1	the weights may be reduc	eed to zero.				
\bigcirc	L1 and L2	(B) L1	(C)	L2	\bigcirc	None of the above
2 . Ba	gging is an ensemble tech	nique that:				
(A) (B) (C) (D)	_	on different subsets of the data by iteratively updating weight	S			
3. W	hich of the following is/ar	re Limitations of deep learning	?			
\bigcirc	Data labeling		\bigcirc	Obtain huge training dat	asets	:
(C)	Both (A) and (B)		\bigcirc	None of the previous		
4. W	hich neural network has o	only one hidden layer between	the i	nput and output?		
(A) (C)	Shallow neural network Feed-forward neural net	works	(B) (D)	Deep neural network Recurrent neural network	ks	
5 . CN	IN is mostly used when th	nere is an?				
\bigcirc	structured data	(B) unstructured data	\bigcirc	both (A) and (B)	\bigcirc	None of the previous
6. W	hich of the following is w	ell suited for perceptual tasks?				
(A) (B) (C) (D)	feed-forward neural network recurrent neural network convolutional neural net Reinforcement learning	ks				
7. W	hich of the following is/ar	re Common uses of RNNs?				
(A) (B) (C) (D)	BusinessesHelp securities Detect fraudulent credit- Provide a caption for image All of the above		epor	ts		
8 . Bo	osting is an ensemble tech	hnique that:				
(A) (B) (C) (D)	-	on different subsets of the data by iteratively updating weight	S			
9 . W	hat steps can we take to p	revent overfitting in a Neural l	Netw	ork?		
(A) (C) (E)	Data Augmentation Early Stopping All of the previous		(B) (D)	Weight Sharing Dropout		
10 . V	Which of the following is a	an example of an ensemble lear	ning	algorithm?		
\bigcirc A	Decision tree	B SVM	\bigcirc	Random Forest	(D)	KNN

11 . A	daBoost is an example of	:				
\bigcirc A	Bagging algorithm		\bigcirc B	Boosting algorithm		
\bigcirc	Randomized algorithm		\bigcirc	Reinforcement learning a	algori	thm
12 . G	radient Boosting is an en	semble technique that:				
\bigcirc A	Combines predictions us	sing a weighted average				
\bigcirc B	Trains multiple models	on different subsets of the data				
<u>C</u>	Constructs an ensemble	by iteratively updating weight	S			
\bigcirc	Uses a committee of exp	erts to make predictions				
13 . X	GBoost is a popular impl	ementation of:				
\bigcirc A	Bagging algorithm		\bigcirc	Boosting algorithm		
(C)	Random Forest Algorith	m	D	K-Means clustering algor	rithm	S
14 . S	tacking is an ensemble te	chnique that:				
\bigcirc A	Combines predictions us	sing a weighted average				
\bigcirc B	Trains multiple models of	on different subsets of the data				
(C)		by iteratively updating weight				
(D)	Trains a meta-model to	make predictions based on outp	outs	of base models		
15. V	Which ensemble learning a	algorithm uses bootstrapping a	nd fe	ature sampling?		
\bigcirc A	Random Forest	(B) AdaBoost	(C)	Gradient Boosting	\bigcirc	Stacking
16 . T	he purpose of using ense	mble learning is to:				
\bigcirc A	Reduce overfitting and is	mprove generalization				
\bigcirc B	Increase training time ar	nd complexity				
(C)	Decrease the number of	models required				
(D)	Eliminate the need for la	abeled data				
17 . B	agging algorithms are eff	ective in:				
A	Handling imbalanced da	tasets	\bigcirc B	sequential data prediction	n	
(C)	Clustering high-dimensi	onal data	(D)	Text classification tasks		
18. V	Which ensemble learning a	algorithm assigns weights to ba	ase m	odels based on their perfo	ormar	nce?
\bigcirc A	AdaBoost	(B) Random Forest	\bigcirc	Gradient Boosting	\bigcirc	Stacking
19. V	Thich ensemble learning	algorithm uses a committee of	expe	rts to make predictions?		
\bigcirc A	Bagging	B Boosting	\bigcirc	Random Forest	\bigcirc	Stacking
20. V	Thich ensemble learning	algorithm is prone to overfittin	g if t	he base models are too co	mplex	x?
\bigcirc A	Bagging	(B) Boosting	\bigcirc	Random Forest	\bigcirc	Stacking
21. V	which ensemble learning a	algorithm can handle both regr	essio	n and classification tasks?	>	
\bigcirc	Bagging	B AdaBoost	(C)	Gradient Boosting	\bigcirc	Stacking
22 . E	nsemble learning algorith	nms are useful when:				

A The dataset is small andB The dataset is large andC The dataset is perfectly	d high-dimensional balanced					
(D) The dataset contains ca		_				
	thms can improve model perfor					
(A) Reducing bias	14	(B) Reducing variance				
(C) Increasing interpretabil	•	(D) Increasing training t				
ing?	algorithm can handle both hui	merical and categorical data	without requiring one-hot encod-			
(A) Bagging	(B) AdaBoost	© Graident Boosting	(D) Stacking			
25. Which ensemble learning	algorithm is less sensitive to o	outliers?				
(A) Bagging	B Boosting	© Random Forest	(D) Stacking			
26 . The majority voting meth	nod in ensemble learning refers	s to:				
 A Combining predictions by averaging their probabilities B Combining predictions by taking the mode of their classes C Combining predictions by multiplying their probabilities D Combining predictions by taking the median of their values 						
27. Which ensemble learning	algorithm can handle missing	values in the dataset?				
(A) Bagging	B AdaBoost	© Gradient Boosting	(D) Stacking			
28. Ensemble learning algorit	hms are useful for:					
(A) Improving model stabil	ity	(B) Increasing model co	mplexity			
© Reducing feature impor	rtance	D Eliminating the need	d for cross-validation			
29 . Which ensemble learning	algorithm can handle non-line	ear relationships in the data	?			
(A) Bagging	B AdaBoost	© Graident Boosting	(D) Stacking			
30 . Ensemble learning algorit	thms are effective in:					
A Reducing model interpr	retability	(B) Increasing model training				
© Handling unbalanced d	atasets	(D) Eliminating the need	d for hyperparameter tuning			
31 . Which ensemble learning	algorithm can handle both nu	merical and categorical feat	tures effectively?			
(A) Bagging	(B) AdaBoost	© Gradient Boosting	(D) Stacking			
32 . Which ensemble learning	algorithm is less susceptible to	o overfitting compared to o	thers?			
(A) Bagging	B Boosting	© Random Forest	(D) Stacking			
33. Which ensemble learning	algorithm uses a weighted sur	m of predictions from base	models?			
(A) Bagging	B AdaBoost	© Gradient boosting	(D) Stacking			
34 . Which ensemble learning	algorithm can be used to iden	tify important features in a	dataset?			
(A) Bagging	(B) AdaBoost	© Gradient Boosting	(D) Stacking			

