| 1 the weights may be r   | eaucea to zero.   |   |  |
|--|---|---|--|
| (a) L1 and L2  | (b) L1  | (c) L2  | d None of the above                                  |
| training data set.   | optimal set of weight, we cho   |   | function concerning $\boldsymbol{w}$ over the entire |
| <ul> <li>a to increase computate</li> <li>b to reduce the number</li> <li>c to prevent overfitting</li> <li>d to speed up the train</li> </ul> | r of layers in a neural network   |   |  |
| 4. Which of the following  | regularization techniques adds  | a penalty term based on t                                     | the absolute values of the weights?                  |
| (a) L1 regularization  | b L2 regularization   | (c) Dropout   | d Elastic Net  |
| 5. In neural networks, who   | at does L2 regularization encou   | ırage?  | -  |
| <ul><li>a Sparse weight matric</li><li>c small weight values</li></ul>   | res   | (b) large weight valued (d) No impact on we                   |  |
| 6. How does dropout regu   | llarization work in a neural net  | work?   |  |
| b It randomly drops en c It adds noise to the i  | put features during training ntire layers during training nput data ty term for large weights.  |   |  |
| 7. Which regularization te   | chnique combines both L1 and  | L2 penalties?   |  |
| <ul><li>a Dropout</li><li>c Elastic Net</li></ul>  |   | <ul><li>b Ride regression</li><li>d Batch Normaliza</li></ul> | ation  |
| 8. What is the purpose of  | early stopping as a form of reg   | ularization?  |  |
| b To prevent the mode c To speed up the con-   | process when the model is und<br>I from memorizing the training<br>vergence of the training process<br>t of outliers in the training data | g data<br>s   |  |
| 9. Which of the following  | statements is true about the bia  | as-variance tradeoff in the                                   | context of regularization?                           |
| b Regularization alway c Regularization can h  | es increases bias and decreases so increases both bias and varial elp balance bias and variance o impact on the bias-variance to          | nnce  |  |
| 10. In the context of neura  | l networks, what does weight o  | decay refer to?   |  |
| b The gradual decrease c The removal of unne   | in weight values during traini<br>in weight values during train<br>cessary weights from the netw<br>noise to the weight values            | ing   |  |
| 11. Which of the following   | ; is a disadvantage of using a h  | igh regularization strengtl                                   | h in a neural network?                               |
| <ul><li>a Increased risk of ove</li><li>b Faster convergence of</li><li>c Enhanced generalizated</li><li>d Reduced capacity to</li></ul>       | luring training   |   |  |

| <b>12</b> . What is the role of the temperature parameter in the co  | ontext of knowledge distillation as a form of regularization?         |
|--|---|
| <ul> <li>a Controls the learning rate</li> <li>b Adjusts the level of noise in the input data</li> <li>c Regulates the softness of the target distribution</li> <li>d Sets the threshold for dropout during training</li> </ul>  |   |
| 13. In the context of neural networks, what does dropout   | rate refer to?  |
| <ul> <li>a The percentage of training samples used during each</li> <li>b The rate at which weight are decayed during trainin</li> <li>c The probability of dropping out a unit in the hidden</li> <li>d The learning rate for stochastic gradient descent.</li> </ul> | g   |
| <b>14</b> . Which of the following is a technique used for dynamiconvergence in deep learning?   | mic adjustment of the learning rate during training to improve        |
| <ul><li>a Adversarial training</li><li>c Batch Normalization</li></ul>   | <ul><li>b Learning rate annealing</li><li>d Feature Scaling</li></ul> |
| 15. What is the purpose of adding noise to the input data  | as a form of regularization?  |
| <ul> <li>a To make the training process deterministic</li> <li>b To improve model interpretability</li> <li>c To reduce the impact of outliers in the input data</li> <li>d To prevent the model from memorizing the training</li> </ul>                               | data  |
| 16. In the context of regularization, what does the term "s  | hrinkage" refer to?   |
| <ul> <li>a Reducing the size of the input data</li> <li>b Reducing the number of hidden layers in the network</li> <li>c Constraining the magnitude of the weights in the media</li> <li>d Eliminating unnecessary features from the dataset</li> </ul>                |   |
| 17. Which of the following statements is true about the dr   | opout technique?  |
| <ul> <li>a Dropout is more effective in shallow networks than</li> <li>b Dropout can be applied only to input layers</li> <li>c Dropout introduces random variations only during to</li> <li>d Dropout helps prevent co-adaptation of hidden units</li> </ul>          | testing   |
| 18. What is the primary goal of ensemble methods in mac  | hine learning?  |
| <ul> <li>a To reduce the computational complexity of models</li> <li>b To increase the training time of individual models</li> <li>c To improve the predictive performance of a model b</li> <li>d To decrease the diversity among base models</li> </ul>              | y combining multiple models   |
| 19. Which of the following statements is true about baggin   | ng (Bootstrap Aggregating)?   |
| <ul><li>a It trains multiple models sequentially.</li><li>b It trains multiple models independently on different</li><li>c It combines models using a weighted average.</li></ul>  | subsets of the training data.   |

