MACHINE LEARNING ASSIGNMENT

1. **A**
2. **A**
3. **B**
4. **B**
5. **C**
6. **B**
7. **D**
8. **D**
9. **A**
10. **B**
11. **B**
12. **A,B &D**
13. Regularization is a technique used in machine learning to prevent overfitting by adding a penalty term to the model's loss function. It involves introducing additional information (a penalty) to favor simpler models among equally performing models, reducing the complexity of the model and thus enhancing its generalization to new, unseen data. Regularization helps in controlling the model's complexity, thereby improving its ability to perform well on both the training and test datasets.

14.
Several algorithms are used for regularization in machine learning:

1. **Ridge Regression (L2 Regularization):** Adds the squared magnitude of coefficients as a penalty term to the loss function.
2. **Lasso Regression (L1 Regularization):** Adds the absolute value of the magnitude of coefficients as a penalty term to the loss function. Lasso also performs feature selection by shrinking some coefficients to exactly zero.
3. **Elastic Net:** Combines L1 (Lasso) and L2 (Ridge) regularization, which adds both the absolute and squared magnitudes of coefficients as penalty terms.
4. **Dropout:** Primarily used in neural networks, where random neurons are dropped during training to prevent overfitting.
5. **Early Stopping:** Stops the training process before the model overfits by monitoring the performance on a validation dataset.

These algorithms help in controlling the complexity of models and preventing overfitting by imposing different penalties on the model parameters.

15.
In the context of a linear regression equation, the error refers to the disparity between the predicted values produced by the regression model and the actual observed values in the dataset.

Mathematically, for each data point, the error or residual (𝜀) is calculated as the the actual observed value (𝑦) minus the predicted value (𝑦^). It's represented as:

$$\varepsilon = y - \hat{y}$$

The goal of linear regression is to minimize these errors collectively across all data points by finding the line (or hyperplane in higher dimensions) that best fits the data. This line is determined by minimizing the sum of squared errors (SSE) or the mean squared error (MSE) between the predicted and actual values.

Reducing these errors means finding the line that has the smallest overall difference between the predicted values and the true observed values, resulting in a regression model that accurately represents the relationship between the independent variables and the dependent variable