10	:	Add dense layer contains 128 units with activation function is ReLU.
STEP 11	:	Add dropout layer to ignore few neurons randomly with a rate of 0.1.
STEP 12	:	Add dense layer contains 128 units with activation function is ReLU.
STEP 13	:	Add dense layer contains 256 units with activation function is ReLU.
STEP 14	:	Select different optimizer, epoch =350 and early stopping by monitoring mean square error with patience =50.
STEP 15	:	Train the model.
STEP 16	:	Save the model and test the model with test dataset.
STEP 17	:	Apply the concept of Hyper Parameter of tuning with different optimizer as well as different learning rate and find the best results with minimum errors.

The above steps are significant and sufficient to prepare an accurate model which once developed then it will be ready to deal with other datasets also.

4.6 OUTCOMES WITH HYPER PARAMETER TUNING

The control of a machine learning model's behavior requires hyperparameter adjustment. Our predicted model parameters will yield less-than-ideal outcomes if our hyperparameters aren't properly tuned to minimize the loss function. This indicates that our model has more flaws.

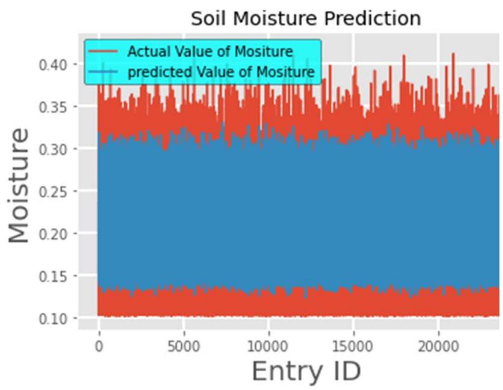
In the suggested research two parameters were selected for hyper-parameter adjustment to improve the model's performance. The optimizer function is the first, and the learning rate is the second. The analysis, both mathematical and pictorial, is displayed below. Additionally, the research is conducted using several activation functions, like ReLU and Sigmoid, although nothing changes inside. The plots of Prediction accuracy analysis of Model for Gallipoli-Turkey Weather Dataset with different optimizer function are shown in figure 4.5 (A to D). The outcomes for various optimizer functions are shown in Table 4.8. It is clear that the AdaGrad optimizer performs significantly worse than the ADAM, RMSprop, and SGD algorithms. We choose the ADAM optimizer since it makes the model run faster.

Optimizer	**MSE**	**RMSE**	**MAE**
ADAM	0.0021	0.0460	0.0362
RMSprop	0.0021	0.0460	0.0363
AdaGrad	0.0035	0.0596	0.0499
SGD	0.0021	0.0460	0.0363

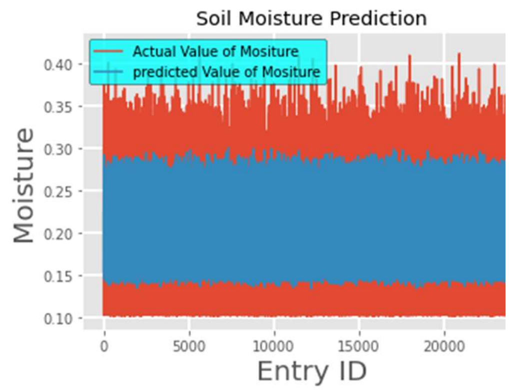
Table 4.8 Proposed ANN model Analysis for different Optimizer Functions

Learning Rate	**MSE**	**RMSE**	**MAE**
0.00001	0.0021	0.0460	0.0363
0.0005	0.0021	0.0461	0.0363
0.001	0.0021	0.0460	0.0362
0.00146	0.0022	0.0472	0.0370
0.01	0.0022	0.0472	0.0373
0.1	0.0044	0.0670	00566

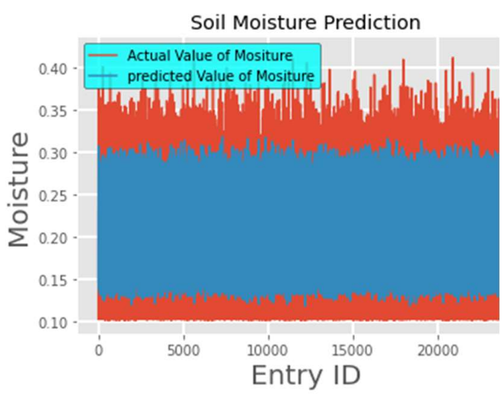
Table 4.9 Proposed ANN model Analysis for different Learning Rates