d It is not suitable for high-variance models.

20. What is the purpose of random forests in ensemble learning?

| b To reduce the number of   | sion trees with high correlation<br>f trees in the ensemble<br>as by considering a random sul   |  |              |                             |
|---|---|--|--------------|-----------------------------|
| d To eliminate the need for   | r decision trees in the ensembl   | e  |              |                             |
| 21. In boosting, how are the w  | reights assigned to misclassifie  | ed instances during training?            |              |                             |
| <ul><li>a Equally to all instances</li><li>b Proportional to the diffic</li><li>c Sequentially, with higher</li><li>d Inversely proportional to</li></ul> | r weights for misclassified inst  | rances                                   |              |                             |
| <b>22</b> . Which ensemble method are learned based on the perfo  | _   | ase models by taking a weigh             | ted av       | rerage, where the weights   |
| (a) Bagging   | (b) Stacking  | © Boosting                               | $\bigcirc$ d | Random Forest               |
| 23. What is the primary advar   | ntage of ensemble methods over  | er individual base models?               |              |                             |
| b Ensemble methods can h c Ensemble methods often d Ensemble methods are n 24. In the context of boosting, a A model with high train                      | ing accuracy<br>slightly better than random cha   | s.  nproved robustness.  rner" refer to? |              |                             |
| d A model that is highly o  | -   |  |              |                             |
| <b>25</b> . Which ensemble method is sor?   | s known for building a sequen   | ce of weak learners, each corre          | ecting       | the errors of its predeces- |
| (a) Bagging   | (b) AdaBoost  | c Random Forest                          | $\bigcirc$ d | Gradient Boosting           |
| <b>26</b> . Which ensemble method t   | rains multiple models indeper   | ndently on different subsets of          | the tr       | aining data?                |
| (a) Boosting  | (b) Stacking  | © Bagging                                | $\bigcirc$ d | Random Forest               |
| 27. What is bagging short for   | in the context of ensemble me   | thods?                                   |              |                             |
| a Bootstrap Aggregating   | (b) Boosting Algorithm  | © Bagged Aggregation                     | $\bigcirc$ d | Batch Aggregation           |
| <ul><li>a Equally to all instances</li><li>b Proportional to the diffic</li></ul>   | reights assigned to misclassified culty of the instance register weights for misclassified inst |  |              |                             |
| <b>29</b> . Which ensemble method c   | combines the predictions of bar   | se models by taking a weighted           | d avei       | age?                        |
| <ul><li>a Bagging</li><li>b Stacking</li><li>c Boosting</li><li>d Random Forest</li></ul>   |   |  |              |                             |
| 30. Which ensemble method is  | s known for building a sequen   | ce of weak learners, each corre          | ecting       | the errors of its predeces- |

sor?

