SUPPLEMENTARY MATERIALS

Note: We provide detailed figures for multi-aspect logit distillation in Section A, implementation and dataset details in Section B, additional ablation study results in Section C, further details on the visualization of the logit distribution in Section D, and computational cost analyses in Section E, which were not included in the main paper due to space limitations.

A DETAILS OF MULTI-ASPECT LOGIT DISTILLATION

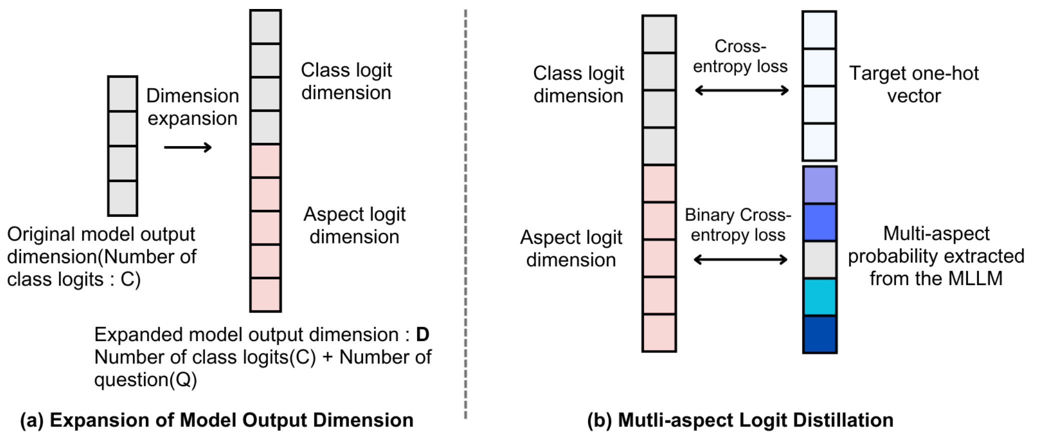


Figure 1: **Multi-aspect knowledge distillation.** To distill knowledge about multi-aspect questions into the model, we simply expand the dimension of model output. Also, we consider the expanded dimensions as the class logit dimension and the aspect logit dimension. We apply cross-entropy loss to the class logit dimension and binary cross-entropy loss to the aspect logit dimension.

B IMPLEMENTATION DETAILS

B.1 DATASET DETAILS

StanfordCars Krause et al. (2013). StanfordCars contains 16,185 images of 196 classes of cars. The data is split into 8,144 training images and 8,041 testing images, where each class has been split roughly in a 50-50 split. Classes are typically at the level of Make, Model, Year, ex. 2012 Tesla Model S or 2012 BMW M3 coupe.

OxfordPets Parkhi et al. (2012). OxfordPets comprises 7,384 images of 37 distinct cat and dog breeds, with around 200 images per class. It is divided into 3,690 images for training and 3,694 images for testing. The dataset features significant variations in scale, pose, lighting, and others.

Describable Textures Dataset (DTD) Cimpoi et al. (2014). DTD consists of 47 texture classes and a total of 5,640 images. It is divided into 3,760 images for training and 1,880 for testing, with each class containing 120 images. The image sizes range from 300x300 to 640x640 pixels, and each image contains at least 90% of the surface area representing the category's attribute.

102Flowers Nilsback & Zisserman (2008). 102Flowers is designed for image classification, featuring 102 different flower classes. It is divided into 6,552 training images and 1,637 testing images. Each class includes between 40 and 258 images, with significant variations in scale, pose, and lighting conditions across the images.

CUB200 Wah et al. (2011). CUB200 is one of the most commonly used datasets for fine-grained visual categorization tasks. It comprises 11,788 images across 200 bird subcategories, with 5,994 images for training and 5,794 for testing. Each image has detailed annotations, including 1 subcategory label, 15 part locations, 312 binary attributes, and 1 bounding box.

FGVC-Aircraft Maji et al. (2013). FGVC-Aircraft consists of 9,967 aircraft images, with around 100 images corresponding to each of the 100 different model variants, the majority being airplanes. The dataset is divided into 6,667 images for training and 3,300 for testing. Each image includes annotations with a tight bounding box and a hierarchical label for the airplane model. The aircraft models are arranged in a four-level hierarchical structure.

Caltech101 Fei-Fei et al. (2004). Caltech101 includes images from 101 object categories, along with a background category consisting of images unrelated to those 101 categories. To focus purely on class classification, we exclude the background category. The dataset is divided into 4,310 images for training and 4,367 images for testing. Each category contains between 40 and 800 images, with most classes having approximately 50 images. The image resolution is roughly 300×200 pixels.

Mini-ImageNet Ravi & Larochelle (2016). Mini-ImageNet is a reduced version of the larger ImageNet Deng et al. (2009) dataset, specifically designed for few-shot learning tasks. It consists of 50,000 training images and 10,000 testing images distributed across 100 classes. Additionally, to use a higher resolution, we utilize the dataset from Ravi & Larochelle (2016).

Microsoft Common Objects in Context (MS-COCO) Lin et al. (2014). MS-COCO is a large-scale object detection, segmentation, key-point detection, and captioning dataset. The dataset consists of 328K images. We use the MS-COCO dataset's 2017 version, which consists of a training/validation split of 118K/5K images.

B.2 Training Details

For the image classification experiments, we employed baseline models such as ResNet18, ResNet34, MobileNet-V1, and EfficientNet-b0 across various fine-grained datasets, including StanfordCars, OxfordPets, DTD, 102Flowers, CUB200, and FGVC-Aircraft, as well as coarse-grained datasets such as Caltech101 and Mini-ImageNet.

Data preprocessing. Input images were normalized using the channel-wise mean (0.485, 0.456, 0.406) and standard deviation (0.229, 0.224, 0.225) for RGB channels. For training, we applied a series of transformations: RandomResizedCrop with a target size of 224, followed by RandomHorizontalFlip, conversion to tensor using ToTensor, and normalization.

Hyperparameters for fine-grained datasets. The models were trained for 240 epochs with a batch size of 16. The initial learning rate was set to 0.01 and decreased by a factor of 10 at the 150th, 180th, and 210th epochs. We use the SGD optimizer with a momentum of 0.9 for all experiments, and weight decay is set to 5e-4.

Hyperparameters for Caltech101 dataset. The models were trained for 240 epochs with a batch size of 16. The initial learning rate was set to 0.01 and decreased by a factor of 10 at the 150th, 180th, and 210th epochs. We use the SGD optimizer with a momentum of 0.9 for all experiments, and weight decay is set to 5e-4.

Hyperparameters for Mini-ImageNet dataset. The models were trained for 100 epochs with a batch size of 64. The initial learning rate was set to 0.2 and decreased by a factor of 10 at the 30th, 60th, and 90th epochs. We use the SGD optimizer with a momentum of 0.9 for all experiments, and weight decay is set to 5e-4.

B.3 Multi-aspect Question Samples

Table 8, 9, 10, 11, 12, 13, 14, and 15 present the multi-aspect questions generated by GPT-4o for the StanfordCars, OxfordPets, DTD, 102Flowers, CUB200, FGVC-Aircraft, Caltech101, and Mini-ImageNet datasets, respectively. Meanwhile, Table 16, 17, and 18 show the multi-aspect questions generated by GPT-3.5-turbo for the StanfordCars, OxfordPets, and Caltech101 datasets, respectively.

B.4 details of Logit Distillation with MLLM

We also include how MLLM distills logit to student model, as described in Section 4.4 and 5.1 of the main paper.

In traditional knowledge distillation, the teacher model typically outputs soft targets as a probability distribution over classes. The student model is then trained based on the KL divergence loss between the soft targets and the student's predicted target logits, as well as the cross-entropy loss with the actual hard targets. To enable MLLM to perform logit distillation, we make the following assumption:

'*Could the logits generated for both the predicted class index token and the remaining class index token logits during zero-shot classification be considered soft targets?*'

In this assumption, since MLLM receives information about the range of possible answers through prompts, it restricts the range of tokens generated. Given a first logit vector $\mathbf{z} \in \mathbb{R}^V$, where V is the vocabulary size of tokenizer, the logits corresponding to the numerical tokens are indexed by the set $\mathcal{N} \subseteq \{1, 2, \ldots, C\}$. The softmax function applied to the logits of the numerical tokens within a specified range $[1, C]$ is given by:

$$P(t \mid 1 \leq t \leq C) = \frac{\exp(z_t)}{\sum_{n \in \mathcal{N}, 1 \leq n \leq C} \exp(z_n)} \quad \text{for} \quad t \in \mathcal{N}, 1 \leq t \leq C$$

where z_t is the logit corresponding to token t and the sum in the denominator is computed over all numerical tokens n in the range $[1, C]$. This can be interpreted as MLLM producing a probability distribution for classifying specific classes, allowing it to generate soft targets as a teacher model. These generated soft targets can be used for training in the same way as in traditional knowledge distillation, as they remain unchanged while the student model is being trained.

C ADDITIONAL ABLATION STUDY RESULTS

In this section, we provide the additional ablation results for the OxfordPets fine-grained dataset and Caltech101 coarse-grained dataset. The additional ablation study results are presented in Table 1 and 2, showing the outcomes for the OxfordPets and Caltech101 datasets, respectively. Table 3 displays the results of the extension to logit distillation on the OxfordPets dataset.

Table 1: **Additional Ablation study on OxfordPets.** Each table reports the accuracy(%) on OxfordPets. Res18 for ResNet18, Res34 for ResNet34, Mb-N1 for MobileNetV1 and EffiNet for EfficientNet-b0. Rand for our method with random logits instead of multi-aspect logits. KL for our method with KL-Divergence loss on multi-aspect logit. α for the weighting factor of multi-aspect logit loss. We run each experiment 3 times and report the average results.