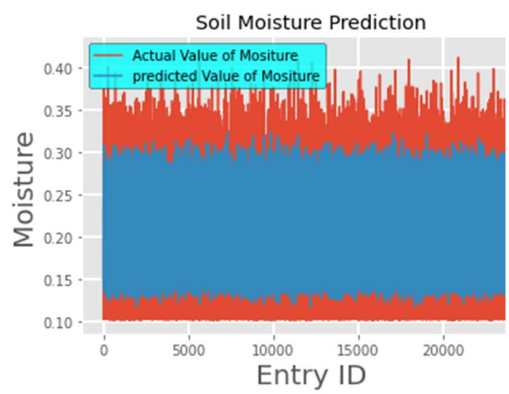
[A] ADAM Optimizer



[B] RMSprop Optimizer



[C] AdaGrad Optimizer



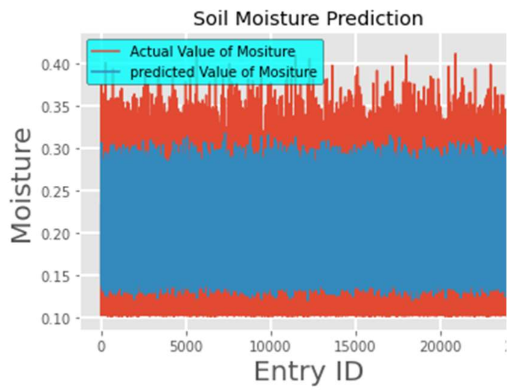
[D] SGD Optimizer

Figure 4.5 [A to D] Prediction accuracy analysis of Model for Gallipoli-Turkey Weather Dataset with different Optimizer Function

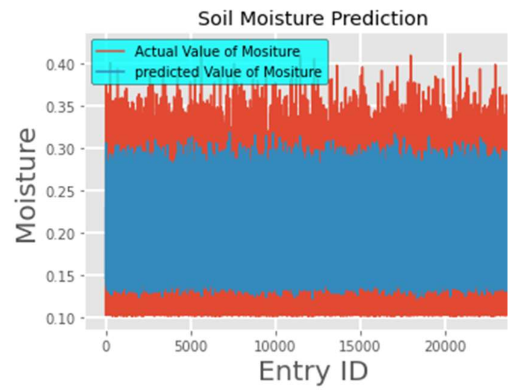
The main parameter that can be adjusted and used to train neural networks is the learning rate, in particular. It normally has a somewhat positive value between 0.0 and 1.0. The learning rate controls how quickly the model adjusts to the problem. Table 4.9 displays the results of a model with various learning rates. A learning rate of 0.1 fails because it produces more errors than other rates do. We choose a learning rate of 0.001 out of the remaining entities because it works the best and speeds up the model. Figure 4.6 (A to G) Prediction accuracy analysis of Model with different Learning Rate.

4.7 LINEAR REGRESSION

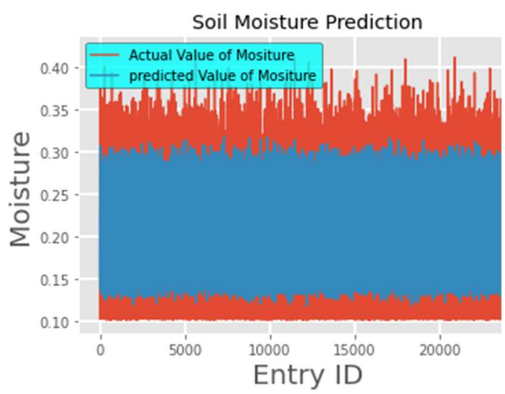
Linear regression is a popular traditional technique to predict the target variables. In many problems this method performs, excellent compared to a new advanced technique like Support Vector Machine and Artificial Neural Networks.