| (a)  | Bagging  |            |                            |                                |
|--|--|------------|----------------------------|--------------------------------|
| (b)  | AdaBoost<br>Random Forest  |            |                            |                                |
| $\begin{pmatrix} c \\ d \end{pmatrix}$                   | Gradient Boosting  |            |                            |                                |
| $\overline{}$  | •  | n ind      | ividual base models?       |                                |
|  | What is the primary advantage of ensemble methods ove  | I IIIU     | ividual base inodels:      |                                |
| (a)  | Faster training time   |            |                            |                                |
| (b)<br>(c)   | Improved generalization and robustness  Lower computational complexity                                 |            |                            |                                |
| (d)  | Higher sensitivity to outliers   |            |                            |                                |
| $\cup$   | Which ensemble method is based on constructing a fores   | t of c     | lecision trees with high d | liversity?                     |
| (a)  | Bagging (b) AdaBoost   | (c)        | Random Forest              | d Stacking                     |
| $\bigcirc$   | What does the acronym "LSTM" stand for in the context of   | $\bigcirc$ |                            | O O                            |
| (a)  | Long Short-Term Memory   | (b)        | Linear Short-Term Mem      | iory                           |
| $\begin{pmatrix} \mathbf{c} \end{pmatrix}$               | Limited Short-Term Memory  | (d)        | Lasting Short-Term Mer     | •                              |
| $\bigcirc$   | n boosting, what is the purpose of the learning rate para  | $\bigcirc$ |                            | 1101 y                         |
|  |  |            |                            | un datad dunina aaah itanatian |
| (a)<br>(b)   | It controls the number of weak learners It adjusts the ar<br>It determines the depth of decision trees | moui       | it by which weights are t  | apdated during each iteration  |
| (c)  | It sets the threshold for feature selection  |            |                            |                                |
| $\bigcirc$   | What distinguishes Random Forest from traditional bagg   | ing t      | ochniquos?                 |                                |
|  |  | nig i      | echniques:                 |                                |
| (a)<br>(b)   | Random Forest uses a single decision tree  |            |                            |                                |
| $\begin{pmatrix} \mathbf{b} \\ \mathbf{c} \end{pmatrix}$ | Random Forest trains models sequentially Random Forest introduces randomness by considering            | a rar      | idom subset of features f  | or each tree                   |
| (d)  | Random Forest assigns equal weights to all instances   | u rui      | additionable of features i | or each tree                   |
| $\sim$   | How does stacking differ from bagging and boosting in e  | ensen      | able methods?              |                                |
| (a)  | Stacking trains models independently on different subs   |            |                            |                                |
| (b)  | Stacking combines predictions using a weighted average   |            |                            |                                |
| (c)  | Stacking builds a sequence of weak learners  | , -        |                            |                                |
| (d)  | Stacking uses multiple base models to form a meta-models   | del        |                            |                                |
| 37. V  | What role does the concept of "bias-variance tradeoff" pla   | ıy in      | ensemble methods?          |                                |
| (a)  | Ensemble methods eliminate the bias-variance tradeoff  |            |                            |                                |
| $\widecheck{b}$  | Ensemble methods intensify the bias-variance tradeoff  |            |                            |                                |
| (c)  | Ensemble methods help balance bias and variance  |            |                            |                                |
| $\overline{\mathbf{d}}$                                  | Ensemble methods have no impact on bias and variance   | e          |                            |                                |
| <b>38</b> . V  | What is the primary limitation of using too many weak le   | earne      | rs in boosting?            |                                |
| (a)  | Increased risk of overfitting  | (b)        | Decreased computation      | al complexity                  |
| $\widetilde{\mathbb{C}}$                                 | Improved generalization  | $\bigcirc$ | Faster training time       |                                |
| <b>39</b> . I1   | n bagging, how are the subsets of the training data creat  | ed fo      | r each base model?         |                                |
| (a)  | Randomly and with replacement  |            |                            |                                |
| $\widecheck{b}$  | Randomly and without replacement   |            |                            |                                |
| $\bigcirc$   | Sequentially and with replacement  |            |                            |                                |
| $\overline{\mathbf{d}}$                                  | Sequentially and without replacement   |            |                            |                                |