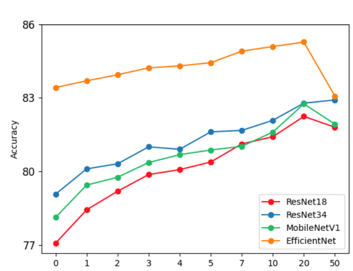
(a) Effect of the loss function

	Res18	Res34	Mb-N1	EffiNet
KL	75.96	79.52	79.71	83.92
Ours	**82.24**	**82.78**	**82.75**	**85.27**

(b) Effect of the multi-aspect logit

	Res18	Res34	Mb-N1	EffiNet
Rand	78.64	79.17	77.70	83.23
Ours	**82.24**	**82.78**	**82.75**	**85.27**

(c) Weights to the multi-aspect loss



(d) Effect of LLM and MLLM

	Res18	Res34	Mb-N1	EffiNet
Base	77.07	79.07	78.12	83.42
Ours(L: GPT-3.5)	82.72	**83.08**	82.66	85.22
Ours(M: LLaVA)	**82.94**	83.04	**82.94**	85.19
Ours	82.24	82.78	82.75	**85.27**

D ADDITIONAL DETAILS OF VISUALIZATION (HISTOGRAM, T-SNE AND ERROR BAR)

In this section, we provide additional visualizations for our analysis, including error bars for the experimental results on each dataset, visualization of the average logit distribution, visualization of

Table 2: **Additional Ablation study on Caltech101.** Each table reports the accuracy(%) on Caltech101. Res18 for ResNet18, Res34 for ResNet34, Mb-N1 for MobileNetV1 and EffiNet for EfficientNet-b0. Rand for our method with random logits instead of multi-aspect logits. KL for our method with KL-Divergence loss on multi-aspect logit. α for the weighting factor of multi-aspect logit loss. We run each experiment 3 times and report the average results.

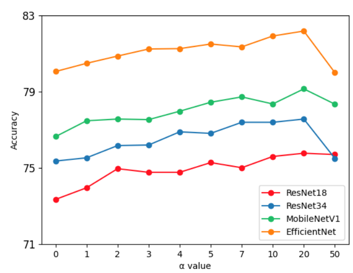
(a) Effect of the loss function

	Res18	Res34	Mb-N1	EffiNet
KL	75.10	74.74	77.67	80.73
Ours	**75.77**	**77.56**	**79.14**	**82.17**

(b) Effect of the multi-aspect logit

	Res18	Res34	Mb-N1	EffiNet
Rand	73.90	74.94	76.64	79.80
Ours	**75.77**	**77.56**	**79.14**	**82.17**

(c) Weights to the multi-aspect loss



(d) Effect of LLM and MLLM

	Res18	Res34	Mb-N1	EffiNet
Base	73.35	75.36	76.64	80.05
Ours(L: GPT-3.5)	**76.16**	76.78	79.13	81.95
Ours(M: LLaVA)	76.02	77.46	78.81	81.65
Ours	75.77	**77.56**	**79.14**	**82.17**

Table 3: **Extension to logit distillation on OxfordPets.** We can simply extend our method to logit distillation. We run each experiment three times and report the average results.

	Teacher	ResNet34(79.07)	EfficientNet-b0(83.42)
Dataset	Student	ResNet18(77.07)	MobileNetV1(78.12)
OxfordPets	KD	79.01	80.90
	Ours + KD	**82.68**	**83.13**

t-SNE embedding, and visualizations of the probability values between the MLLM and the classification model for the multi-aspect questions.

Error bar. To help in evaluating the quality of the experiments, we include error bars representing the standard error for the conducted experiments. The error bars for the StanfordCars, OxfordPets, DTD, 102Flowers, CUB200, FGVC-Aircraft, Caltech101, and Mini-ImageNet datasets are presented in Figure 2. We run each experiment 3 times and report the average results.

Visualization of the average logit distribution. We provide the average logit distribution for all aspects of the datasets. The visualizations of the average logit distribution graphs for the StanfordCars, OxfordPets, DTD, 102Flowers, CUB200, FGVC-Aircraft, Caltech101, and Mini-ImageNet datasets are shown in Figure 3, 4, 5, 6, 7, 8, 9, and 10, respectively.

Visualization of t-SNE embeddings. We use t-SNE to reduce the dimensionality of the predicted aspect logit probabilities from our ResNet18 and the MLLM's aspect logit probabilities to better visualize the results. For each dataset, we display the train and test results across 50 aspects. Yellow points represent a higher probability of 'Yes' (closer to 1), while purple points represent a higher probability of 'Yes' (closer to 0). The ground-truth and predicted result t-SNE embedding visualizations for the training data from the StanfordCars, OxfordPets, DTD, 102Flowers, CUB200, FGVC-Aircraft, Caltech101, and Mini-ImageNet datasets are shown in Figure 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, and 26.

E Details of computational costs

We calculate the computational cost on StanfordCars and OxfordPets using a single NVIDIA RTX 3090 GPU. Training refers to the average of three experiments and represents the number of seconds taken per epoch. Inference indicates the number of seconds required to process all test sets. Table 4 shows that even with the extension of our method, there is no significant difference in time.

StanfordCars						
	ResNet18			ResNet34		
Aspect	**Training**	**Inference**	**FLOPs**	**Training**	**Inference**	**FLOPs**
0	25.418	20.5869	58.1873G	60.416	51.6867	117.4380G
10	25.916	21.0294	58.1875G	60.639	51.8848	117.4382G
20	26.411	21.4692	58.1877G	60.861	52.0821	117.4384G
30	26.910	21.9126	58.1878G	61.233	52.4127	117.4386G
50	27.903	22.7951	58.1882G	61.529	52.6757	117.4389G
OxfordPets						
	ResNet18			**ResNet34**		
Aspect	**Training**	**Inference**	**FLOPs**	**Training**	**Inference**	**FLOPs**
0	11.522	9.3810	24.0335G	16.169	12.5678	48.5060G
10	11.772	9.6062	24.0337G	16.520	12.8841	48.5062G
20	12.022	9.8315	24.0338G	16.871	13.2003	48.5064G
30	12.311	9.0919	24.0340G	17.277	13.5661	48.5066G
50	12.825	10.5550	24.0344G	17.998	14.2157	48.5069G

Table 4: **The computational cost.**

Table 5: **Dataset class indices.** We provide the class indices for DTD, 102Flowers, and FGVC-Aircraft, which have 47, 102, and 100 classes, respectively.

Index	DTD Class	102Flowers Class	FGVC-Aircraft Class
0	banded	alpine_sea_holly	707-320
1	blotchy	anthurium	727-200
2	braided	artichoke	737-200
3	bubbly	azalea	737-300
4	bumpy	ball_moss	737-400
5	chequered	balloon_flower	737-500
6	cobwebbed	barbeton_daisy	737-600
7	cracked	bearded_iris	737-700
8	crosshatched	bee_balm	737-800
9	crystalline	bird_of_paradise	737-900
10	dotted	bishop_of_llandaff	747-100
11	fibrous	black-eyed_susan	747-200
12	flecked	blackberry_lily	747-300
13	freckled	blanket_flower	747-400
14	frilly	bolero_deep_blue	757-200
15	gauzy	bougainvillea	757-300
16	grid	bromelia	767-200
17	grooved	buttercup	767-300
18	honeycombed	californian_poppy	767-400
19	interlaced	camellia	777-200
20	knitted	canna_lily	777-300
21	lacelike	canterbury_bells	A300B4
22	lined	cape_flower	A310
23	marbled	carnation	A318
24	matted	cautleya_spicata	A319
25	meshed	clematis	A320
26	paisley	coltsfoot	A321
27	perforated	columbine	A330-200
28	pitted	common_dandelion	A330-300
29	pleated	corn_poppy	A340-200
30	polka-dotted	cyclamen	A340-300
31	porous	daffodil	A340-500

Index	DTD Class	102Flowers Class	FGVC-Aircraft Class
32	potholed	desert-rose	A340-600
33	scaly	english_marigold	A380
34	smeared	fire_lily	ATR-42
35	spiralled	foxglove	ATR-72
36	sprinkled	frangipani	An-12
37	stained	fritillary	BAE-125
38	stratified	garden_phlox	BAE_146-200
39	striped	gaura	BAE_146-300
40	studded	gazania	Beechcraft_1900
41	swirly	geranium	Boeing_717
42	veined	giant_white_arum_lily	C-130
43	waffled	globe-flower	C-47
44	woven	globe_thistle	CRJ-200
45	wrinkled	grape_hyacinth	CRJ-700
46	zigzagged	great_masterwort	CRJ-900
47		hard-leaved_pocket_orchid	Cessna_172
48		hibiscus	Cessna_208
49		hippeastrum	Cessna_525
50		japanese_anemone	Cessna_560
51		king_protea	Challenger_600
52		lenten_rose	DC-10
53		lotus_lotus	DC-3
54		love_in_the_mist	DC-6
55		magnolia	DC-8
56		mallow	DC-9-30
57		marigold	DH-82
58		mexican_aster	DHC-1
59		mexican_petunia	DHC-6
60		monkshood	DHC-8-100
61		moon_orchid	DHC-8-300
62		morning_glory	DR-400
63		orange_dahlia	Dornier_328
64		osteospermum	E-170
65		oxeye_daisy	E-190
66		passion_flower	E-195
67		pelargonium	EMB-120
68		peruvian_lily	ERJ_135
69		petunia	ERJ_145
70		pincushion_flower	Embraer_Legacy_600
71		pink-yellow_dahlia	Eurofighter_Typhoon
72		pink_primrose	F-16A
73		poinsettia	FA-18
74		primula	Falcon_2000
75		prince_of_wales_feathers	Falcon_900
76		purple_coneflower	Fokker_100
77		red_ginger	Fokker_50
78		rose	Fokker_70
79		ruby-lipped_cattleya	Global_Express
80		siam_tulip	Gulfstream_IV
81		silverbush	Gulfstream_V
82		snapdragon	Hawk_T1
83		spear_thistle	Il-76
84		spring_crocus	L-1011
85		stemless_gentian	MD-11
86		sunflower	MD-80
87		sweet_pea	MD-87
88		sweet_william	MD-90
89		sword_lily	Metroliner

Index	DTD Class	102Flowers Class	FGVC-Aircraft Class
90		thorn_apple	Model_B200
91		tiger_lily	PA-28
92		toad_lily	SR-20
93		tree_mallow	Saab_2000
94		tree_poppy	Saab_340
95		trumpet_creeper	Spitfire
96		wallflower	Tornado
97		water_lily	Tu-134
98		watercress	Tu-154
99		wild_pansy	Yak-42
100		windflower	
101		yellow_iris	

Table 6: **Dataset class indices.** We provide the class indices for StanfordCars, and CUB200, which have 196, and 200 classes, respectively.