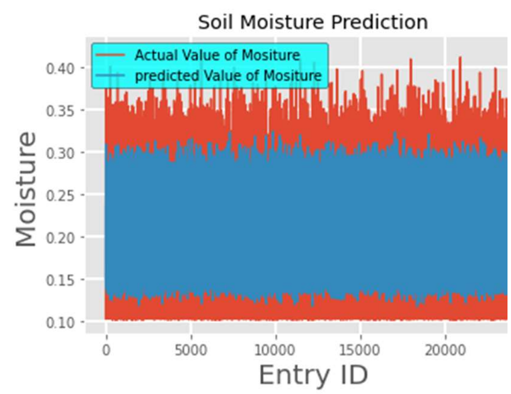
[A] Learning Rate = 0.00001



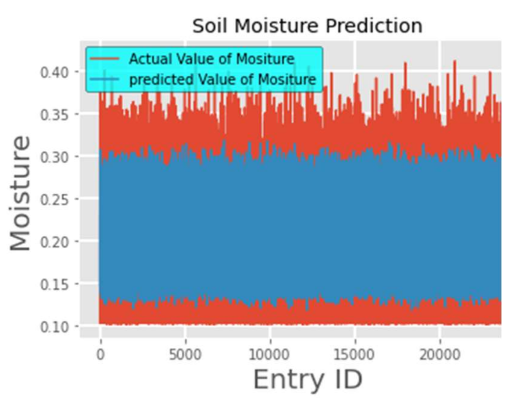
[B] Learning Rate = 0.0005



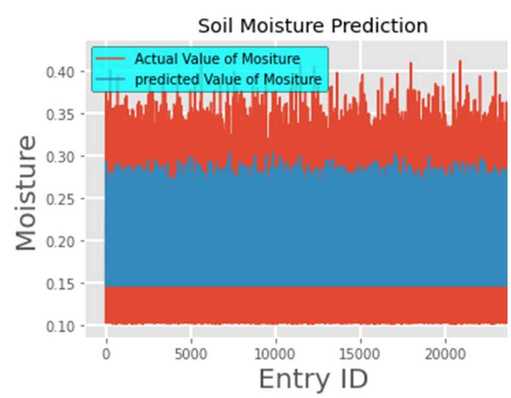
[C] Learning Rate = 0.001



[D] Learning Rate = 0.00146



[E] Learning Rate = 0.01



[F] Learning Rate = 0.1

Figure 4.6 [A to G] Prediction accuracy analysis of Model for Gallipoli-Turkey Weather Dataset with different Learning Rate.

But in some cases, due to its limitation, the researchers apply other methods. Also, it is quite challenging, to develop a model based on SVM and ANN which gives the same performance for a Particular dataset where LR provides the best outcomes. Here soil Moisture is dependent on the other eight parameters mentioned above. So here we have to go for multiple linear regressions as

$$Y' = A_0 + A_1X_1 + A_2X_2 + \ldots\ldots + A_pX_P \quad (4.4)$$

Where

Y' = predicted value of the dependent variable
X_1 through X_p = p distinct independent or predictor variables,
A_0 = the value of Y when all of the independent variables (X_1 to X_p) are equal to zero
A_1 through A_p = the estimated regression coefficients.

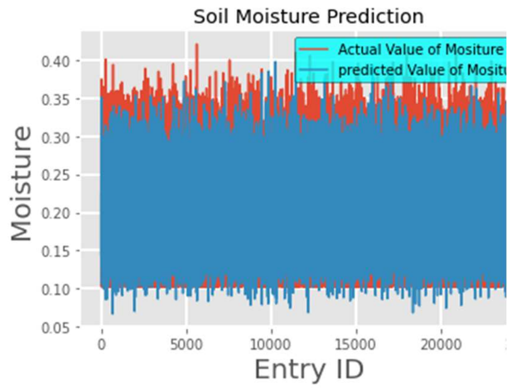
4.7.1 Different LR Techniques Analysis for Soil Moisture Prediction

Here few popular LR approaches are analyzed to find the best results for forecasting moisture inside the soil. Lasso, Ridge, Bayesian Ridge, and ElasticNet are excellent regression techniques to predict the target variables. Figure 4.7 shows the graphical analysis of different techniques. The performance investigation of all these methods, regarding MAE MSE and RMSE, is shown in Table 4.7.

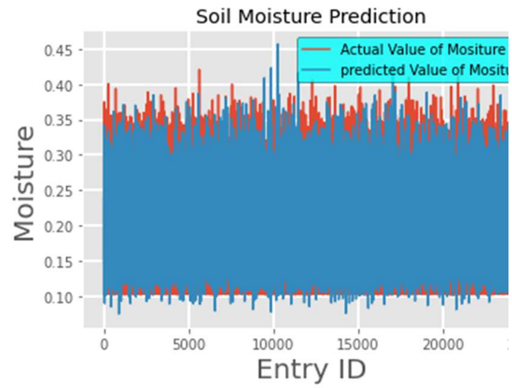
Technique	**MSE**	**RMSE**	**MAE**
Lasso	0.0020	0.0452	0.0353
Ridge	0.0019	0.0440	0.0340
ElasticNet	0.0020	0.0452	0.0353
Bayesian Ridge	0.0019	0.0440	0.0340