| <b>1</b> 0. / \ | riat is the primary advan                                   | mage of using gradient boosti                    | ng ov      | ei tiaditioliai Adaboost:   |            |                          |
|-----------------|---|--|------------|-----------------------------|------------|--------------------------|
| a               | Faster convergence  |  | (b)        | Better handling of outlie   | rs         |                          |
| $\bigcirc$      | Reduced risk of overfitting                                 | ng   | (d)        | Simplicity in implementa    | ation      |                          |
| <b>41</b> . W   | hich ensemble method is                                     | s prone to becoming computa                      | tional     | lly expensive as the numb   | er of      | models increases?        |
| a               | Bagging   | (b) Stacking                                     | $\bigcirc$ | Boosting                    | $\bigcirc$ | Random Forest            |
| 42. W           | hat does the term "stacki                                   | ing" refer to in ensemble lear                   | ning?      |                             |            |                          |
| (b)<br>(c)      | Constructing a sequence                                     | ndently on different subsets<br>of weak learners |            |                             |            |                          |
| (d)             | Using multiple base mod                                     | dels to form a meta-model                        |            |                             |            |                          |
| 43. W           | Thich ensemble method is                                    | s known for its ability to hand                  | lle bo     | th linear and non-linear re | elation    | nships in the data?      |
| a               | Bagging   | (b) Stacking                                     | $\bigcirc$ | Random Forest               | $\bigcirc$ | Gradient Boosting        |
| <b>44</b> . E   | xplain the concept of "out                                  | t-of-bag" error in the context                   | of bag     | gging.                      |            |                          |
| $\simeq$        | It is the error rate calculates It is the error rate on the |  |            |                             |            |                          |
| $\times$        |   | st error obtained from the un                    |            |                             |            |                          |
| (d)             | It is a measure of the mo                                   | odel's performance on out-of-                    | distrik    | oution data                 |            |                          |
| 45. W           | That is the role of the hyp                                 | perparameter "max depth" in o                    | decisi     | on trees within a Random    | Fores      | st?                      |
| $\times$        | It controls the number of                                   |  |            |                             |            |                          |
| $\simeq$        |   | epth of individual decision tr                   | ees        |                             |            |                          |
| $\times$        | It sets the learning rate for                               | ŭ .  | 200        |                             |            |                          |
| $\cup$          | ,   | signed to misclassified instanc                  |            |                             |            | 1                        |
|                 |   | methods, what is "early stop                     |            |                             |            |                          |
| (a)             | Early stopping involves simplicity.                         | terminating the training pro                     | ocess      | when the model is under     | rfittin    | g, contributing to model |
| (b)             | Early stopping prevents data.                               | overfitting by stopping the tra                  | aining     | process when the model      | starts     | to memorize the training |
| $\bigcirc$      | Early stopping introduce                                    | es noise to the input data duri                  | ing tra    | aining, preventing overfitt | ing.       |                          |
| $\bigcirc$ d    | Early stopping is not rela                                  | ated to regularization in enser                  | mble :     | methods.                    |            |                          |
| 47. W           | hat is the impact of incre                                  | easing the number of base mo                     | dels       | on the computational com    | plexit     | ty of stacking?          |
| a               | The computational comp                                      | plexity decreases linearly                       |            |                             |            |                          |
| <b>b</b>        | The computational comp                                      | plexity increases linearly                       |            |                             |            |                          |
| $\bigcirc$      | The computational comp                                      | plexity remains constant                         |            |                             |            |                          |
| (d)             | The computational comp                                      | plexity depends on the type of                   | f base     | models used                 |            |                          |
| <b>48</b> . E:  | xplain the concept of "adv                                  | versarial training" in the conto                 | ext of     | ensemble methods.           |            |                          |
| a               | Adversarial training invo                                   | olves training models to be ro                   | bust a     | against adversarial attacks |            |                          |
| <b>b</b>        | Adversarial training focu                                   | uses on maximizing the accur                     | acy o      | n the training set.         |            |                          |
| $\bigcirc$      | · ·   | ninates the need for ensemble                    |            |                             |            |                          |
| (d)             | Adversarial training refe                                   | rs to using adversarial examp                    | les as     | additional training data.   |            |                          |

49. How does the concept of "stacking with cross-validation" address the risk of overfitting in stacking?

| c I                     | Decreased model performance  | (d) Improved generalization                          |
|-------------------------|--|--|
| <b>51</b> . Ex          | plain the concept of "feature importance" in the context   | of Random Forest.                                    |
| (b) I                   | Feature importance represents the number of times a ferenture importance indicates the relevance of a feature Feature importance is not applicable to ensemble method Feature importance measures the computational cost of              | in predicting the target variable.                   |
| <b>52</b> . W<br>Boosti | *  | n ensemble methods such as Random Forest and Gradien |
| (b) I<br>(c) I          | t controls the learning rate in boosting algorithms.  It sets the maximum depth of individual decision trees.  It specifies the number of base models in the ensemble.  It determines the subset of features considered for each         | base model.  |
| <b>53</b> . Ex          | plain the concept of "stacking with meta-features" in th   | e context of ensemble methods.                       |
| (b) S                   | Stacking with meta-features involves using the output of<br>Stacking with meta-features eliminates the need for mu<br>Stacking with meta-features refers to combining models<br>Stacking with meta-features involves using only one type | ltiple base models.<br>s using a weighted average.   |
| <b>54</b> . W           | nat is Dropout in the context of neural networks?  |  |
| (b) I                   | Adding noise to input features Removing random neurons during training Reducing the learning rate Increasing the number of hidden layers   |  |
| 55. W                   | nat is the main purpose of Dropout in neural networks  | ?  |
| (b) 7                   | To increase overfitting To speed up the training process To prevent co-adaptation of neurons To eliminate the need for activation functions  |  |
| 56. W                   | nich of the following statements is true about the applie  | cation of Dropout during training?                   |
| (b) I<br>(c) I<br>(d) I | Oropout is only applied to input layers Oropout is applied to all layers except the output layer Oropout is applied during both training and testing Oropout is never applied to neural networks   |  |
| <b>57</b> . Ho          | ow does Dropout contribute to regularization in neural   | networks?  |