Index	StanfordCars Class	CUB200 Class
0	AM General Hummer SUV 2000	Acadian_Flycatcher
1	Acura Integra Type R 2001	American_Crow
2	Acura RL Sedan 2012	American_Goldfinch
3	Acura TL Sedan 2012	American_Pipit
4	Acura TL Type-S 2008	American_Redstart
5	Acura TSX Sedan 2012	American_Three_toed_Woodpecker
6	Acura ZDX Hatchback 2012	Anna_Hummingbird
7	Aston Martin V8 Vantage Convertible 2012	Artic_Tern
8	Aston Martin V8 Vantage Coupe 2012	Baird_Sparrow
9	Aston Martin Virage Convertible 2012	Baltimore_Oriole
10	Aston Martin Virage Coupe 2012	Bank_Swallow
11	Audi 100 Sedan 1994	Barn_Swallow
12	Audi 100 Wagon 1994	Bay_breasted_Warbler
13	Audi A5 Coupe 2012	Belted_Kingfisher
14	Audi R8 Coupe 2012	Bewick_Wren
15	Audi RS 4 Convertible 2008	Black_Tern
16	Audi S4 Sedan 2007	Black_and_white_Warbler
17	Audi S4 Sedan 2012	Black_billed_Cuckoo
18	Audi S5 Convertible 2012	Black_capped_Vireo
19	Audi S5 Coupe 2012	Black_footed_Albatross
20	Audi S6 Sedan 2011	Black_throated_Blue_Warbler
21	Audi TT Hatchback 2011	Black_throated_Sparrow
22	Audi TT RS Coupe 2012	Blue_Grosbeak
23	Audi TTS Coupe 2012	Blue_Jay
24	Audi V8 Sedan 1994	Blue_headed_Vireo
25	BMW 1 Series Convertible 2012	Blue_winged_Warbler
26	BMW 1 Series Coupe 2012	Boat_tailed_Grackle
27	BMW 3 Series Sedan 2012	Bobolink
28	BMW 3 Series Wagon 2012	Bohemian_Waxwing
29	BMW 6 Series Convertible 2007	Brandt_Cormorant
30	BMW ActiveHybrid 5 Sedan 2012	Brewer_Blackbird
31	BMW M3 Coupe 2012	Brewer_Sparrow
32	BMW M5 Sedan 2010	Bronzed_Cowbird
33	BMW M6 Convertible 2010	Brown_Creeper
34	BMW X3 SUV 2012	Brown_Pelican
35	BMW X5 SUV 2007	Brown_Thrasher
36	BMW X6 SUV 2012	Cactus_Wren
37	BMW Z4 Convertible 2012	California_Gull
38	Bentley Arnage Sedan 2009	Canada_Warbler
39	Bentley Continental Flying Spur Sedan 2007	Cape_Glossy_Starling

Index	StanfordCars Class	CUB200 Class
40	Bentley Continental GT Coupe 2007	Cape_May_Warbler
41	Bentley Continental GT Coupe 2012	Cardinal
42	Bentley Continental Supersports Conv. Convertible 2012	Carolina_Wren
43	Bentley Mulsanne Sedan 2011	Caspian_Tern
44	Bugatti Veyron 16.4 Convertible 2009	Cedar_Waxwing
45	Bugatti Veyron 16.4 Coupe 2009	Cerulean_Warbler
46	Buick Enclave SUV 2012	Chestnut_sided_Warbler
47	Buick Rainier SUV 2007	Chipping_Sparrow
48	Buick Regal GS 2012	Chuck_will_Widow
49	Buick Verano Sedan 2012	Clark_Nutcracker
50	Cadillac CTS-V Sedan 2012	Clay_colored_Sparrow
51	Cadillac Escalade EXT Crew Cab 2007	Cliff_Swallow
52	Cadillac SRX SUV 2012	Common_Raven
53	Chevrolet Avalanche Crew Cab 2012	Common_Tern
54	Chevrolet Camaro Convertible 2012	Common_Yellowthroat
55	Chevrolet Cobalt SS 2010	Crested_Auklet
56	Chevrolet Corvette Convertible 2012	Dark_eyed_Junco
57	Chevrolet Corvette Ron Fellows Edition Z06 2007	Downy_Woodpecker
58	Chevrolet Corvette ZR1 2012	Eared_Grebe
59	Chevrolet Express Cargo Van 2007	Eastern_Towhee
60	Chevrolet Express Van 2007	Elegant_Tern
61	Chevrolet HHR SS 2010	European_Goldfinch
62	Chevrolet Impala Sedan 2007	Evening_Grosbeak
63	Chevrolet Malibu Hybrid Sedan 2010	Field_Sparrow
64	Chevrolet Malibu Sedan 2007	Fish_Crow
65	Chevrolet Monte Carlo Coupe 2007	Florida_Jay
66	Chevrolet Silverado 1500 Classic Extended Cab 2007	Forsters_Tern
67	Chevrolet Silverado 1500 Extended Cab 2012	Fox_Sparrow
68	Chevrolet Silverado 1500 Hybrid Crew Cab 2012	Frigatebird
69	Chevrolet Silverado 1500 Regular Cab 2012	Gadwall
70	Chevrolet Silverado 2500HD Regular Cab 2012	Geococcyx
71	Chevrolet Sonic Sedan 2012	Glaucous_winged_Gull
72	Chevrolet Tahoe Hybrid SUV 2012	Golden_winged_Warbler
73	Chevrolet TrailBlazer SS 2009	Grasshopper_Sparrow
74	Chevrolet Traverse SUV 2012	Gray_Catbird
75	Chrysler 300 SRT-8 2010	Gray_Kingbird
76	Chrysler Aspen SUV 2009	Gray_crowned_Rosy_Finch
77	Chrysler Crossfire Convertible 2008	Great_Crested_Flycatcher
78	Chrysler PT Cruiser Convertible 2008	Great_Grey_Shrike
79	Chrysler Sebring Convertible 2010	Green_Jay
80	Chrysler Town and Country Minivan 2012	Green_Kingfisher
81	Daewoo Nubira Wagon 2002	Green_Violetear
82	Dodge Caliber Wagon 2007	Green_tailed_Towhee
83	Dodge Caliber Wagon 2012	Groove_billed_Ani
84	Dodge Caravan Minivan 1997	Harris_Sparrow
85	Dodge Challenger SRT8 2011	Heermann_Gull
86	Dodge Charger SRT-8 2009	Henslow_Sparrow
87	Dodge Charger Sedan 2012	Herring_Gull
88	Dodge Dakota Club Cab 2007	Hooded_Merganser
89	Dodge Dakota Crew Cab 2010	Hooded_Oriole
90	Dodge Durango SUV 2007	Hooded_Warbler
91	Dodge Durango SUV 2012	Horned_Grebe
92	Dodge Journey SUV 2012	Horned_Lark
93	Dodge Magnum Wagon 2008	Horned_Puffin
94	Dodge Ram Pickup 3500 Crew Cab 2010	House_Sparrow
95	Dodge Ram Pickup 3500 Quad Cab 2009	House_Wren
96	Dodge Sprinter Cargo Van 2009	Indigo_Bunting
97	Eagle Talon Hatchback 1998	Ivory_Gull