35 . Th	ne ReLu activation has no	effect on back-propagation ar	nd the vanishing gradient.	
\sim	True can be true and false		B FalseD can't say	
36 . W	hy is the vanishing gradi	ient a problem?		
(B) (C)	with back propagation, t	radient is large and slow if it's he gradient becomes smaller a d multiplying two numbers be	s it works back through the n	net
		nctions can be used as an active, $(p_1,, p_k)$ such that sum of p over	-	layer if we wish to predict the
\bigcirc A	Softmax	B ReLu	© Sigmoid	(D) tanh
A B C D E	Weight between input an Weight between hidden Biases of all hidden layer Activation Function of o none of the previous	and output layer r neurons utput layer		
	•	odel with 3 neurons and inpuation function is a linear const	•	ne input neurons are 4,5 and on the output?
\bigcirc A	32	B 64	© 96	(D) 128
	he input image has been will be the size of the co		ze 28 X 28 and a kernel/filter	of size 7 X 7 with a stride of 1
\bigcirc A	20×20	\bigcirc B 21×21	\bigcirc 22 × 22	\bigcirc 25 × 25
	ne number of nodes in the layer to the hidden layer		en layer is 5. The maximum r	number of connections from the
\bigcirc A	50	B less than 50	© more than 50	(D) it's an arbitrary value.
(A) (B) (C)	Thich of the following state of the literal can help in dimensional that can be used for feature at the suffers less overfitting all of the previous	e pooling	1 imes 1 convolutions in a CNN 3	?
43 . Do	eep learning algorithms a	aremore accurate than mach	nine learning algorithm in im	age classification.
\bigcirc A	33 %	B 37%	© 40%	(D) 41%
44 . W	hich of the following are	universal approximators?		
\bigcirc A	Kernel SVM	B Neural Networks	© Boosted Decision trees	(D) All of the above
45 . In	which of the following a	applications can we use deep le	earning to solve the problem?	

(A) Protein structure pr	rediction	(B) Prediction of chemic	cal reactions		
© Detection of exotic	Detection of exotic particles D all of the previous				
46. Which of following ac	ctivation function can't be	used at output layer to classify an i	image ?		
(A) Sigmoid	(B) tanh	© ReLU	(D) None of the previous		
47 . Dropout can be applied	ed at visible layer of Neura	l Network model?			
(A) True		B False			
48 . Which of the following	ng neural network training	challenge can be solved using batc	h normalization?		
(A) overfitting		B Restrict activation to	o become too high or low		
© Training is too slow	V	\bigcirc Both \bigcirc and \bigcirc			
(E) All of the previous					
49 . Changing Sigmoid act	tivation to ReLu will help t	to get over the vanishing gradient is	ssue?		
(A) True		B False			
50 . In CNN, having max p	pooling always decrease th	e parameters?			
(A) True	(B) False	© can be true and false	e D can't say		
51 . Bagging is more sensi	tive to noise.				
(A) True		(B) False			
52 . What is true about th	e functions of a Multi Lay	er Perceptron?			
(A) The first neural net	s that were born out of the	e need to address teh inaccuracy of	an early classifier, the perceptron		
<u> </u>	coup of given set of inputs				
(C) It generates a score(D) all of the previous	that determines the confid	lence level of the prediction			
53. Select reason(s) for us	sing a Deep Neural Netwo	k.			
(A) Some patterns are v	very complex and can't be	deciphered precisely by alternate m	neans		
<u> </u>	0 01	nd using them as building blocks in			
(C) We finally have the(D) All of the above	technology, GPUs, to acce	elerate the training process by seven	ral folds of magnitude.		
	:	4 1: 4: 41-			
	ing Deep Learning is a ma		D		
(A) True	(B) False	(C) Can be true and fals	se (D) can't say		
	not be applied when using				
(A) True		(B) False			
	ourpose of regularization is	ı deep learning?			
(A) to increase computa (B) to reduce the numb	•	arroule			
(C) to prevent overfitting	er of layers in a neural net ng	WOIK			
(D) to speed up the train					