(b) Increased risk of overfitting

(a) It eliminates the need for cross-validation in stacking.

(c) It increases the depth of individual base models.

(d) It has no impact on the risk of overfitting.

Slower convergence

(b) It uses multiple cross-validated models, reducing overfitting.

50. What is the primary drawback of using a high learning rate in boosting algorithms?

| a                       | By increasing the number of parameters  |
|-------------------------|---|
| (b)                     | By introducing noise to the input data  |
| (c)                     | By reducing the model's capacity  |
| (d)                     | By promoting co-adaptation of neurons   |
| <b>58</b> . I           | n terms of training, what does it mean if a neuron is "dropped out"?  |
| a                       | The neuron's weights are set to zero  |
| (b)                     | The neuron is removed from the network temporarily  |
| $\bigcirc$              | The neuron's activation function is bypassed  |
| (d)                     | The neuron's output is squared  |
| 59. V                   | Vhat challenge does Dropout aim to address in neural networks?  |
| a                       | Underfitting (b) Overfitting (c) Vanishing gradients (d) Exploding gradients  |
| <b>60</b> . F           | How does Dropout affect the training time of a neural network?  |
| a                       | Slows down the training process   |
| <b>b</b>                | Speeds up the training process  |
| $\bigcirc$              | No impact on training time  |
| $\bigcirc$ d            | Depends on the type of activation function used   |
| <b>61</b> . V           | What is the recommended range for Dropout rates in neural networks?   |
| (a)                     | 0.0 to 0.1  |
| $\widecheck{b}$         | 0.2 to 0.5  |
| (c)                     | 0.5 to 0.8  |
| $\overline{\mathbf{d}}$ | 0.9 to 1.0  |
| <b>62</b> . F           | How does Dropout contribute to model generalization?  |
| a                       | By memorizing the training data   |
| (b)                     | By promoting co-adaptation of neurons   |
| $\bigcirc$              | By reducing the sensitivity of neurons to specific input features   |
| $\bigcirc$              | By increasing the number of hidden layers   |
| 63. V                   | When applying Dropout, which phase is used for adjusting the weights of the neural network?   |
| (a)                     | Training phase  |
| (b)                     | Testing phase   |
| (c)                     | Both training and testing phases  |
| $\overline{\mathbf{d}}$ | Neither training nor testing phases   |
| <b>64</b> . E           | explain the term "co-adaptation of neurons" in the context of neural networks and how Dropout addresses it.   |
| a                       | Co-adaptation refers to neurons relying too much on each other, and Dropout breaks these dependencies by randomly dropping neurons during training. |
| <b>b</b>                | Co-adaptation is a form of regularization, and Dropout exacerbates co-adaptation by introducing noise.  |
| $\bigcirc$              | Co-adaptation occurs when neurons are independent, and Dropout enforces co-adaptation by removing dependencies                                      |
| $\bigcirc$              | Co-adaptation is unrelated to Dropout; Dropout only affects the learning rate.  |
| <b>65</b> . F           | How does the effectiveness of Dropout vary with the size and complexity of a neural network?  |
| a                       | Dropout is more effective in small and simple networks  |
| (b)                     | Dropout is more effective in large and complex networks   |
| $\overline{\mathbf{c}}$ | Dropout is equally effective across all network sizes and complexities  |
| (d)                     | Dropout is irrelevant to network size and complexity  |