Index	StanfordCars Class	CUB200 Class
98	FIAT 500 Abarth 2012	Kentucky_Warbler
99	FIAT 500 Convertible 2012	Laysan_Albatross
100	Ferrari 458 Italia Convertible 2012	Lazuli_Bunting
101	Ferrari 458 Italia Coupe 2012	Le_Conte_Sparrow
102	Ferrari California Convertible 2012	Least_Auklet
103	Ferrari FF Coupe 2012	Least_Flycatcher
104	Fisker Karma Sedan 2012	Least_Tern
105	Ford E-Series Wagon Van 2012	Lincoln_Sparrow
106	Ford Edge SUV 2012	Loggerhead_Shrike
107	Ford Expedition EL SUV 2009	Long_tailed_Jaeger
108	Ford F-150 Regular Cab 2007	Louisiana_Waterthrush
109	Ford F-150 Regular Cab 2012	Magnolia_Warbler
110	Ford F-450 Super Duty Crew Cab 2012	Mallard
111	Ford Fiesta Sedan 2012	Mangrove_Cuckoo
112	Ford Focus Sedan 2007	Marsh_Wren
113	Ford Freestar Minivan 2007	Mockingbird
114	Ford GT Coupe 2006	Mourning_Warbler
115	Ford Mustang Convertible 2007	Myrtle_Warbler
116	Ford Ranger SuperCab 2011	Nashville_Warbler
117	GMC Acadia SUV 2012	Nelson_Sharp_tailed_Sparrow
118	GMC Canyon Extended Cab 2012	Nighthawk
119	GMC Savana Van 2012	Northern_Flicker
120	GMC Terrain SUV 2012	Northern_Fulmar
121	GMC Yukon Hybrid SUV 2012	Northern_Waterthrush
122	Geo Metro Convertible 1993	Olive_sided_Flycatcher
123	HUMMER H2 SUT Crew Cab 2009	Orange_crowned_Warbler
124	HUMMER H3T Crew Cab 2010	Orchard_Oriole
125	Honda Accord Coupe 2012	Ovenbird
126	Honda Accord Sedan 2012	Pacific_Loon
127	Honda Odyssey Minivan 2007	Painted_Bunting
128	Honda Odyssey Minivan 2012	Palm_Warbler
129	Hyundai Accent Sedan 2012	Parakeet_Auklet
130	Hyundai Azera Sedan 2012	Pelagic_Cormorant
131	Hyundai Elantra Sedan 2007	Philadelphia_Vireo
132	Hyundai Elantra Touring Hatchback 2012	Pied_Kingfisher
133	Hyundai Genesis Sedan 2012	Pied_billed_Grebe
134	Hyundai Santa Fe SUV 2012	Pigeon_Guillemot
135	Hyundai Sonata Hybrid Sedan 2012	Pileated_Woodpecker
136	Hyundai Sonata Sedan 2012	Pine_Grosbeak
137	Hyundai Tucson SUV 2012	Pine_Warbler
138	Hyundai Veloster Hatchback 2012	Pomarine_Jaeger
139	Hyundai Veracruz SUV 2012	Prairie_Warbler
140	Infiniti G Coupe IPL 2012	Prothonotary_Warbler
141	Infiniti QX56 SUV 2011	Purple_Finch
142	Isuzu Ascender SUV 2008	Red_bellied_Woodpecker
143	Jaguar XK XKR 2012	Red_breasted_Merganser
144	Jeep Compass SUV 2012	Red_cockaded_Woodpecker
145	Jeep Grand Cherokee SUV 2012	Red_eyed_Vireo
146	Jeep Liberty SUV 2012	Red_faced_Cormorant
147	Jeep Patriot SUV 2012	Red_headed_Woodpecker
148	Jeep Wrangler SUV 2012	Red_legged_Kittiwake
149	Lamborghini Aventador Coupe 2012	Red_winged_Blackbird
150	Lamborghini Diablo Coupe 2001	Rhinoceros_Auklet
151	Lamborghini Gallardo LP 570-4 Superleggera 2012	Ring_billed_Gull
152	Lamborghini Reventon Coupe 2008	Ringed_Kingfisher
153	Land Rover LR2 SUV 2012	Rock_Wren
154	Land Rover Range Rover SUV 2012	Rose_breasted_Grosbeak
155	Lincoln Town Car Sedan 2011	Ruby_throated_Hummingbird

Index	StanfordCars Class	CUB200 Class
156	MINI Cooper Roadster Convertible 2012	Rufous_Hummingbird
157	Maybach Landaulet Convertible 2012	Rusty_Blackbird
158	Mazda Tribute SUV 2011	Sage_Thrasher
159	McLaren MP4-12C Coupe 2012	Savannah_Sparrow
160	Mercedes-Benz 300-Class Convertible 1993	Sayornis
161	Mercedes-Benz C-Class Sedan 2012	Scarlet_Tanager
162	Mercedes-Benz E-Class Sedan 2012	Scissor_tailed_Flycatcher
163	Mercedes-Benz S-Class Sedan 2012	Scott_Oriole
164	Mercedes-Benz SL-Class Coupe 2009	Seaside_Sparrow
165	Mercedes-Benz Sprinter Van 2012	Shiny_Cowbird
166	Mitsubishi Lancer Sedan 2012	Slaty_backed_Gull
167	Nissan 240SX Coupe 1998	Song_Sparrow
168	Nissan Juke Hatchback 2012	Sooty_Albatross
169	Nissan Leaf Hatchback 2012	Spotted_Catbird
170	Nissan NV Passenger Van 2012	Summer_Tanager
171	Plymouth Neon Coupe 1999	Swainson_Warbler
172	Porsche Panamera Sedan 2012	Tennessee_Warbler
173	Ram C-V Cargo Van Minivan 2012	Tree_Sparrow
174	Rolls-Royce Ghost Sedan 2012	Tree_Swallow
175	Rolls-Royce Phantom Drophead Coupe Convertible 2012	Tropical_Kingbird
176	Rolls-Royce Phantom Sedan 2012	Vermilion_Flycatcher
177	Scion xD Hatchback 2012	Vesper_Sparrow
178	Spyker C8 Convertible 2009	Warbling_Vireo
179	Spyker C8 Coupe 2009	Western_Grebe
180	Suzuki Aerio Sedan 2007	Western_Gull
181	Suzuki Kizashi Sedan 2012	Western_Meadowlark
182	Suzuki SX4 Hatchback 2012	Western_Wood_Pewee
183	Suzuki SX4 Sedan 2012	Whip_poor_Will
184	Tesla Model S Sedan 2012	White_Pelican
185	Toyota 4Runner SUV 2012	White_breasted_Kingfisher
186	Toyota Camry Sedan 2012	White_breasted_Nuthatch
187	Toyota Corolla Sedan 2012	White_crowned_Sparrow
188	Toyota Sequoia SUV 2012	White_eyed_Vireo
189	Volkswagen Beetle Hatchback 2012	White_necked_Raven
190	Volkswagen Golf Hatchback 1991	White_throated_Sparrow
191	Volkswagen Golf Hatchback 2012	Wilson_Warbler
192	Volvo 240 Sedan 1993	Winter_Wren
193	Volvo C30 Hatchback 2012	Worm_eating_Warbler
194	Volvo XC90 SUV 2007	Yellow_Warbler
195	smart fortwo Convertible 2012	Yellow_bellied_Flycatcher
196		Yellow_billed_Cuckoo
197		Yellow_breasted_Chat
198		Yellow_headed_Blackbird
199		Yellow_throated_Vireo

Table 7: **Dataset class indices.** We provide the class indices for OxfordPets, Caltech101, and Mini-ImageNet, which have 37, 101, and 100 classes, respectively.

Index	OxfordPets Class	Caltech101 Class	Mini-ImageNet Class
0	Abyssinian	Faces	African_hunting_dog
1	Bengal	Faces_easy	Arctic_fox
2	Birman	Leopards	French_bulldog
3	Bombay	Motorbikes	Gordon_setter
4	British_Shorthair	accordion	Ibizan_hound
5	Egyptian_Mau	airplanes	Newfoundland
6	Maine_Coon	anchor	Saluki
7	Persian	ant	Tibetan_mastiff

Index	OxfordPets Class	Caltech101 Class	Mini-ImageNet Class
8	Ragdoll	barrel	Walker_hound
9	Russian_Blue	bass	aircraft_carrier
10	Siamese	beaver	ant
11	Sphynx	binocular	ashcan
12	american_bulldog	bonsai	barrel
13	american_pit_bull_terrier	brain	beer_bottle
14	basset_hound	brontosaurus	black-footed_ferret
15	beagle	buddha	bolete
16	boxer	butterfly	bookshop
17	chihuahua	camera	boxer
18	english_cocker_spaniel	cannon	cannon
19	english_setter	car_side	carousel
20	german_shorthaired	ceiling_fan	carton
21	great_pyrenees	cellphone	catamaran
22	havanese	chair	chime
23	japanese_chin	chandelier	cliff
24	keeshond	cougar_body	clog
25	leonberger	cougar_face	cocktail_shaker
26	miniature_pinscher	crab	combination_lock
27	newfoundland	crayfish	consomme
28	pomeranian	crocodile	coral_reef
29	pug	crocodile_head	crate
30	saint_bernard	cup	cuirass
31	samoyed	dalmatian	dalmatian
32	scottish_terrier	dollar_bill	dishrag
33	shiba_inu	dolphin	dome
34	staffordshire_bull_terrier	dragonfly	dugong
35	wheaten_terrier	electric_guitar	electric_guitar
36	yorkshire_terrier	elephant	file
37		emu	fire_screen
38		euphonium	frying_pan
39		ewer	garbage_truck
40		ferry	golden_retriever
41		flamingo	goose
42		flamingo_head	green_mamba
43		garfield	hair_slide
44		gerenuk	harvestman
45		gramophone	holster
46		grand_piano	horizontal_bar
47		hawksbill	hotdog
48		headphone	hourglass
49		hedgehog	house_finch
50		helicopter	iPod
51		ibis	jellyfish
52		inline_skate	king_crab
53		joshua_tree	komondor
54		kangaroo	ladybug
55		ketch	lion
56		lamp	lipstick
57		laptop	malamute
58		llama	meerkat
59		lobster	miniature_poodle
60		lotus	miniskirt
61		mandolin	missile
62		mayfly	mixing_bowl
63		menorah	nematode
64		metronome	oboe
65		minaret	orange

Index	OxfordPets Class	Caltech101 Class	Mini-ImageNet Class
66		nautilus	organ
67		octopus	parallel_bars
68		okapi	pencil_box
69		pagoda	photocopier
70		panda	poncho
71		pigeon	prayer_rug
72		pizza	reel
73		platypus	rhinoceros_beetle
74		pyramid	robin
75		revolver	rock_beauty
76		rhino	school_bus
77		rooster	scoreboard
78		saxophone	slot
79		schooner	snorkel
80		scissors	solar_dish
81		scorpion	spider_web
82		sea_horse	spike
83		snoopy	stage
84		soccer_ball	street_sign
85		stapler	tank
86		starfish	theater_curtain
87		stegosaurus	three-toed_sloth
88		stop_sign	tile_roof
89		strawberry	tobacco_shop
90		sunflower	toucan
91		tick	triceratops
92		trilobite	trifle
93		umbrella	unicycle
94		watch	upright_piano
95		water_lilly	vase
96		wheelchair	white_wolf
97		wild_cat	wok
98		windsor_chair	worm_fence
99		wrench	yawl
100		yin_yang	