Table 4.10 Performance analysis of Different Regression Technique for Gallipoli-Turkey Weather Dataset

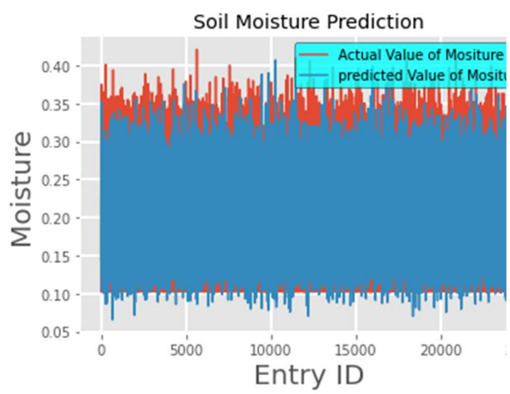
From the graphical study, as shown in figure 4.7, and the outcomes shown in table 4.10. it is fairly apparent that Ridge and Bayesian Ridge outperform well as compared Lasso and ElasticNet techniques. The MSE, RMSE and MAE are 0.0019, 0.0440, and 0.340 respectively for both Ridge and Bayesian Ridge, while it is 0.0020, 0.0452 and 0.0353 respectively for both Lasso and ElasticNet Techniques.



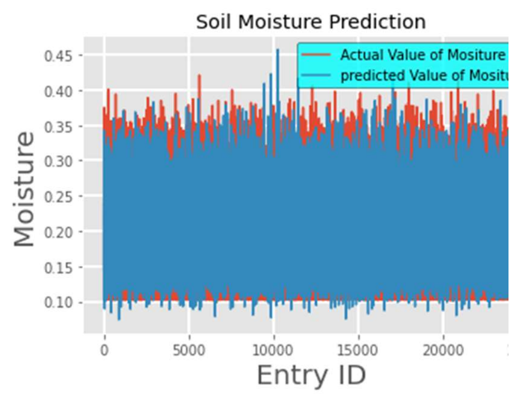
[A] Lasso Technique



[B] Ridge Technique



[C] ElasticNet Technique



[D] Bayesian Ridge Technique

Figure 4.7 Prediction accuracy analysis of Model for Gallipoli-Turkey Weather Dataset with different LR Techniques.

4.8 SVM BASED MODEL

For the same dataset, the SVM technique is also applied to discover the prediction of soil moisture. As mentioned in section 3.5.2 this method has excellent characteristics for prediction purposes. The table 4.11 shows the performance of SVM technique regarding MAE, MSE and RMSE. Also, the plot of prediction is shown in figure 4.8.