| 66. What is the relationship between Dropout and the concep  | pt of ensemble learning?       |                        |
|--|--------------------------------|------------------------|
| a Dropout is a type of ensemble learning                     |                                |                        |
| (b) Ensemble learning and Dropout are unrelated concepts     | 3                              |                        |
| (c) Dropout and ensemble learning achieve the same result    | t in terms of model diversity  | 7                      |
| d Dropout eliminates the need for ensemble learning          |                                |                        |
| 67. Explain the trade-off between using a high Dropout rate  | and a low Dropout rate in n    | eural networks.        |
| (a) High Dropout rates lead to overfitting, while low Drop   | out rates may result in unde   | erfitting.             |
| b High Dropout rates always improve model generalization     | ion, while low Dropout rates   | reduce model capacity. |
| (c) There is no trade-off; the Dropout rate does not impact  | model performance.             |                        |
| d The trade-off depends on the type of activation function   | n used in the network.         |                        |
| 68. How does Dropout contribute to mitigating the vanishing  | g gradient problem in deep 1   | neural networks?       |
| (a) a. By increasing the learning rate                       |                                |                        |
| (b) By preventing co-adaptation of neurons                   |                                |                        |
| © By introducing noise to the input data                     |                                |                        |
| d By reducing the sensitivity of neurons to specific input   | features                       |                        |
| 69. What is the primary goal of data augmentation in machin  | ne learning?                   |                        |
| (a) To decrease the size of the dataset                      |                                |                        |
| b To increase the computational complexity                   |                                |                        |
| (c) To improve model performance by increasing the diver     | sity of the training data      |                        |
| d To eliminate the need for validation data                  |                                |                        |
| 70. Which of the following is a common technique used in d   | ata augmentation for image     | data?                  |
| (a) Principal Component Analysis (PCA)                       | (b) Feature scaling            |                        |
| (c) Image rotation   | d Lasso regularization         |                        |
| 71. How does data augmentation contribute to preventing ov   | verfitting in machine learning | g models?              |
| (a) By reducing the size of the training dataset             |                                |                        |
| (b) By increasing the number of layers in the model          |                                |                        |
| (c) By introducing noise to the input data                   |                                |                        |
| d By providing a more diverse set of training examples       |                                |                        |
| 72. In text data augmentation, what technique involves repla | cing words with their synon    | ıyms?                  |
| (a) Tokenization (b) Embedding                               | © Word substitution            | d Lemmatization        |
| 73. Which of the following is a disadvantage of data augmer  | itation?                       |                        |
| (a) Increased model generalization                           |                                |                        |
| (b) Potential introduction of unrealistic patterns           |                                |                        |
| (c) Improved model robustness                                |                                |                        |
| d Decreased computational efficiency                         |                                |                        |
| 74. What is the purpose of random cropping in image data a   | ugmentation?                   |                        |
| (a) To decrease the image resolution                         |                                |                        |
| (b) To remove irrelevant features from the image             |                                |                        |
| (c) To create variations in the spatial location of objects  |                                |                        |
| d To increase the image contrast                             |                                |                        |

| 75. V            | Which type of data augm   | entation is commonl                             | y used for time                         | series data?                                      |                                    |
|------------------|---|---|---|---|------------------------------------|
| a                | Image rotation  | b Time warping                                  | g c                                     | Word substitution                                 | d Feature scaling                  |
| <b>76</b> . I    | Explain the concept of "jit   | ttering" in the contex                          | t of data augme                         | ntation.  |                                    |
| (a) (b) (c) (d)  | Jittering refers to the int<br>Jittering involves the ran<br>Jittering is a synonym for<br>Jittering is irrelevant to | ndom selection of a sor image rotation          | -                                       | oints   |                                    |
| 77. I            | n the context of image da   | ata augmentation, w                             | hat is the purpo                        | se of horizontal flippir                          | ng?                                |
| (a)<br>(c)       | To rotate images clockw<br>To adjust the image brig   |   | (b)<br>(d)                              | To create mirror image To resize images           | ges                                |
| <b>78</b> . I    | How does data augmenta  | ition differ from feat                          | ure engineering                         | ?   |                                    |
| a b c d          | Data augmentation focus<br>Feature engineering is I<br>Data augmentation invo<br>Feature engineering and              | limited to image data<br>olves scaling features | a, while data aug<br>s, while feature o | gmentation is applicab<br>engineering involves ra | 7.5                                |
| 79. V            | What is the role of dropou  | ut in the context of d                          | lata augmentatio                        | on?   |                                    |
| a<br>b<br>c<br>d | Dropout is not related to Dropout enhances data Dropout is a type of data Dropout prevents data a                     | augmentation by rate augmentation tech          | ndomly removir<br>nnique                |   | ning                               |
| 80. V            | Which data augmentation   | n technique is commo                            | only used for au                        | dio data to introduce                             | variations in pitch?               |
| a<br>c           | Time warping Random cropping  |   | (b)<br>(d)                              | Spectrogram augmen<br>Jittering                   | ntation                            |
| <b>81</b> . V    | What is the purpose of ela  | astic deformation in                            | image data aug                          | mentation?  |                                    |
| a<br>b<br>c<br>d | To adjust the image con<br>To introduce non-linear<br>To resize the image<br>To rotate the image                      |   | nage                                    |   |                                    |
|                  | In natural language pro<br>mentation?   | cessing, which tech                             | nique involves 1                        | randomly removing w                               | vords from sentences during data   |
| a b c d          | Tokenization Word substitution Sentence splitting Sentence dropout  |   |   |   |                                    |
| 83. I            | Explain the concept of "ac  | dversarial training" i                          | n the context of                        | data augmentation and                             | d how it addresses robustness.     |
| a                |   | cuses on creating adv                           |   |   | obustness against unseen patterns  |
| (b)              | Adversarial training is i   | irrelevant to data au <sub>{</sub>              | gmentation.                             |   |                                    |
| c<br>d           | Adversarial training inv<br>Adversarial training enl  | _   |   |   | e during the augmentation process. |