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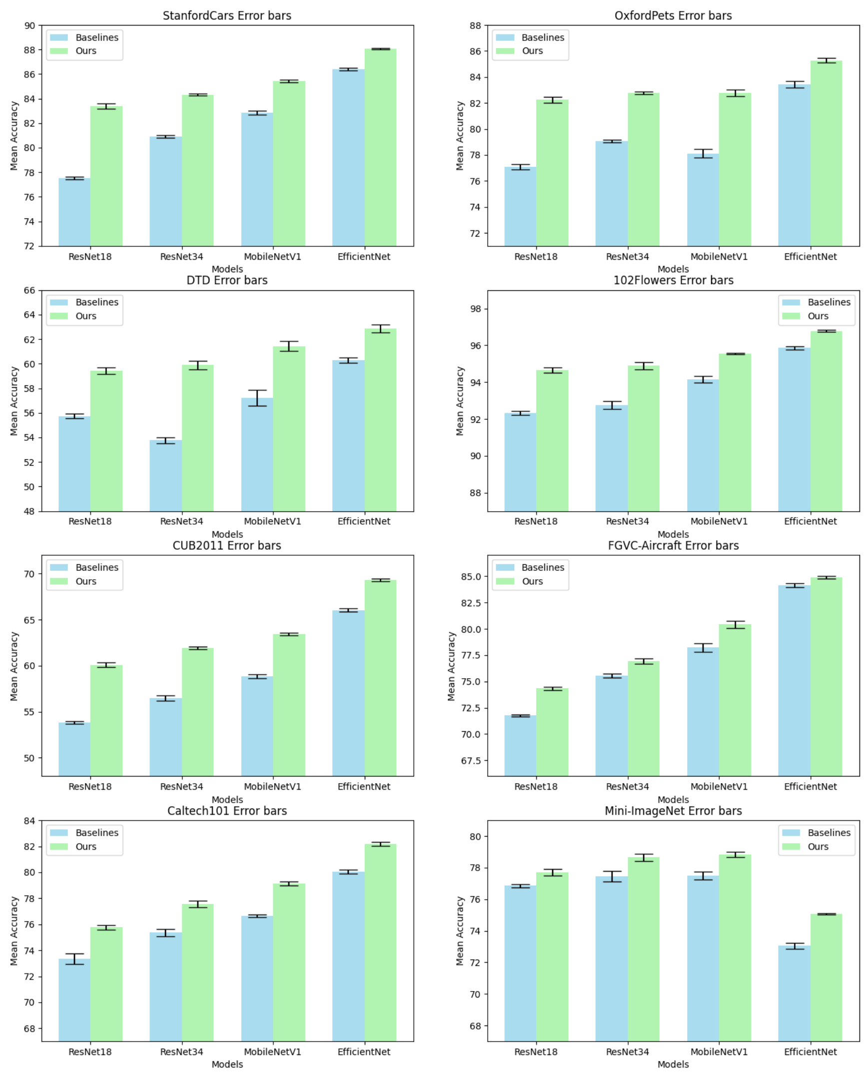

Figure 2: **Error bars of SOTA experimental results on fine-grained and coarse-grained datasets.** We run each experiment three times and report the average results. This results represent the standard deviation of the performance across multiple runs for both fine-grained and coarse-grained datasets, reflecting the variability and stability of the SOTA experiment results.

1. Does the car belong to the high-end luxury category (like Bugatti, Bentley, etc.)?
2. Is the car's make year post-2010?
3. Is the car equipped with a V8 engine?
4. Is the car's model a hatchback?
5. Is the car model a SUV?
6. Is the car a diesel-powered model?
7. Is the car a model of Chevrolet brand?
8. Does the car have a convertible roof?
9. Is the car a sports coupe model?
10. Does the car belong to the sedan category?
11. Does the picture depict a sports version of a typical car model (like Audi RS, Aston Martin V8 Vantage etc.)?
12. Is the car a hybrid vehicle?
13. Is the car from the minivan category?
14. Does the car have a noticeable rear spoiler?
15. Is the car model from the smaller Compact Class?
16. Is the make of the car BMW?
17. Is the car part of the Ford family?
18. Have the car images been taken after 2007?
19. Is the car a part of the Italian luxury car brands (like Ferrari, Lamborghini)?
20. Was the car model made in the V12 engine series?
21. Does the car have scissor doors?
22. Does the car have distinctive gull-wing doors?
23. Does the car have a rear engine layout?
24. Is the car an off-road vehicle or designed for rugged terrain usage?
25. Does the car feature a dual exhaust system?
26. Is the car a roadster model?
27. Is the car equipped with side skirts?
28. Is the car a station wagon?
29. Does the car feature a distinctive front grille with vertical slats?
30. Is the car from the Japanese automaker, Honda?
31. Is the car a part of the electric car category (like Tesla Model S, Chevrolet Bolt, etc.)?
32. Does the car have a long wheelbase version?
33. Does the car have a soft-top roof?
34. Is the car a coupe with two doors?
35. Is the car from a Korean manufacturer (like Hyundai, Kia)?
36. Does the car have a distinctive round headlight design?
37. Does the car belong to the pickup truck category?
38. Does the car have a distinctive boxy shape?
39. Is the car a 4-door model?
40. Is the car equipped with a turbocharger?
41. Is the car a plug-in hybrid?
42. Does the car feature a panoramic sunroof?
43. Is the car a muscle car (like Dodge Challenger, Chevrolet Camaro)?
44. Does the car have a noticeable hood scoop?
45. Does the car have all-wheel drive (AWD)?
46. Is the car a vintage model made before 2000?
47. Does the car have a prominent air intake on the front bumper?
48. Does the car have a distinctive rear diffuser?
49. Is the car from an American manufacturer?
50. Is the car a convertible with a hardtop?

Table 8: **Multi-aspect questions generated by GPT-4o for the StanfordCars dataset.**

1. Does the animal have a flat face?
2. Does the animal display a prominent ruff around the neck?
3. Are the ears of the breed long and floppy?
4. Is the animal's fur long?
5. Does the animal have a robust and muscular build?
6. Does the breed have a compact and muscular build?
7. Does the animal have long drooping ears?
8. Does the animal have distinctive facial markings?
9. Does the animal have striking blue eyes?
10. Does the animal have a brachycephalic (shortened head) skull?
11. Does the animal have a double coat?
12. Is the animal's body unusually slender and tall?
13. Is the breed's coat spotted or dappled?
14. Is the tail of the animal bushy or feathered?
15. Does the animal have webbed feet?
16. Does the animal have a short, stubby nose?
17. Does the animal have floppy ears?
18. Is the animal's coat curly or wavy?
19. Is the fur of the animal curly or wavy?
20. Does the animal have hairless skin?
21. Does the breed have a plumed tail?
22. Does the animal have a long, flowing coat?
23. Is the animal small-sized, typically less than 10 pounds?
24. Does the breed have a square-shaped body?
25. Is the animal typically solid-colored?
26. Is the animal predominantly white in color?
27. Is the breed characterized by a high-set tail?
28. Does the breed have a short snout?
29. Is the breed's tail bushy or fluffy?
30. Does the animal have a pronounced underbite?
31. Does the animal have an unusually squarish or boxy muzzle?
32. Is the fur patterned with spots or stripes?
33. Does the breed have a pointed muzzle?
34. Does the animal have a characteristically flat or pushed-in face with large, round eyes?
35. Does the animal have large, round eyes?
36. Is the animal's coat silky to the touch?
37. Does the breed have a long and slender tail?
38. Is the breed's coat rough or wiry?
39. Is the animal known for having a sleek and shiny coat?
40. Is the breed known for having a slender body?
41. Is the breed known for its distinctive coloration or pattern?
42. Does the breed have a broad chest?
43. Does the breed have a distinctive ruff or collar of fur around the neck?
44. Is the animal predominantly black in color?
45. Does the breed have large, bat-like ears?
46. Is the breed's coat short and dense?
47. Does the breed have a docked or naturally short tail?
48. Does the breed have small, pointed ears?
49. Is the animal known for having a lion-like appearance?
50. Is the animal's coat thick and woolly?

Table 9: **Multi-aspect questions generated by GPT-4o for the OxfordPets dataset.**

1. Are there noticeable cracks or fissures?
2. Does the texture have a scaly or reptilian appearance?
3. Does the texture feature honeycomb-like hexagonal shapes?
4. Does the texture look like a net or web?
5. Are there regular, grid-like patterns?
6. Are there noticeable swirls or spiral patterns?
7. Is the texture characterized by a dotted or spotted pattern?
8. Are there visible grooves or indentations?
9. Are there waffle-like grid patterns on the texture?
10. Does the texture have a marbled appearance with blended colors?
11. Is the texture perforated or has holes?
12. Is the pattern composed of crisscrossing lines?
13. Are there distinct, irregular blotches?
14. Does the texture have a checkered or chequered pattern?
15. Are there fibrous or thread-like elements visible?
16. Does the texture have a veined appearance?
17. Does the texture have a crystalline or gem-like appearance?
18. Are there raised, bumpy areas on the texture?
19. Does the texture appear braided with intertwining strands?
20. Is the texture wrinkled or creased?
21. Is the texture characterized by fine, lace-like details?
22. Does the texture have a smeared or smudged appearance?
23. Is the texture smeared with streaks or smears?
24. Are there visible stains or discolorations on the texture?
25. Does the texture feature pleated or folded sections?
26. Is the pattern composed of zigzag lines?
27. Does the texture have a sprinkled or speckled look?
28. Are there any interwoven or braided elements in the texture?
29. Is the texture banded with stripes of varying widths?
30. Is the texture composed of overlapping or interlaced elements?
31. Is the texture flecked with small, random spots?
32. Are there frilly or ruffled edges in the texture?
33. Does the texture have a porous or sponge-like look?
34. Is the texture marked by potholes or deep indentations?
35. Is the texture covered with polka dots?
36. Are there visible knitted or crocheted patterns?
37. Does the texture have a paisley or teardrop-shaped pattern?
38. Are there pitted or dimpled areas on the texture?
39. Does the texture have a stratified or layered appearance?
40. Does the texture feature stratified layers or bands?
41. Are there visible bubbles or circular shapes?
42. Is the texture cobwebbed with thin, thread-like lines?
43. Does the texture resemble fabric or woven material?
44. Is the texture marked by crosshatched lines?
45. Does the texture have parallel lines?
46. Are there noticeable stained or dirty areas?
47. Does the texture have a woven or interlaced look?
48. Is the texture swirly with swirling patterns?
49. Are there noticeable wrinkles or creases?
50. Does the texture have a zigzagged pattern?