Technique	MSE	RMSE	MAE
SVM	0.0026	0.0517	0.0425

Table 4.11 Outcomes of SVM based Model for Gallipoli-Turkey Weather Dataset

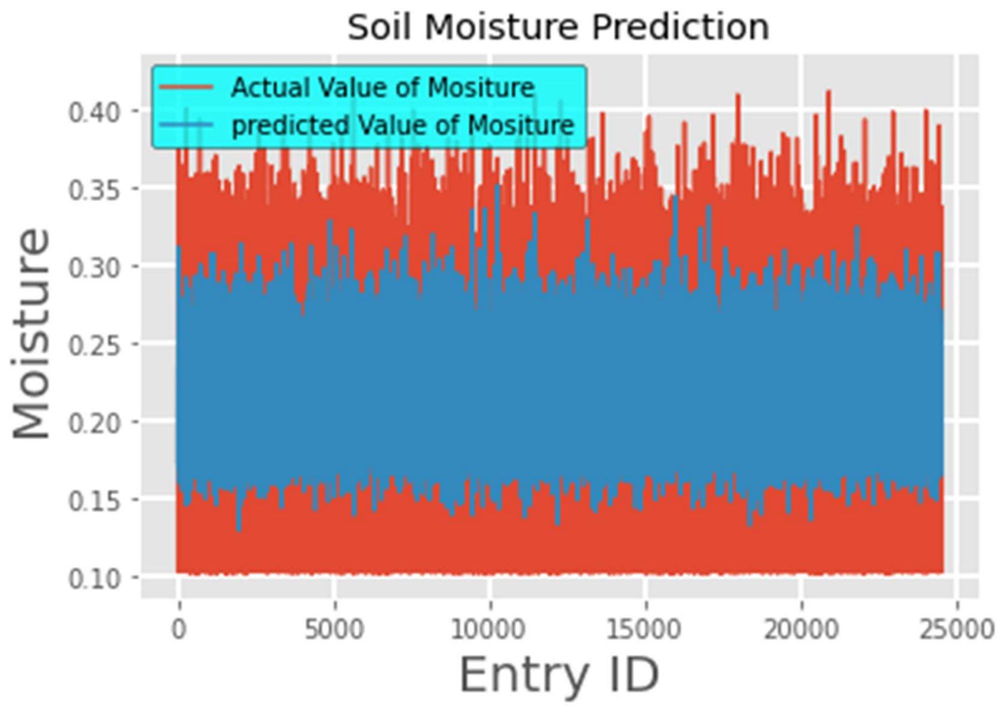


Figure 4.8 Prediction accuracy analysis of Model for Gallipoli-Turkey Weather Dataset with SVM Technique

4.9 COMPARISON OF DIFFERENT ML BASED MODELS

The soil moisture prediction for the Gallipoli-Turkey dataset is executed with different techniques. However traditional Linear Regression methods perform excellently when data is linear. But when the data is non-linear, the regression technique fails to give an accurate result. It is quite challenging to develop a model based on ANN and SVM which performs fine, not only with non-linear data but give the same performance as compared to the Regression technique when data is linear.

ML Techniques	MSE	RMSE	MAE
Linear Regression (Ridge/ Bayesian Ridge)	0.0019	0.0440	0.0340
Neural Network (ADAM optimizer & learning rate = 0.001)	0.0021	0.0460	0.0362
Support Vector Machine	0.0026	0.0517	0.0425

Table 4.12 Outcomes Comparison of different ML Approaches for Gallipoli-Turkey Weather Dataset

The proposed research emphases this objective to predict soil moisture inside the land with high accuracy and good precision with minimal errors. Table 4.12 show the comparison of all ML techniques for the same dataset by taking in to account of MAE, MSE, and RMSE. It is quite observable that ANN model with ADAM optimizer and learning rate = 0.001, performs almost same as Ridge/Bayesian Ridge regression technique. Also, it can handle the curse of non-linearity, if the input data is diverse. The outcomes show that the suggested model has high accuracy with minimal errors which is negligible.

Artificial neural networks have the capacity to give data for parallel processing, allowing them to tackle multiple tasks at once. This implies that the performance of artificial neural networks is affected when one or more cells, or neural networks, are lost. Artificial neural networks are used to store data so that even in the absence of a data pair, the network is still capable of producing results. Artificial neural networks are progressively dissipating, so they won't suddenly stop functioning. Because of this, these networks are gradually dissipating. One can able to train ANNs to draw conclusions from the past and make decisions. The ANNs are dependent on the hardware since, as we previously indicated, they hang along with the execution of parallel processing and require processors that support it. Anyone may not be able to define what is the right network topology of an Artificial Neural network because it resembles the functions of the human brain. work that answers problem statements but we don't fully understand the basis on which it will do so, and this time, ANN is not a trustworthy method.

Implementing linear regression is straightforward, and it is simpler to understand the output coefficients. However, because the bounds of the linear regression technique are linear, outliers can have a significant impact on the regression. This algorithm is the best to apply when you know the relationship between the independent and dependent variable has a linear relationship because it is less difficult than other algorithms. A different assumption made by linear regression is that the relationship between the dependent and independent variables is linear. This implies that a straight-line link between them is assumed. between the two. Over-fitting can occur with linear regression; however, it can be prevented by employing cross-validation, regularization (L1 and L2) techniques, and some dimensionality reduction approaches. The link between the mean of the dependent and independent variables is then additionally examined by linear regression. Similar to how the mean does not adequately describe a single variable, linear regression does not adequately describe connections between variables. Because it oversimplifies real-world issues by assuming a linear relationship between the variables, linear regression is a great tool for analyzing the relationships between the variables but isn't advised for the majority of actual applications.

When there is a large gap between classes, SVM performs comparatively well. In large dimensional spaces, SVM performs better. If there are more dimensions than samples, SVM works well in certain situations. SVM utilizes memory well. Large data sets are not a good fit for the SVM algorithm. When the target classes are overlapping and the data set includes more noise, SVM does not perform very well. The SVM will perform poorly when there are more training data samples than features for each data point. There is no probabilistic justification for the classification because the support vector classifier places data points above and below the classifying hyperplane.