| (d) Data augmentation reduces the need for addressing class imbalance  |
|--|
| 85. What challenges might arise when applying data augmentation to non-image data types, such as tabular data?   |
| <ul> <li>a Difficulty in implementing data augmentation for non-image data</li> <li>b Limited applicability of data augmentation to non-image data</li> <li>c The potential introduction of unrealistic patterns</li> <li>d No challenges; data augmentation is equally effective for all data types</li> </ul>  |
| <b>86</b> . Explain the term "mixup" in the context of data augmentation and how it differs from traditional augmentation techniques.  |
| <ul> <li>a Mixup involves blending two or more samples, creating new synthetic samples with averaged labels.</li> <li>b Mixup is a synonym for image rotation.</li> <li>c Mixup refers to the addition of random noise to input features.</li> <li>d Mixup is irrelevant to data augmentation.</li> </ul>  |
| 87. How does data augmentation impact the interpretability of machine learning models?   |
| <ul> <li>a Data augmentation improves model interpretability by providing more diverse training examples.</li> <li>b Data augmentation has no impact on model interpretability.</li> <li>c Data augmentation reduces model interpretability due to the introduction of synthetic samples.</li> <li>d Data augmentation improves model interpretability by eliminating the need for validation data.</li> </ul> |
| 88. What is the role of "cutout" in image data augmentation?   |
| <ul> <li>a To remove random portions from images</li> <li>b To blur the edges of images</li> <li>c To rotate images</li> <li>d To resize images</li> </ul>   |
| 89. In the context of data augmentation, explain how the technique of "shearing" is applied to image data.   |
| <ul> <li>a Shearing involves adjusting the brightness of images.</li> <li>b Shearing is irrelevant to data augmentation.</li> <li>c Shearing introduces non-linear distortions to the image by tilting it along one of its axes.</li> <li>d Shearing is a synonym for image rotation.</li> </ul>   |
|  |

84. How does data augmentation contribute to handling class imbalance in classification tasks?

Data augmentation generates additional samples for minority classes, addressing class imbalance

a Data augmentation exacerbates class imbalanceb Data augmentation is not related to class imbalance