Table 10: **Multi-aspect questions generated by GPT-4o for the DTD dataset.**

1. Does the flower have multiple petals arranged in a symmetrical pattern?
2. Does the flower have heart-shaped petals?
3. Does the flower have a prominent central disk surrounded by petals?
4. Are there multiple small flowers arranged in a cluster?
5. Is the flower predominantly blue or purple?
6. Does the flower exhibit a gradient of colors?
7. Does the flower have a spiky or thistle-like appearance?
8. Does the flower have a large, singular bloom?
9. Is the primary colors of the flower yellow?
10. Are the petals long and narrow, resembling a lily?
11. Does the flower have a tubular shape?
12. Is the flower predominantly red?
13. Are the petals arranged in layers or rows?
14. Are the petals overlapping?
15. Are the petals fringed or ruffled?
16. Does the flower grow in a cluster on a single stem?
17. Are the petals shaped like a star or have pointed tips?
18. Does the flower have a distinct, pronounced lip or 'tongue' petal?
19. Does the flower have a spurred petal or elongated appendage?
20. Are the petals arranged in a spiral pattern?
21. Does the flower have a strong fragrance?
22. Is the flower predominantly pink?
23. Does the flower have a bell or trumpet shape?
24. Does the flower have a daisy-like appearance?
25. Does the flower have a cup-shaped structure?
26. Does the flower have hairy or fuzzy petals?
27. Are the petals thin and delicate?
28. Are the petals bi-colored?
29. Are the petals flat and wide?
30. Does the flower have a central crown or corona?
31. Is the flower predominantly white?
32. Are the petals veined or patterned?
33. Are the petals rounded at the tips?
34. Does the flower have strap-like petals?
35. Are the petals twisted or curled?
36. Does the flower have a single petal?
37. Does the flower have a dome-shaped appearance?
38. Is the flower predominantly orange?
39. Does the flower have a flattened top?
40. Are the petals spoon-shaped?
41. Are the petals translucent or semi-transparent?
42. Does the flower have prominent stamens?
43. Is the flower predominantly green?
44. Does the flower have a geometric pattern on its petals?
45. Does the flower have a papery texture?
46. Are the petals serrated or jagged?
47. Are the petals clustered tightly together?
48. Is the flower predominantly violet?
49. Does the flower have drooping petals?
50. Are the petals reflexed or bent backward?

Table 11: **Multi-aspect questions generated by GPT-4o for the 102Flowers dataset.**

1. Does the bird have a curved beak?
2. Is the bird's beak long and pointed?
3. Is the bird predominantly blue?
4. Is the bird's primary habitat coastal areas?
5. Is the bird primarily found in water habitats?
6. Is the bird's beak hooked?
7. Is the bird's underside orange?
8. Does the bird have a long neck?
9. Is the bird's plumage mostly white?
10. Is the bird predominantly found in forests?
11. Does the bird have a thin, needle-like beak?
12. Does the bird have a crest on its head?
13. Does the bird have iridescent feathers?
14. Is the bird's beak short and thick?
15. Is the bird's beak conical?
16. Is the bird's plumage predominantly brown?
17. Does the bird have a fan-shaped tail?
18. Does the bird have a black and white striped pattern?
19. Does the bird have a red patch on its wings?
20. Is the bird's breast yellow?
21. Does the bird have a white eye stripe?
22. Does the bird have webbed feet?
23. Does the bird have a notched tail?
24. Is the bird's chest streaked?
25. Does the bird have a ring around its neck?
26. Does the bird have a black cap on its head?
27. Does the bird have a speckled breast?
28. Does the bird have long legs?
29. Is the bird's back green?
30. Does the bird have a black tail?
31. Does the bird have a mask-like pattern on its face?
32. Does the bird have a prominent eye ring?
33. Is the bird's tail short and square?
34. Does the bird have spots on its wings?
35. Is the bird's belly white?
36. Does the bird have a distinctive call that includes trills?
37. Does the bird have a yellow belly?
38. Is the bird's tail forked?
39. Is the bird's head and back grey?
40. Is the bird's wingspan larger than 12 inches?
41. Does the bird have a barred tail?
42. Is the bird's chest red?
43. Does the bird have a blue throat patch?
44. Does the bird have a bright orange beak?
45. Is the bird's head black?
46. Is the bird's beak straight?
47. Is the bird predominantly found in open grasslands?
48. Is the bird larger than a sparrow?
49. Does the bird have a yellow stripe on its wings?
50. Is the bird primarily insectivorous?

Table 12: **Multi-aspect questions generated by GPT-4o for the CUB200 dataset.**

1. Is this aircraft a turboprop model?
2. Does this aircraft have four engines?
3. Does this aircraft have a high-wing design?
4. Does this aircraft have two engines?
5. Is this a single-engine aircraft?
6. Is this aircraft used primarily for military purposes?
7. Is this aircraft a trijet (three engines)?
8. Does this aircraft feature a swept-wing design?
9. Is this aircraft a wide-body model?
10. Does the aircraft have propellers instead of jet engines?
11. Does the aircraft feature a T-tail design?
12. Does this aircraft have retractable landing gear?
13. Is this aircraft primarily used for cargo transportation?
14. Does this aircraft have an open cockpit?
15. Is the aircraft primarily used for commercial passenger flights?
16. Does this aircraft have a twin-jet engine configuration?
17. Is this aircraft primarily used for private or corporate purposes?
18. Does the aircraft have a delta wing configuration?
19. Does this aircraft have a single vertical stabilizer?
20. Is this aircraft a supersonic jet?
21. Is this aircraft used primarily for short regional flights?
22. Does this aircraft have an all-metal body?
23. Does this aircraft have winglets?
24. Does the aircraft have a long-range flight capacity?
25. Does this aircraft have a radial engine?
26. Does this aircraft have a tailwheel landing gear configuration?
27. Is this aircraft a high-performance jet?
28. Does this aircraft feature a pressurized cabin?
29. Does this aircraft have a twin-boom tail design?
30. Does this aircraft have a glass cockpit?
31. Does the aircraft feature swept-back wings?
32. Does this aircraft have a distinctive nose design?
33. Does this aircraft have a forward-swept wing design?
34. Does this aircraft have an all-composite body structure?
35. Does this aircraft have rear-mounted engines?
36. Does this aircraft have a tricycle landing gear configuration?
37. Does this aircraft have variable-sweep wings?
38. Does this aircraft have a high-wing design?
39. Does this aircraft have a distinctive humpback design?
40. Does this aircraft have a high bypass ratio engine?
41. Is this aircraft primarily designed for long-haul flights?
42. Is this aircraft often used for regional transportation?
43. Is this aircraft a narrow-body model?
44. Does the aircraft have turbojet engines?
45. Does this aircraft have twin tail fins?
46. Does this aircraft have a straight-wing design?
47. Is the aircraft designed for short takeoff and landing (STOL)?
48. Does the aircraft feature fixed landing gear?
49. Is this aircraft designed to operate from aircraft carriers?
50. Is the aircraft known for its high maneuverability?

Table 13: **Multi-aspect questions generated by GPT-4o for the FGVC-Aircraft dataset.**

1. Does the object have a recognizable face?
2. Does the object have wings?
3. Is the object known for its ability to fly?
4. Does the object have a screen and interface for digital interaction?
5. Does the object have limbs and a recognizable head/body structure?
6. Is the object known for its speed or ability to move quickly?
7. Does the object have wheels and an enclosed space for passengers?
8. Does the object have multiple legs?
9. Does the object have a prominent trunk or elongated nose?
10. Does the object have fur or hair?
11. Does the object have claws or pincers?
12. Is the object typically found in water or aquatic environments?
13. Is the object known for its ability to cut or pierce?
14. Does the object have a blade or sharp edge for cutting?
15. Does the object have feathers?
16. Is the object a type of vehicle used for transportation?
17. Is the object a type of instrument used to produce sound?
18. Does the object have keys or buttons for producing musical notes?
19. Does the object have a flat surface for placing items on?
20. Is the object used for capturing images or videos?
21. Is the object commonly associated with human activities or use?
22. Is the object typically found outdoors in a natural environment?
23. Does the object have a distinct shape?
24. Is the object commonly found in a garden or botanical setting?
25. Is the object primarily composed of organic materials?
26. Does the object have a shell or hard outer covering?
27. Is the object likely to be found in a domestic setting (home, kitchen)?
28. Is the object typically seen in a kitchen setting?
29. Does the object have any moving parts or mechanisms?
30. Does the object have a repeating pattern or design on its surface?
31. Is the object a type of plant?
32. Does the object have scales or a rough texture?
33. Does the object have an elongated neck?
34. Does the object have a circular or rounded shape?
35. Does the object have a cylindrical shape?
36. Does the object have a distinctive pattern on its surface, like spots or stripes?
37. Does the object have a clear, defined purpose or function?
38. Does this object occupy a large part of the image?
39. Is the object likely part of a larger system or assembly (e.g., part of a car)?
40. Is the object's primary purpose for entertainment or recreation?
41. Is the object typically used for writing or drawing?
42. Is the object often associated with religious or spiritual practices?
43. Is the object often used in sporting activities?
44. Is the object an example of marine life?
45. Is the object a piece of furniture used for seating?
46. Is the dominant color of the object a warm color (red, orange, yellow)?
47. Is the dominant color of the object a cool color (blue, skyblue, gray)?
48. Does the object appear to be handheld or designed for human interaction?
49. Is the object's shape primarily geometric (circles, squares, etc.)?
50. Is the object known for producing light?