57 . W	Which of the following reg	gularization techn	iques adds a penal	ty term based or	n the absolute	values of the weights?
\bigcirc	L1 regularization	B L2 regulari	zation (C)	Dropout	D	Elastic Net
58 . Ir	n neural networks, what d	loes L2 regulariza	ation encourage?			
\bigcirc A	Sparse weight matrices		\bigcirc B	large weight va	lues	
\bigcirc	small weight values		D	No impact on w	veight values	
59 . H	low does dropout regulari	ization work in a	neural network?			
\widehat{A}	It randomly drops input	features during t	raining			
$\widetilde{\mathbb{B}}$	It randomly drops entire	e layers during tra	nining			
(C)	It adds noise to the input	t data				
\bigcirc	It introduces a penalty to	erm for large wei	ghts.			
60 . V	hich regularization tech	nique combines b	oth L1 and L2 pena	alties?		
\bigcirc A	Dropout		\bigcirc B	Ride regression		
$\overline{\mathbb{C}}$	Elastic Net		\bigcirc	Batch Normaliz	ation	
61 . V	What is the purpose of ear	ly stopping as a f	orm of regularizati	ion?		
(A)	To stop the training prod	cess when the mo	del is underfitting			
(B)	To prevent the model from	om memorizing tl	ne training data			
$\overline{\mathbb{C}}$	To speed up the converg	gence of the traini	ing process			
D	To reduce the impact of	outliers in the tra	ining data			
62 . W	which of the following sta	itements is true al	bout the bias-varia	nce tradeoff in th	he context of r	egularization?
(A)	Regularization always in	ncreases bias and	decreases variance	:		
$\stackrel{\smile}{\mathbb{B}}$	Regularization always in	ncreases both bias	and variance			
(C)	Regularization can help	balance bias and	variance			
\bigcirc	Regularization has no in	npact on the bias-	variance tradeoff			
63 . Ir	the context of neural ne	tworks, what doe	es weight decay ref	er to?		
\bigcirc	The gradual increase in	weight values du	ring training			
$\overline{\mathbf{B}}$	The gradual decrease in	weight values du	ring training			
(C)	The removal of unnecess	sary weights fron	n the network			
\bigcirc	The introduction of nois	se to the weight v	alues			
64 . W	Which of the following is a	a disadvantage of	using a high regul	arization strengt	th in a neural 1	network?
\bigcirc A	Increased risk of overfitt	ting				
\bigcirc B	Faster convergence durin	ng training				
\bigcirc	Enhanced generalization	ı to new data				
\bigcirc	Reduced capacity to cap	ture complex patt	terns			
65 . V	hat is weight decay?					
A	A regularization techniquiteration.	ue (such as L2 reg	ularization) that re	esults in gradient	descent shrink	king the weights on every
\bigcirc B	Gradual corruption of th	ne weights in the	neural network if i	t's training on n	oisy data.	
$\tilde{\mathbb{C}}$	The process of gradually	decreasing the le	earning rate during	g training		
\bigcirc	A technique to avoid var	nishing gradient l	oy imposing a ceili	ng on the values	of the weight	S.

66 . If	You have 10,000,000 examples, how	would you split the t	rain/dev/test set?	
\bigcirc A	98% train. 1% dev. 1% test			
\bigcirc B	33% train. 33% dev. 33% test			
\bigcirc	60% train. 20% dev. 20% test			
67 . T	he dev and test set should:			
(A)	Come from the same distribution			
(B)	Come from different distributions			
<u>C</u>	Be identical to each other (same (x, y)	y) pairs)		
\bigcirc	Have the same number of examples			
	Your Neural Network model seems to see all that apply)	to have high variance	e, what of the following	g would be promising things to try?
(A)	Make the Neural network deeper		B Get more training of	data
$\stackrel{\smile}{\mathbb{C}}$	Get more test data		D Increase the number	er of units in each hidden layer
E	Add regularization		_	
and c	ou are working on an automated cheoranges. Suppose your classifier obtain romising things to try to improve you	ns a training set erro	r of 0.5% and a dev set	
A	Increase the regularization parameter	er lambda		
\bigcirc B	decrease the regularization parameter	er lambda		
(C)	get more training data			
(D)	use a bigger neural network			
70. V	What happens when you increase the	regularization hyper	parameter lambda?	
\bigcirc A	Weights are pushed twoard becomin	ng smaller (closer to ())	
\bigcirc B	weights are pushed toward becomin	g bigger (further from	m 0)	
(C)	doubling lambda should roughly res	ult in doubling the w	reights	
D	Gradient descent taking bigger steps	s with each iteration	(proportional to lambd	a)
71. V	Vith the inverted dropout, at test time	::		
A	You don't apply dropout (do not ran in training	domly eliminate uni	ts), but keep 1/keep_p	prob factor in the calculations used
\bigcirc B	You don't apply dropout (do not randitions usd in the training	domly eliminate unit	s) and do not keep the	1/keep_prob factor in the calcula-
\bigcirc	You apply dropout (randomly elimin	ate units) but keep 1	/keep_prob factor in	the calculations used in training
D	You apply dropout (randomly elimitraining	nate units) and do r	oot keep 1/keep_prob	o factor in the calculations used in
72. V	Which of these techniques are useful f	or reducing variance	(reduce overfitting)? (c	check all that apply)
\bigcirc A	Dropout	B Gradient Checki	ng C	Data augmentation
\bigcirc	Vanishing gradient (E Xavier initializat	tion (F)	L2 regularization
\bigcirc	Exploding gradient			
73. W	Why do we normalize the inputs x ?			

(\mathbf{A})	Normalization is another word for regularization—it he	lps to reduce variance
\bigcirc B	It makes the cost function faster to optimize	
\bigcirc	It makes it easier to visualize the data.	
\bigcirc	It makes the parameter initialization faster.	
74. V	What is the role of the temperature parameter in the con-	text of knowledge distillation as a form of regularization?
\bigcirc	Controls the learning rate	
\bigcirc B	Adjusts the level of noise in the input data	
\bigcirc	Regulates the softness of the target distribution	
D	Sets the threshold for dropout during training	
75 . Ii	n the context of neural networks, what does dropout rate	e refer to?
\bigcirc	The percentage of training samples used during each it	reration
\bigcirc B	The rate at which weight are decayed during training	
\bigcirc	The probability of dropping out a unit in the hidden la	yers during training
\bigcirc	The learning rate for stochastic gradient descent.	
	Which of the following is a technique used for dynamic ergence in deep learning?	adjustment of the learning rate during training to improve
(A)	Adversarial training	(B) Learning rate annealing
(c)	Batch Normalization	(D) Feature Scaling
77. V	What is the purpose of adding noise to the input data as	a form of regularization?
\widehat{A}	To make the training process deterministic	
(B)	To improve model interpretability	
(c)	To reduce the impact of outliers in the input data	
D	To prevent the model from memorizing the training da	ta
78 . Ii	n the context of regularization, what does the term "shri	nkage" refer to?
\bigcirc A	Reducing the size of the input data	
\bigcirc B	Reducing the number of hidden layers in the network	
\bigcirc	Constraining the magnitude of the weights in the mode	el
\bigcirc	Eliminating unnecessary features from the dataset	
79. V	Which of the following statements is true about the drop	out technique?
\bigcirc A	Dropout is more effective in shallow networks than de-	ep networks
\bigcirc B	Dropout can be applied only to input layers	
\bigcirc	Dropout introduces random variations only during test	ting
\bigcirc	Dropout helps prevent co-adaptation of hidden units	
80 . V	What is the primary goal of ensemble methods in machin	ne learning?
\bigcirc A	To reduce the computational complexity of models	
$\stackrel{\smile}{\mathbb{B}}$	To increase the training time of individual models	
(c)	To improve the predictive performance of a model by o	combining multiple models