## **Solutions to the Exercises**

- 1. (b) L1
- 2.
- 3. (c) to prevent overfitting
- 4. (a) L1 regularization
- 5. (c) small weight values
- 6. (b) It randomly drops entire layers during training
- 7. (c) Elastic Net
- 8. (b) To prevent the model from memorizing the training
- 9. (c) Regularization can help balance bias and variance
- **10**. (b) The gradual decrease in weight values during training
- 11. (d) Reduced capacity to capture complex patterns
- 12. (c) Regulates the softness of the target distribution
- **13**. **(c)** The probability of dropping out a unit in the hidden layers during training
- **14**. **(b)** Learning rate annealing
- 15. (c) To reduce the impact of outliers in the input data
- 16. (c) Constraining the magnitude of the weights in the model
- 17. (d) Dropout helps prevent co-adaptation of hidden units
- **18**. **(c)** To improve the predictive performance of a model by combining multiple models
- **19**. **(b)** It trains multiple models independently on different subsets of the training data.
- **20**. **(c)** To introduce randomness by considering a random subset of features for each tree
- **21**. **(c)** Sequentially, with higher weights for misclassified instances
- **22**. **(b)** Stacking
- 23. (c) Ensemble methods often generalize better and have improved robustness.
- **24**. **(b)** A model that performs slightly better than random chance
- 25. (b) AdaBoost
- 26. (c) Bagging
- 27. (a) Bootstrap Aggregating
- **28**. **(c)** Sequentially, with higher weights for misclassified instances
- **29**. **(b)** Stacking
- **30**. **(b)** AdaBoost
- 31. (b) Improved generalization and robustness
- 32. (c) Random Forest
- 33. (a) Long Short-Term Memory
- **34**. (a) It adjusts the amount by which weights are updated during each iteration
- **35**. (c) Random Forest introduces randomness by considering a random subset of features for each tree
- **36**. **(d)** Stacking uses multiple base models to form a metamodel
- 37. (c) Ensemble methods help balance bias and variance
- 38. (a) Increased risk of overfitting
- 39. (a) Randomly and with replacement
- **40**. **(b)** Better handling of outliers
- 41. (c) Boosting

- 42. (d) Using multiple base models to form a meta-model
- 43. (c) Random Forest
- 44. (c) It is an estimate of the test error obtained from the unused samples during training
- **45**. (b) It limits the maximum depth of individual decision trees
- **46**. (b) Early stopping prevents overfitting by stopping the training process when the model starts to memorize the training data.
- 47. (b) The computational complexity increases linearly
- **48**. (a) Adversarial training involves training models to be robust against adversarial attacks.
- **49**. **(b)** It uses multiple cross-validated models, reducing overfitting.
- 50. (b) Increased risk of overfitting
- **51**. **(b)** Feature importance indicates the relevance of a feature in predicting the target variable.
- **52**. (c) It specifies the number of base models in the ensemble.
- 53. (a) Stacking with meta-features involves using the output of base models as features for a meta-model.
- 54. (b) Removing random neurons during training
- 55. (c) To prevent co-adaptation of neurons
- **56**. **(b)** Dropout is applied to all layers except the output layer
- **57**. **(c)** By reducing the model's capacity
- **58**. **(b)** The neuron is removed from the network temporarily
- 59. (b) Overfitting
- 60. (a) Slows down the training process
- **61**. **(b)** 0.2 to 0.5
- **62**. **(c)** By reducing the sensitivity of neurons to specific input features
- 63. (a) Training phase
- **64**. **(a)** Co-adaptation refers to neurons relying too much on each other, and Dropout breaks these dependencies by randomly dropping neurons during training.
- **65**. (b) Dropout is more effective in large and complex networks
- **66**. **(c)** Dropout and ensemble learning achieve the same result in terms of model diversity
- **67**. **(a)** High Dropout rates lead to overfitting, while low Dropout rates may result in underfitting.
- 68. (c) By introducing noise to the input data
- **69**. **(c)** To improve model performance by increasing the diversity of the training data
- **70**. **(c)** Image rotation
- 71. (d) By providing a more diverse set of training examples
- 72. (c) Word substitution
- 73. (b) Potential introduction of unrealistic patterns
- 74. (c) To create variations in the spatial location of objects
- 75. (b) Time warping
- **76.** (a) Jittering refers to the introduction of noise to input features
- 77. (b) To create mirror images
- **78**. (a) Data augmentation focuses on creating new samples, while feature engineering manipulates existing features.

- **79**. **(b)** Dropout enhances data augmentation by randomly removing features during training
- 80. (b) Spectrogram augmentation
- 81. (b) To introduce non-linear distortions to the image
- 82. (d) Sentence dropout
- 83. (a) Adversarial training focuses on creating adversarial examples to test the model's robustness against unseen patterns introduced by data augmentation.
- **84**. **(c)** Data augmentation generates additional samples for minority classes, addressing class imbalance
- 85. (c) The potential introduction of unrealistic patterns
- **86**. (a) Mixup involves blending two or more samples, creating new synthetic samples with averaged labels.
- 87. (c) Data augmentation reduces model interpretability due to the introduction of synthetic samples.
- 88. (a) To remove random portions from images
- **89**. (c) Shearing introduces non-linear distortions to the image by tilting it along one of its axes.