Table 14: **Multi-aspect questions generated by GPT-4o for the Caltech101 dataset.**

1. Is the animal in the image a type of bird?
2. Is a creature known for its colorful appearance depicted in the image?
3. Does the image show a vehicle with wheels?
4. Does the image feature a musical instrument?
5. Is there something used for communication in the image?
6. Does the image contain a dog breed with long ears?
7. Is a creature with a distinct mane shown in the image?
8. Is the object in the image made of glass?
9. Is the object in the image typically found in a bathroom?
10. Is a weapon depicted in the image?
11. Is something used in artistic creation featured in the image?
12. Is a type of mushroom shown in the image?
13. Is something used for navigation present in the image?
14. Is something used for measurement present in the image?
15. Is something used for entertainment featured in the image?
16. Is a primarily nocturnal creature depicted in the image?
17. Is a mammal known for swimming depicted in the image?
18. Is there a clothing accessory in the image?
19. Can an amphibian be seen in the image?
20. Is the object shown typically found in a kitchen?
21. Does the image contain an animal with stripes?
22. Is the object depicted primarily used for transportation?
23. Does the image show an object used for cooling?
24. Is there an item associated with food preparation in the image?
25. Is a venomous creature shown in the image?
26. Can a type of beetle be seen in the image?
27. Is the object in the image typically found in water?
28. Is the depicted animal a type of cat?
29. Is there a vehicle without wheels in the image?
30. Is something typically used in a garden present in the image?
31. Can a large marine vessel be seen in the image?
32. Does the image feature an object used in sports?
33. Does the image contain a type of marine life?
34. Is a wild cat depicted in the image?
35. Is something used for timekeeping present in the image?
36. Is the depicted animal a type of amphibian?
37. Is something used for personal grooming in the image?
38. Is a herding dog breed shown in the image?
39. Can an insect with wings be seen in the image?
40. Is the animal in the image known for its speed?
41. Does the image contain a type of fruit?
42. Is the depicted animal a type of reptile?
43. Is something used in photography shown in the image?
44. Is something in the image commonly used for storage?
45. Does the image feature an object used in construction?
46. Is a rodent depicted in the image?
47. Is something typically found in an office present in the image?
48. Does the image contain an animal with a shell?
49. Is there protective gear depicted in the image?
50. Is a creature known for its strength depicted in the image?

Table 15: **Multi-aspect questions generated by GPT-4o for the Mini-ImageNet dataset.**

1. Is the car color black?
2. Is the car a convertible?
3. Is the car a sedan?
4. Is the car from the year 2012?
5. Is the car from the make Acura?
6. Is the car from the make Audi?
7. Is the car from the make BMW?
8. Is the car from the make Chevrolet?
9. Is the car from the make Dodge?
10. Is the car from the make Ferrari?
11. Is the car from the make Ford?
12. Is the car from the make Honda?
13. Is the car from the make Hyundai?
14. Is the car from the make Jeep?
15. Is the car from the make Lamborghini?
16. Is the car from the make Mercedes-Benz?
17. Is the car from the make Nissan?
18. Is the car from the make Porsche?
19. Is the car from the make Rolls-Royce?
20. Is the car from the make Toyota?
21. Is the car from the make Volkswagen?
22. Is the car a coupe?
23. Is the car an SUV?
24. Is the car a hatchback?
25. Is the car a wagon?
26. Is the car a hybrid?
27. Is the car a van?
28. Is the car a minivan?
29. Is the car a crew cab?
30. Is the car a regular cab?
31. Is the car a quad cab?
32. Is the car a club cab?
33. Is the car from the luxury category?
34. Is the car from the sports category?
35. Is the car from the economy category?
36. Is the car from the midsize category?
37. Is the car from the full-size category?
38. Is the car a high-performance model?
39. Is the car a low-performance model?
40. Is the car a high-end model?
41. Is the car a budget-friendly model?
42. Is the car a classic model?
43. Is the car a modern model?
44. Is the car a luxury sports car?
45. Is the car a sedan with a sunroof?
46. Is the car a coupe with a spoiler?
47. Is the car a convertible with a soft top?
48. Is the car a hatchback with a rear spoiler?
49. Is the car a wagon with roof racks?
50. Is the car a van with tinted windows?

Table 16: **Multi-aspect questions generated by GPT-3.5-turbo for the StanfordCars dataset.**

1. Does the breed have a short coat?
2. Does the breed have a long coat?
3. Are the ears of the breed floppy?
4. Are the ears of the breed erect?
5. Does the breed have a solid-colored coat?
6. Does the breed have a spotted coat pattern?
7. Is the breed known for its distinctive facial markings?
8. Is the breed large in size?
9. Is the breed small in size?
10. Does the breed have a curly tail?
11. Does the breed have a bushy tail?
12. Is the breed known for its playful nature?
13. Is the breed known for being affectionate?
14. Does the breed have a brachycephalic (short-nosed) face?
15. Is the coat of the breed fluffy?
16. Does the breed have a stocky build?
17. Is the breed known for its intelligence?
18. Is the breed known for its hunting abilities?
19. Is the breed known for its vocal nature?
20. Does the breed have a specific color pattern unique to its breed?
21. Does the breed have a distinct pattern on its face?
22. Does the breed have a breed-specific tail shape?
23. Is the breed known for its expressive eyes?
24. Does the breed have a muscular build?
25. Does the breed have a sleek and shiny coat?
26. Is the breed known for its agility?
27. Does the breed have a fluffy mane or collar?
28. Is the breed known for its endurance or stamina?
29. Does the breed have a double coat?
30. Is the breed known for its calm temperament?
31. Does the breed have a distinctive vocalization?
32. Is the breed known for its protective instincts?
33. Does the breed have prominent whiskers?
34. Does the breed have a distinctive head shape?
35. Is the breed known for its high energy levels?
36. Does the breed have a short, stubby nose?
37. Is the breed known for its unique tail carriage?
38. Does the breed have a sleek and elegant posture?
39. Is the breed known for its friendly disposition?
40. Does the breed have a sleek and slender build?
41. Is the breed known for its independent nature?
42. Does the breed have a luxurious coat texture?
43. Is the breed known for its social nature?
44. Does the breed have a silky or velvety coat?
45. Is the breed known for its athletic abilities?
46. Does the breed have distinctive facial hair or markings?
47. Is the breed known for its guarding instincts?
48. Does the breed have a thick, protective coat?
49. Is the breed known for its clownish behavior?
50. Does the breed have a unique tail length relative to its body size?

Table 17: **Multi-aspect questions generated by GPT-3.5-turbo for the OxfordPets dataset.**

1. Does the object have wheels?
2. Is the object a type of musical instrument?
3. Does the object have wings?
4. Is the object commonly found in water?
5. Does the object have fur?
6. Is the object commonly used for transportation?
7. Does the object have a shell?
8. Is the object typically found in a household setting?
9. Is the object typically found in nature?
10. Does the object have a long neck?
11. Is the object typically found in an office environment?
12. Does the object have scales?
13. Is the object a type of bird?
14. Does the object have antennas?
15. Does the object have claws?
16. Is the object commonly used for entertainment?
17. Does the object have a tail?
18. Is the object a type of plant?
19. Does the object have a sharp beak?
20. Is the object typically used for sports?
21. Does the object have multiple legs?
22. Is the object typically found in a museum?
23. Does the object have a curved shape?
24. Is the object typically used for cooking?
25. Does the object have a distinctive color pattern?
26. Is the object a type of reptile?
27. Does the object have a smooth texture?
28. Is the object typically found in the sky?
29. Does the object have horns?
30. Is the object typically used for communication?
31. Does the object have a protective shell?
32. Is the object typically found in tropical regions?
33. Does the object have a distinctive smell?
34. Is the object commonly found in urban environments?
35. Does the object have a long tail?
36. Is the object typically used for relaxation?
37. Does the object have a shiny surface?
38. Is the object typically found in cold climates?
39. Does the object have a round shape?
40. Is the object commonly associated with music?
41. Does the object have stripes?
42. Is the object typically found near water?
43. Does the object have a unique pattern?
44. Is the object typically found in forests?
45. Does the object have large ears?
46. Is the object typically found in a desert environment?
47. Does the object have a broad head?
48. Is the object commonly found on farms?
49. Does the object have a pointy nose?
50. Is the object typically used for navigation?

Table 18: **Multi-aspect questions generated by GPT-3.5-turbo for the Caltech101 dataset.**