 \bigcirc To decrease the diversity among base models

81 . Whic	h of the following stat	tements is	true about bagging	(Boot	strap Aggregating)?		
(A) It t	rains multiple models	sequential	ly.				
B It t	rains multiple models	independe	ently on different su	ıbsets	of the training data.		
© It c	combines models using	g a weighte	ed average.				
(D) It is	s not suitable for high	-variance 1	nodels.				
82 . What	is the purpose of rand	dom forest	s in ensemble learn	ing?			
(A) To	create a forest of decis	sion trees	with high correlatio	on			
B To	reduce the number of	trees in th	e ensemble				
\sim		•	<u> </u>		f features for each tree		
(D) To	eliminate the need for	decision t	rees in the ensemb	le			
83 . In bo	osting, how are the we	eights assi	gned to misclassifie	ed inst	ances during training?		
A Equ	ually to all instances						
\sim	pportional to the diffic	•					
\sim	quentially, with higher			tances	3		
	ersely proportional to					_	
	ch ensemble method co ed based on the perfor		-	ase mo	odels by taking a weighte	ed ave	erage, where the weights
(A) Bag	gging	B Stack	ting	(C)	Boosting	\bigcirc	Random Forest
85 . What	is the primary advant	tage of ens	emble methods ove	er indi	vidual base models?		
(A) Ens	semble methods are al	ways faste	r than individual m	nodels			
\sim	semble methods can h	•					
C Ens	semble methods often	generalize	better and have in	nprove	ed robustness.		
D Ens	semble methods are m	ore prone	to overfitting.				
86 . In the	e context of boosting,	what does	the term "weak lear	rner" :	refer to?		
(A) Ar	nodel with high traini	ng accurac	cy				
B Ar	nodel that performs sl	lightly bett	er than random cha	ance			
C Ar	nodel with a large nur	mber of pa	rameters				
(D) Ar	nodel that is highly ov	verfit					
87 . Whic	h ensemble method tr	ains multi _l	ole models indepen	dently	on different subsets of tl	he tra	ining data?
(A) Boo	osting	B Stack	xing	\bigcirc	Bagging	\bigcirc	Random Forest
88 . What	is bagging short for i	n the conte	ext of ensemble me	thods	?		
(A) Boo	otstrap Aggregating	B Boos	ting Algorithm	(C)	Bagged Aggregation	(D)	Batch Aggregation
89 . Whic sor?	h ensemble method is	known for	building a sequenc	ce of w	veak learners, each correc	ting t	the errors of its predeces
(A) Bag	gging	B AdaH	Boost	\bigcirc	Random Forest	\bigcirc	Gradient Boosting

\bigcirc A	Faster training time						
\bigcirc B) Improved generalization and robustness						
(C)) Lower computational complexity						
D	Higher sensitivity to outl	iers					
91. V	Which ensemble method is	based on constructing a fores	t of decision trees with high di	versity?			
\bigcirc	Bagging	B AdaBoost	C Random Forest	(D) Stacking			
92. V	What does the acronym "LS	STM" stand for in the context	of deep learning?				
$\widehat{(A)}$	Long Short-Term Memor	y	(B) Linear Short-Term Memo	ory			
$\overline{\mathbb{C}}$	Limited Short-Term Mem	iory	(D) Lasting Short-Term Men	ıory			
93 . Ir	n boosting, what is the pur	pose of the learning rate para	meter?				
\bigcirc A	It controls the number of	weak learners It adjusts the a	amount by which weights are u	pdated during each iteration			
$\overline{\mathbb{B}}$	It determines the depth o	f decision trees					
\bigcirc	It sets the threshold for fe	eature selection					
94. V	/hat distinguishes Randon	n Forest from traditional bagg	ing techniques?				
\bigcirc A	Random Forest uses a sin	gle decision tree					
\bigcirc B	Random Forest trains mo	dels sequentially					
\bigcirc	Random Forest introduce	es randomness by considering	a random subset of features fo	r each tree			
\bigcirc	Random Forest assigns ed	qual weights to all instances					
95 . H	low does stacking differ fr	om bagging and boosting in e	nsemble methods?				
\bigcirc A	Stacking trains models in	dependently on different sub	sets				
\bigcirc B	Stacking combines predic	ctions using a weighted avera	ge				
(C)	Stacking builds a sequence	ce of weak learners					
(\overline{D})	Stacking uses multiple ba	ase models to form a meta-mo	del				
96. V	hat role does the concept	of "bias-variance tradeoff" pl	ay in ensemble methods?				
\bigcirc A	Ensemble methods elimin	nate the bias-variance tradeof	f				
\bigcirc B		sify the bias-variance tradeoff					
(C)	Ensemble methods help b						
(D)	Ensemble methods have	no impact on bias and varianc	ee				
97. V	hat is the primary limitat	ion of using too many weak l	earners in boosting?				
\bigcirc A	Increased risk of overfitti	ng	(B) Decreased computational	d complexity			
(C)	Improved generalization		(D) Faster training time				
98 . Ir	n bagging, how are the sub	osets of the training data creat	ed for each base model?				
\bigcirc A	Randomly and with repla	cement					
\bigcirc B	Randomly and without re	eplacement					
\bigcirc	Sequentially and with rep	olacement					
\bigcirc	Sequentially and without	replacement					

99. What is the primary advantage of using gradient boosting over traditional AdaBoost?

\bigcirc) Faster convergence			B Better handling of outliers				
(C)	Reduced risk of overfitting			(D) Simplicity in implementation				
100.	Which ensemble method	is prone to becoming compu	itation	ally expensive as the nur	nber of	f models increases?		
\bigcirc	Bagging	B Stacking	(C)	Boosting	\bigcirc	Random Forest		
101.	What does the term "stac	king" refer to in ensemble le	arning	?				
\bigcirc	Combining models using	g a weighted average						
\bigcirc B	Training models independent	ndently on different subsets						
(C)	Constructing a sequence							
(D)	Using multiple base mod	dels to form a meta-model						
102.	Which ensemble method	is known for its ability to ha	ındle b	oth linear and non-linear	r relation	onships in the data?		
A	Bagging	B Stacking	\bigcirc	Random Forest	\bigcirc	Gradient Boosting		
103.	Explain the concept of "o	ut-of-bag" error in the conte	xt of ba	agging.				
\bigcirc	It is the error rate calcul	ated on the training set						
\bigcirc B	It is the error rate on the	e validation set						
(C)		est error obtained from the u						
(D)	It is a measure of the mo	odel's performance on out-of	-distril	oution data				
104.	What is the role of the hy	/perparameter "max depth" i	n decis	ion trees within a Rando	m Fore	est?		
A	It controls the number o	of trees in the forest						
(B)		epth of individual decision t	rees					
(C)	It sets the learning rate to							
(D)	_	signed to misclassified insta				_		
		le methods, what is "early sto				_		
(A)	Early stopping involves simplicity.	terminating the training pr	rocess	when the model is unde	erfittin	g, contributing to model		
$\widehat{\text{B}}$		overfitting by stopping the t	raining	process when the mode	l starts	to memorize the training		
	data.	everified by stopping the s		process when the mode.		to memorate une transmig		
\bigcirc	Early stopping introduce	es noise to the input data du	ring tra	ining, preventing overfi	tting.			
D	Early stopping is not rel	ated to regularization in ens	emble i	nethods.				
106.	What is the impact of inc	creasing the number of base i	nodels	on the computational co	mplex	ity of stacking?		
\bigcirc	The computational comp	plexity decreases linearly						
\bigcirc B	_	plexity increases linearly						
(C)		plexity remains constant						
(D)	The computational comp	plexity depends on the type	of base	models used				
107 .	Explain the concept of "a	dversarial training" in the co	ntext o	f ensemble methods.				
$\stackrel{\frown}{\bigcirc}$		olves training models to be r			ζS.			
(B)		uses on maximizing the accu	•	· ·				
(C)	Adversarial training elin	ninates the need for ensembl	le meth	ods.				

(D) Adversarial training refers to using adversarial examples as additional training data.

$\overline{\mathbb{C}}$	It increases the depth of individual base models.			
\bigcirc	It has no impact on the risk of overfitting.			
109.	What is the primary drawback of using a high learning	ate i	e in boosting algorithms?	
(A)	Slower convergence	(B)	B) Increased risk of overfitting	
$\widetilde{\mathbb{C}}$	Decreased model performance	\bigcirc) Improved generalization	
110.	Explain the concept of "feature importance" in the conte	xt of	of Random Forest.	
(A)	Feature importance represents the number of times a fe	atur	cure is selected by a base model.	
\mathbf{B}	Feature importance indicates the relevance of a feature	in p	predicting the target variable.	
$\overline{\mathbb{C}}$	Feature importance is not applicable to ensemble metho	ods.	S.	
D	Feature importance measures the computational cost of	f usii	sing a specific feature.	
111 . Boos	· · · ·	in e	ensemble methods such as Random Forest and Gradien	1t
$\widehat{(A)}$	It controls the learning rate in boosting algorithms.			
(B)	It sets the maximum depth of individual decision trees.			
$\widetilde{\mathbb{C}}$	It specifies the number of base models in the ensemble.			
D	It determines the subset of features considered for each	base	ase model.	
112.	Explain the concept of "stacking with meta-features" in	the c	e context of ensemble methods.	
\bigcirc A	Stacking with meta-features involves using the output	of ba	base models as features for a meta-model.	
$\widetilde{\mathbb{B}}$	Stacking with meta-features eliminates the need for mu	ıltipl	iple base models.	
\bigcirc	Stacking with meta-features refers to combining model	s usi	ısing a weighted average.	
\bigcirc	Stacking with meta-features involves using only one ty	pe o	of base model in the ensemble.	
113.	What is Dropout in the context of neural networks?			
\bigcirc	Adding noise to input features			
\bigcirc B	Removing random neurons during training			
(C)	Reducing the learning rate			
\bigcirc	Increasing the number of hidden layers			
114.	What is the main purpose of Dropout in neural network	s?		
\bigcirc	To increase overfitting			
$\overline{\mathbb{B}}$	To speed up the training process			
(C)	To prevent co-adaptation of neurons			
\bigcirc	To eliminate the need for activation functions			
115.	Which of the following statements is true about the app	licati	ation of Dropout during training?	
\bigcirc A	Dropout is only applied to input layers			
$\widetilde{\mathbb{B}}$	Dropout is applied to all layers except the output layer			
$\widetilde{\mathbb{C}}$	Dropout is applied during both training and testing			
$\overline{(D)}$	Dropout is never applied to neural networks			

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

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

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

\bigcirc A	By increasing the number of parameters								
\bigcirc B	By introducing noise to	By introducing noise to the input data							
\bigcirc	By reducing the model's	By reducing the model's capacity							
\bigcirc	By promoting co-adaptation of neurons								
117 .]	In terms of training, what	does it mean if a neuron is "d	ropped out"?						
\bigcirc	The neuron's weights ar	e set to zero							
\bigcirc B	The neuron is removed f	from the network temporarily							
\bigcirc	The neuron's activation	function is bypassed							
\bigcirc	The neuron's output is s	quared							
118.	What challenge does Dro	pout aim to address in neural	networks?						
\bigcirc	Underfitting	(B) Overfitting	© Vanishing gradients	(D) Exploding gradients					
119.	How does Dropout affect	the training time of a neural r	network?						
\bigcirc A	Slows down the training	process							
\bigcirc B	Speeds up the training p	rocess							
\bigcirc	No impact on training ti	me							
\bigcirc	Depends on the type of a	activation function used							
120.	What is the recommended	d range for Dropout rates in n	eural networks?						
\bigcirc	0.0 to 0.1	B 0.2 to 0.5	© 0.5 to 0.8	① 0.9 to 1.0					
121 .]	How does Dropout contri	bute to model generalization?							
\bigcirc A	By memorizing the train	ing data							
$\overline{\mathbb{B}}$	By promoting co-adapta	tion of neurons							
\bigcirc	By reducing the sensitive	ity of neurons to specific inpu	t features						
\bigcirc	By increasing the number	er of hidden layers							
122 . `	When applying Dropout,	which phase is used for adjust	ting the weights of the neural r	network?					
\bigcirc	Training phase								
\bigcirc	Testing phase								
(C)	Both training and testing	g phases							
D	Neither training nor test	ing phases							
123.	Explain the term "co-adap	otation of neurons" in the cont	ext of neural networks and ho	w 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.								
\bigcirc B	Co-adaptation is a form	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 unrelat	ed to Dropout; Dropout only a	affects the learning rate.						

116. How does Dropout contribute to regularization in neural networks?

124. 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							
\bigcirc B	Dropout is more effective in large and complex networks							
\bigcirc	Dropout is equally effective across all network sizes and complexities							
D	Dropout is irrelevant to network size and complexity							
125.	What is the relationship b	etween Dropout and the conc	ept of ensemble learning?					
\bigcirc A	Dropout is a type of ense	mble learning						
\bigcirc B	Ensemble learning and Dropout are unrelated concepts							
\bigcirc	Dropout and ensemble learning achieve the same result in terms of model diversity							
D	Dropout eliminates the n	eed for ensemble learning						
126 .]	126. Explain the trade-off between using a high Dropout rate and a low Dropout rate in neural networks.							
A	High Dropout rates lead	to overfitting, while low Drop	out rates may result in underfi	ìtting.				
B	High Dropout rates alwa	ys improve model generalizat	ion, while low Dropout rates re	educe	model capacity.			
<u>C</u>	There is no trade-off; the Dropout rate does not impact model performance.							
(D)	The trade-off depends on	the type of activation function	on used in the network.					
127 .]	How does Dropout contril	oute to mitigating the vanishing	ng gradient problem in deep no	eural	networks?			
A	A) a. By increasing the learning rate							
\bigcirc B	By preventing co-adaptat	tion of neurons						
(C)	By introducing noise to t	he input data						
(D)	By reducing the sensitivi	ty of neurons to specific input	t features					
128.	What is the primary goal	of data augmentation in mach	ine learning?					
A	To decrease the size of th	e dataset						
\bigcirc B	To increase the computat	ional complexity						
(C)	To improve model performance by increasing the diversity of the training data							
(D)	To eliminate the need for validation data							
129.	Which of the following is	a common technique used in	data augmentation for image d	lata?				
$\widehat{(A)}$	Principal Component An	alysis (PCA)	(B) Feature scaling					
(c)	Image rotation	•	(D) Lasso regularization					
130 .]	130. How does data augmentation contribute to preventing overfitting in machine learning models?							
$\widehat{(A)}$	(A) By reducing the size of the training dataset							
(B)								
$\stackrel{\smile}{(C)}$	C By introducing noise to the input data							
$\stackrel{\smile}{\mathbb{D}}$	(D) By providing a more diverse set of training examples							
131. In text data augmentation, what technique involves replacing words with their synonyms?								
\bigcirc A	Tokenization	B Embedding	© Word substitution	\bigcirc	Lemmatization			
132. Which of the following is a disadvantage of data augmentation?								

$\widehat{(A)}$	Increased model generalization							
(B)	Potential introduction of unrealistic patterns							
$\widetilde{\mathbb{C}}$	Improved model robustness							
\bigcirc	Decreased computational efficiency							
133.	What is the purpose of random cropping in image data a	ugm	entation?					
\bigcirc A	To decrease the image resolution							
\bigcirc	To remove irrelevant features from the image							
\bigcirc	To create variations in the spatial location of objects							
\bigcirc	To increase the image contrast							
134.	Which type of data augmentation is commonly used for	time	series data?					
\bigcirc	Image rotation (B) Time warping	\bigcirc	Word substitution	\bigcirc	Feature scaling			
135.	Explain the concept of "jittering" in the context of data a	ugm	entation.					
\bigcirc	Jittering refers to the introduction of noise to input feat	tures						
\bigcirc	Jittering involves the random selection of a subset of da	ata po	oints					
\bigcirc	Jittering is a synonym for image rotation							
D	Jittering is irrelevant to data augmentation							
136.	In the context of image data augmentation, what is the p	ourpo	ose of horizontal flipping	?				
\bigcirc	To rotate images clockwise	\bigcirc	To create mirror images					
\bigcirc	To adjust the image brightness	$\bigcirc\!$	To resize images					
137.	How does data augmentation differ from feature engined	ering	?					
\bigcirc	Data augmentation focuses on creating new samples, w	hile	feature engineering man	ipulat	es existing features.			
\bigcirc	Feature engineering is limited to image data, while data	a aug	mentation is applicable t	o all d	lata types.			
\bigcirc	Data augmentation involves scaling features, while feature engineering involves randomization.							
(D)	D Feature engineering and data augmentation are synonymous terms.							
138.	What is the role of dropout in the context of data augme	ntati	on?					
\bigcirc	Dropout is not related to data augmentation							
\bigcirc	B Dropout enhances data augmentation by randomly removing features during training							
(C)	Dropout is a type of data augmentation technique							
D	Dropout prevents data augmentation from introducing unrealistic patterns							
139.	Which data augmentation technique is commonly used	for a	ıdio data to introduce va	riation	ns in pitch?			
\bigcirc	Time warping	\bigcirc B	Spectrogram augmentat	ion				
(C)	Random cropping	D	Jittering					
140.	What is the purpose of elastic deformation in image data	a aug	mentation?					
\bigcirc	To adjust the image contrast							
\bigcirc	B To introduce non-linear distortions to the image							
\bigcirc	To resize the image							
\bigcirc	To rotate the image							

\bigcirc	Sentence splitting
\bigcirc	Sentence dropout
142.	Explain the concept of "adversarial training" in the context of data augmentation and how it addresses robustness.
A	Adversarial training focuses on creating adversarial examples to test the model's robustness against unseen patterns introduced by data augmentation.
\bigcirc B	Adversarial training is irrelevant to data augmentation.
\bigcirc	Adversarial training involves increasing the size of the training set.
\bigcirc	Adversarial training enhances data augmentation by introducing adversarial noise during the augmentation process
143.	How does data augmentation contribute to handling class imbalance in classification tasks?
\bigcirc A	Data augmentation exacerbates class imbalance
\bigcirc B	Data augmentation is not related to class imbalance
\bigcirc	Data augmentation generates additional samples for minority classes, addressing class imbalance
\bigcirc	Data augmentation reduces the need for addressing class imbalance
144.	What challenges might arise when applying data augmentation to non-image data types, such as tabular data?
\bigcirc A	Difficulty in implementing data augmentation for non-image data
\bigcirc B	Limited applicability of data augmentation to non-image data
\bigcirc	The potential introduction of unrealistic patterns
\bigcirc	No challenges; data augmentation is equally effective for all data types
	Explain the term "mixup" in the context of data augmentation and how it differs from traditional augmentation aiques.
\bigcirc A	Mixup involves blending two or more samples, creating new synthetic samples with averaged labels.
\bigcirc B	Mixup is a synonym for image rotation.
\bigcirc	Mixup refers to the addition of random noise to input features.
\bigcirc	Mixup is irrelevant to data augmentation.
146.	How does data augmentation impact the interpretability of machine learning models?
\bigcirc A	Data augmentation improves model interpretability by providing more diverse training examples.
$\stackrel{\circ}{\mathbb{B}}$	Data augmentation has no impact on model interpretability.
\bigcirc	Data augmentation reduces model interpretability due to the introduction of synthetic samples.
\bigcirc	Data augmentation improves model interpretability by eliminating the need for validation data.
147.	What is the role of "cutout" in image data augmentation?
\bigcirc A	To remove random portions from images
$\stackrel{\smile}{\mathbb{B}}$	To blur the edges of images
<u>C</u>	To rotate images
\bigcirc	To resize images

141. In natural language processing, which technique involves randomly removing words from sentences during data

augmentation?

(A) Tokenization

B Word substitution

148 . In the context of data augmentation, explain how the technique of "shearing" is applied to image data.							
\bigcirc A	A Shearing involves adjusting the brightness of images.						
\bigcirc B	B Shearing is irrelevant to data augmentation.						
(C)	© Shearing introduces non-linear distortions to the image by tilting it along one of its axes.						
D	Shearing is a synonym for image rotation.						
149. Which ensemble learning algorithm can be applied to both regression and classification tasks?							
\bigcirc A	Bagging	B AdaBoost	(C)	Random Forest	\bigcirc	Stacking	
150 . Ensemble learning algorithms can be computationally expensive when:							
(A) The dataset is small			(B) The base models are simple				
\bigcirc	The ensemble size is sma	ıll	(D)	The dataset is large			
151. Which ensemble learning algorithm can be used to identify important features in a dataset?							
A	Bagging	B AdaBoost	(C)	Gradient Boosting	D	Stacking	

Solutions to the Exercises

- **1**.(**B**) L1
- 2.(B) Trains multiple models on different subsets of the data
- 3.(C) Both (A) and (B)
- **4.(A)** Shallow neural network
- 5.(B) unstructured data
- **6.(C)** convolutional neural networks
- 7.(**D**) All of the above
- **8.(C)** Constructs an ensemble by iteratively updating weights
- **9**.(**E**) All of the previous
- 10.(C) Random Forest
- 11.(B) Boosting algorithm
- 12.(C) Constructs an ensemble by iteratively updating weights
- 13.(B) Boosting algorithm
- **14.(D)** Trains a meta-model to make predictions based on outputs of base models
- 15.(A) Random Forest
- **16**.(**A**) Reduce overfitting and improve generalization
- 17.(A) Handling imbalanced datasets
- 18.(A) AdaBoost
- 19.(C) Random Forest
- 20.(B) Boosting
- 21.(C) Gradient Boosting
- 22.(B) The dataset is large and high-dimensional
- 23.(B) Reducing variance
- 24.(C) Graident Boosting
- 25.(C) Random Forest
- 26.(B) Combining predictions by taking the mode of their classes
- 27.(A) Bagging
- 28.(A) Improving model stability
- 29.(C) Graident Boosting
- **30**.(C) Handling unbalanced datasets
- 31.(A) Bagging
- 32.(C) Random Forest
- 33.(B) AdaBoost
- **34**.(**C**) Gradient Boosting
- **35**.(**B**) False
- **36**.(**D**) All of the previous
- 37.(A) Softmax
- 38.(A) Weight between input and hidden layer
- **39**.(**C**) 96
- **40.(C)** 22×22
- **41**.(**A**) 50
- **42**.**(D)** all of the previous
- 43.(D) 41%
- **44**.(**D**) All of the above
- **45**.(**D**) all of the previous
- 46.(C) ReLU
- **47**.(**A**) True

- **48**.(E) All of the previous
- **49**.(**A**) True
- **50**.(**B**) False
- **51**.(**B**) False
- **52**.(**D**) all of the previous
- **53**.(**D**) All of the above
- **54**.(**A**) True
- **55**.(**B**) False
- **56**.(**C**) to prevent overfitting
- 57.(A) L1 regularization
- **58**.(**C**) small weight values
- 59.(B) It randomly drops entire layers during training
- **60**.(**C**) Elastic Net
- 61.(B) To prevent the model from memorizing the training data
- **62**.(**C**) Regularization can help balance bias and variance
- **63**.(**B**) The gradual decrease in weight values during training
- **64**.(**D**) Reduced capacity to capture complex patterns
- **65**.(**A**) A regularization technique (such as L2 regularization) that results in gradient descent shrinking the weights on every iteration.
- 66.(A) 98% train. 1% dev. 1% test
- **67**.(**A**) Come from the same distribution
- 68.(B) Get more training data
- (E) Add regularization
- 69.(A) Increase the regularization parameter lambda
- (C) get more training data
- **70**.(**A**) Weights are pushed twoard becoming smaller (closer to 0)
- **71**.(**B**) You don't apply dropout (do not randomly eliminate units) and do not keep the 1/keep_prob factor in the calculations usd in the training
- 72.(A) Dropout
- (C) Data augmentation
- (F) L2 regularization
- 73.(B) It makes the cost function faster to optimize
- 74.(C) Regulates the softness of the target distribution
- **75.**(C) The probability of dropping out a unit in the hidden layers during training
- **76**.(**B**) Learning rate annealing
- 77.(C) To reduce the impact of outliers in the input data
- 78.(C) Constraining the magnitude of the weights in the model
- 79.(D) Dropout helps prevent co-adaptation of hidden units
- **80**.(C) To improve the predictive performance of a model by combining multiple models
- **81**.(**B**) It trains multiple models independently on different subsets of the training data.
- **82**.(C) To introduce randomness by considering a random subset of features for each tree
- **83.**(C) Sequentially, with higher weights for misclassified instances
- 84.(B) Stacking

85.(C) Ensemble methods often generalize better and have improved robustness.

86.(**B**) A model that performs slightly better than random chance

87.(C) Bagging

88.(**A**) Bootstrap Aggregating

89.(B) AdaBoost

90.(B) Improved generalization and robustness

91.(**C**) Random Forest

92.(**A**) Long Short-Term Memory

93.(**A**) It adjusts the amount by which weights are updated during each iteration

94.(C) Random Forest introduces randomness by considering a random subset of features for each tree

95.(D) Stacking uses multiple base models to form a metamodel

96.(C) Ensemble methods help balance bias and variance

97.(A) Increased risk of overfitting

98.(A) Randomly and with replacement

99.(B) Better handling of outliers

100.(**C**) Boosting

101.(**D**) Using multiple base models to form a meta-model

102.(**C**) Random Forest

103.(C) It is an estimate of the test error obtained from the unused samples during training

104.(B) It limits the maximum depth of individual decision trees

105.(B) Early stopping prevents overfitting by stopping the training process when the model starts to memorize the training data.

106.(**B**) The computational complexity increases linearly

107.(**A**) Adversarial training involves training models to be robust against adversarial attacks.

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

109.(B) Increased risk of overfitting

110.(**B**) Feature importance indicates the relevance of a feature in predicting the target variable.

111.(C) It specifies the number of base models in the ensemble.

112.(**A**) Stacking with meta-features involves using the output of base models as features for a meta-model.

113.(B) Removing random neurons during training

114.(**C**) To prevent co-adaptation of neurons

115.(B) Dropout is applied to all layers except the output layer

116.(**C**) By reducing the model's capacity

117.(**B**) The neuron is removed from the network temporarily

118.(**B**) Overfitting

119.(A) Slows down the training process

120.(**B**) 0.2 to 0.5

121.(**C**) By reducing the sensitivity of neurons to specific input features

122.(**A**) Training phase

123.(**A**) Co-adaptation refers to neurons relying too much on each other, and Dropout breaks these dependencies by randomly dropping neurons during training.

124.(**B**) Dropout is more effective in large and complex networks

125.(C) Dropout and ensemble learning achieve the same result in terms of model diversity

126.(A) High Dropout rates lead to overfitting, while low Dropout rates may result in underfitting.

127.(C) By introducing noise to the input data

128.(C) To improve model performance by increasing the diversity of the training data

129.(C) Image rotation

130.(D) By providing a more diverse set of training examples

131.(**C**) Word substitution

132.(B) Potential introduction of unrealistic patterns

133.(**C**) To create variations in the spatial location of objects

134.(**B**) Time warping

135.(**A**) Jittering refers to the introduction of noise to input features

136.(**B**) To create mirror images

137.(**A**) Data augmentation focuses on creating new samples, while feature engineering manipulates existing features.

138.(**B**) Dropout enhances data augmentation by randomly removing features during training

139.(**B**) Spectrogram augmentation

140.(B) To introduce non-linear distortions to the image

141.(**D**) Sentence dropout

142.(**A**) Adversarial training focuses on creating adversarial examples to test the model's robustness against unseen patterns introduced by data augmentation.

143.(**C**) Data augmentation generates additional samples for minority classes, addressing class imbalance

144.(**C**) The potential introduction of unrealistic patterns

145.(**A**) Mixup involves blending two or more samples, creating new synthetic samples with averaged labels.

146.(C) Data augmentation reduces model interpretability due to the introduction of synthetic samples.

147.(**A**) To remove random portions from images

148.(C) Shearing introduces non-linear distortions to the image by tilting it along one of its axes.

149.(**C**) Random Forest

150.(D) The dataset is large

151.(**C**) Gradient Boosting