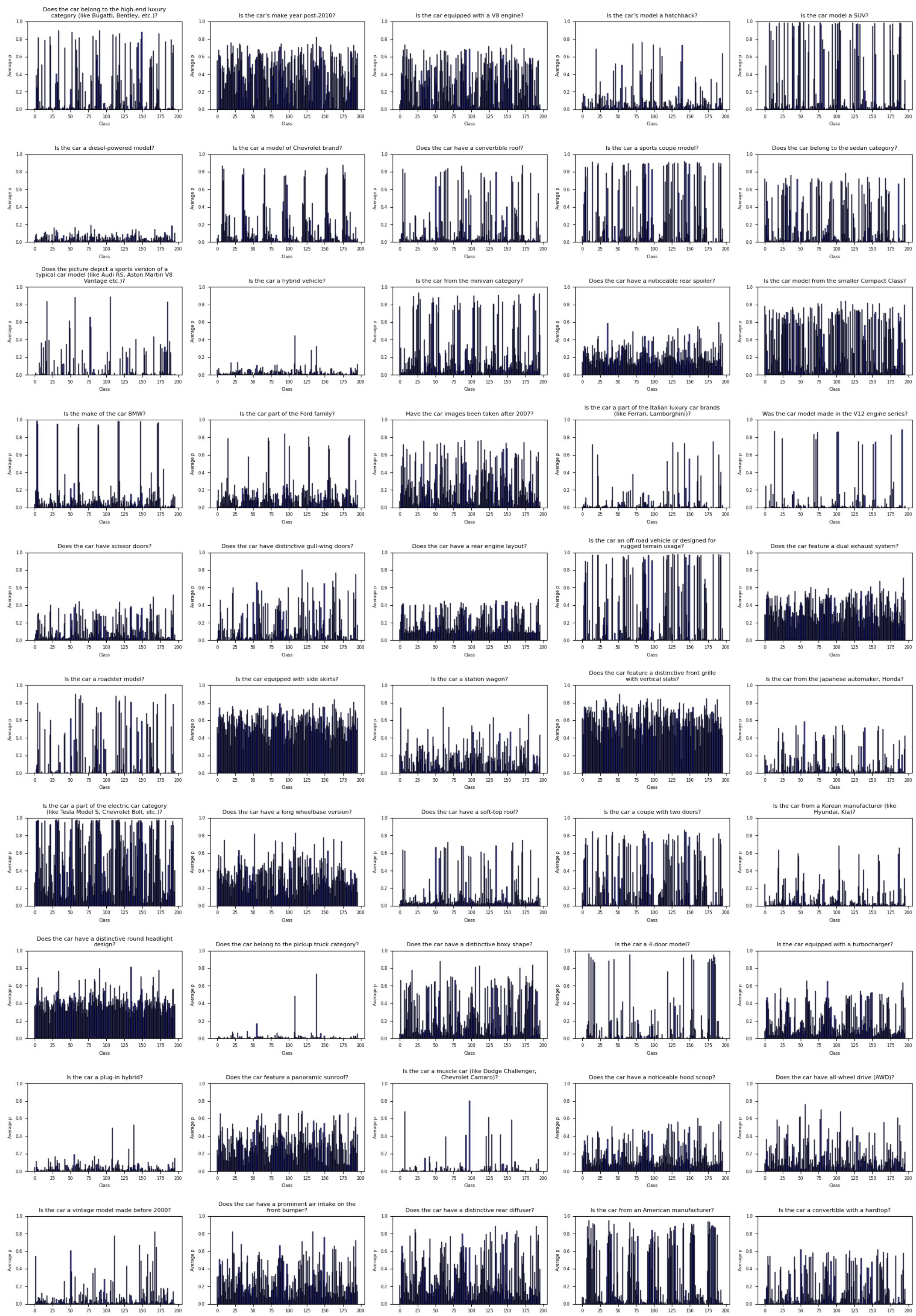

Figure 3: **Visualization of the average logit distribution for StanfordCars.**

Figure 4: **Visualization of the average logit distribution for the multi-aspect of the OxfordPets.**

Figure 5: **Visualization of the average logit distribution for the multi-aspect of the DTD.**

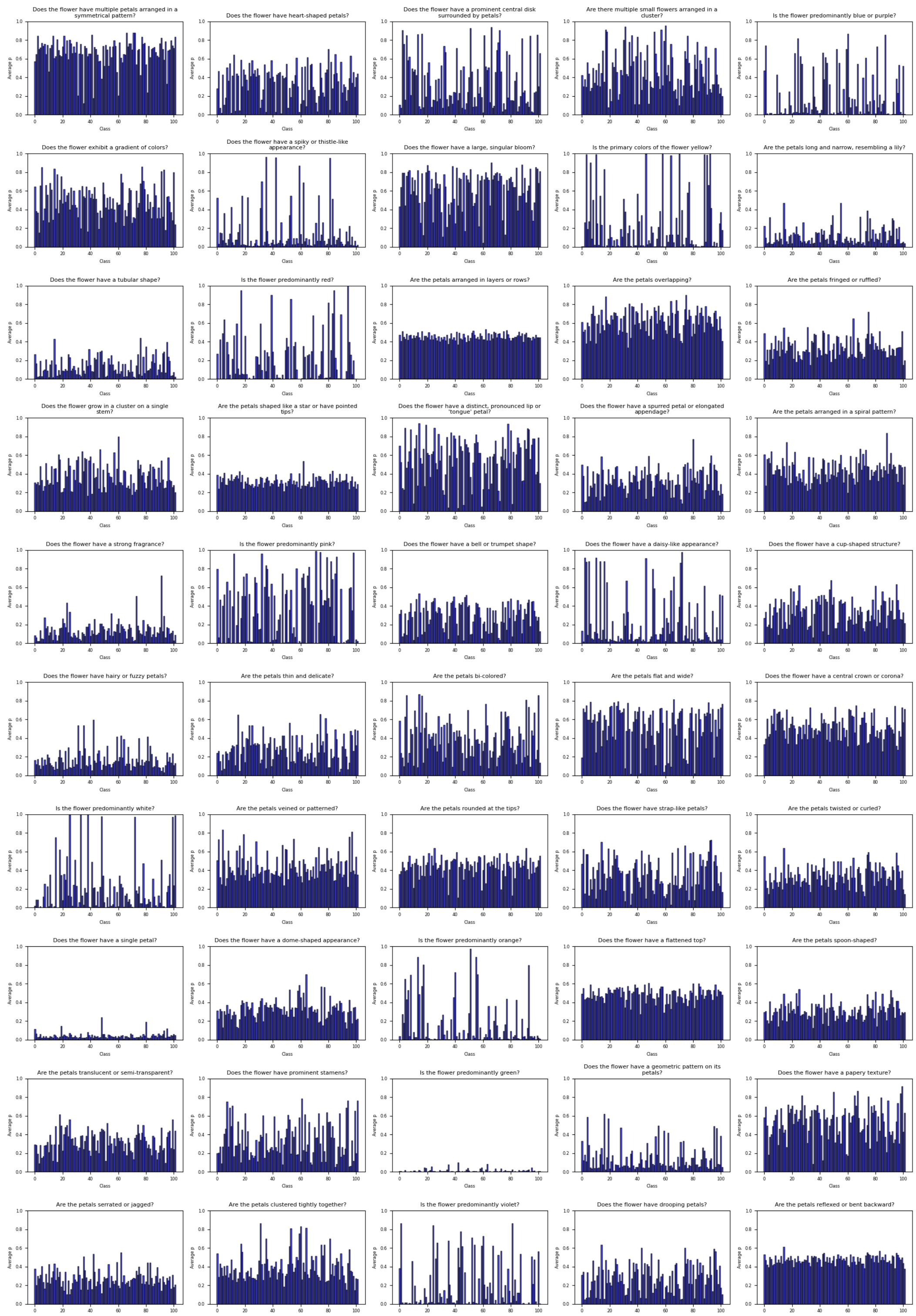

Figure 6: **Visualization of the average logit distribution for the multi-aspect of the 102Flowers.**

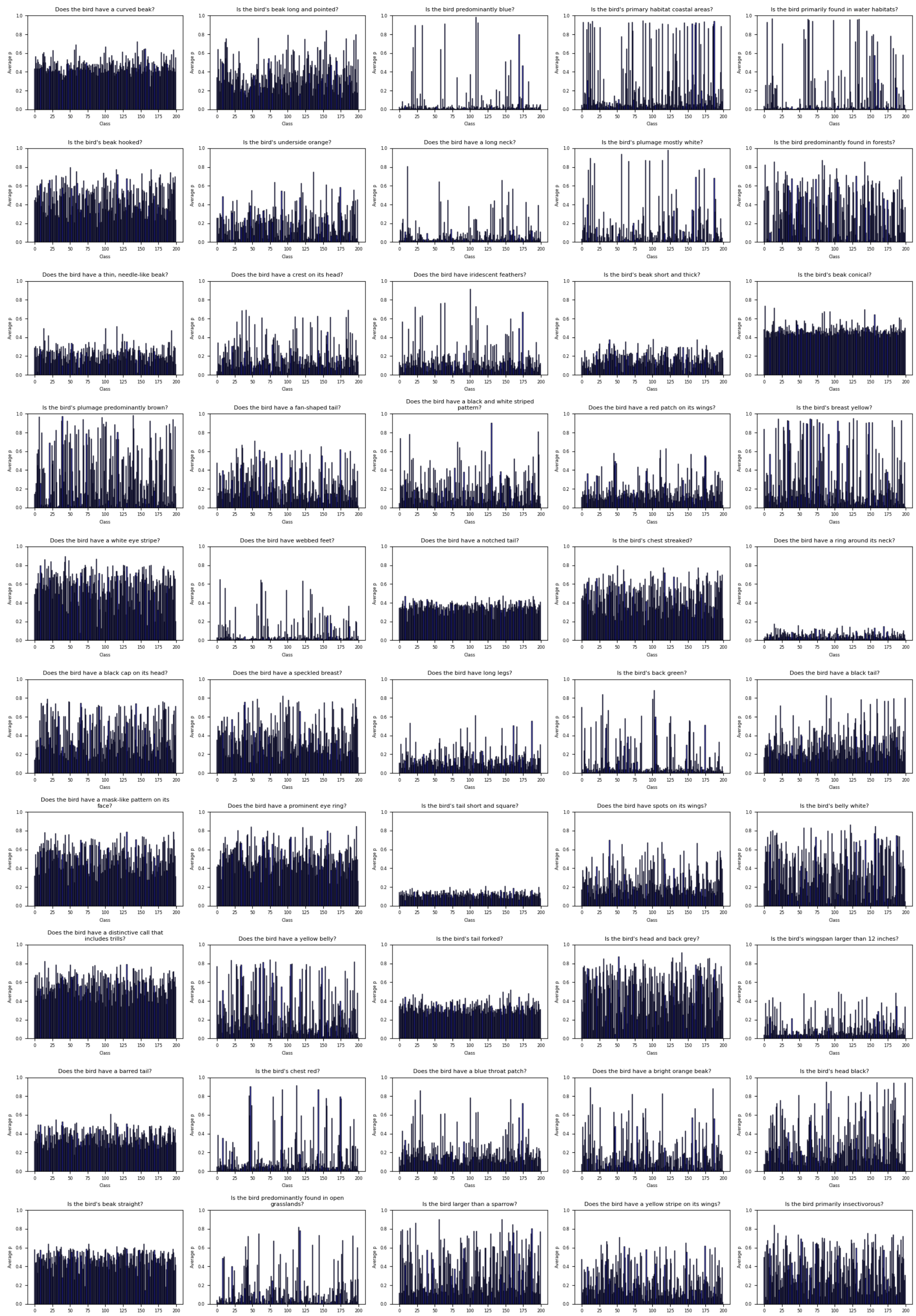

Figure 7: **Visualization of the average logit distribution for the multi-aspect of the CUB200.**

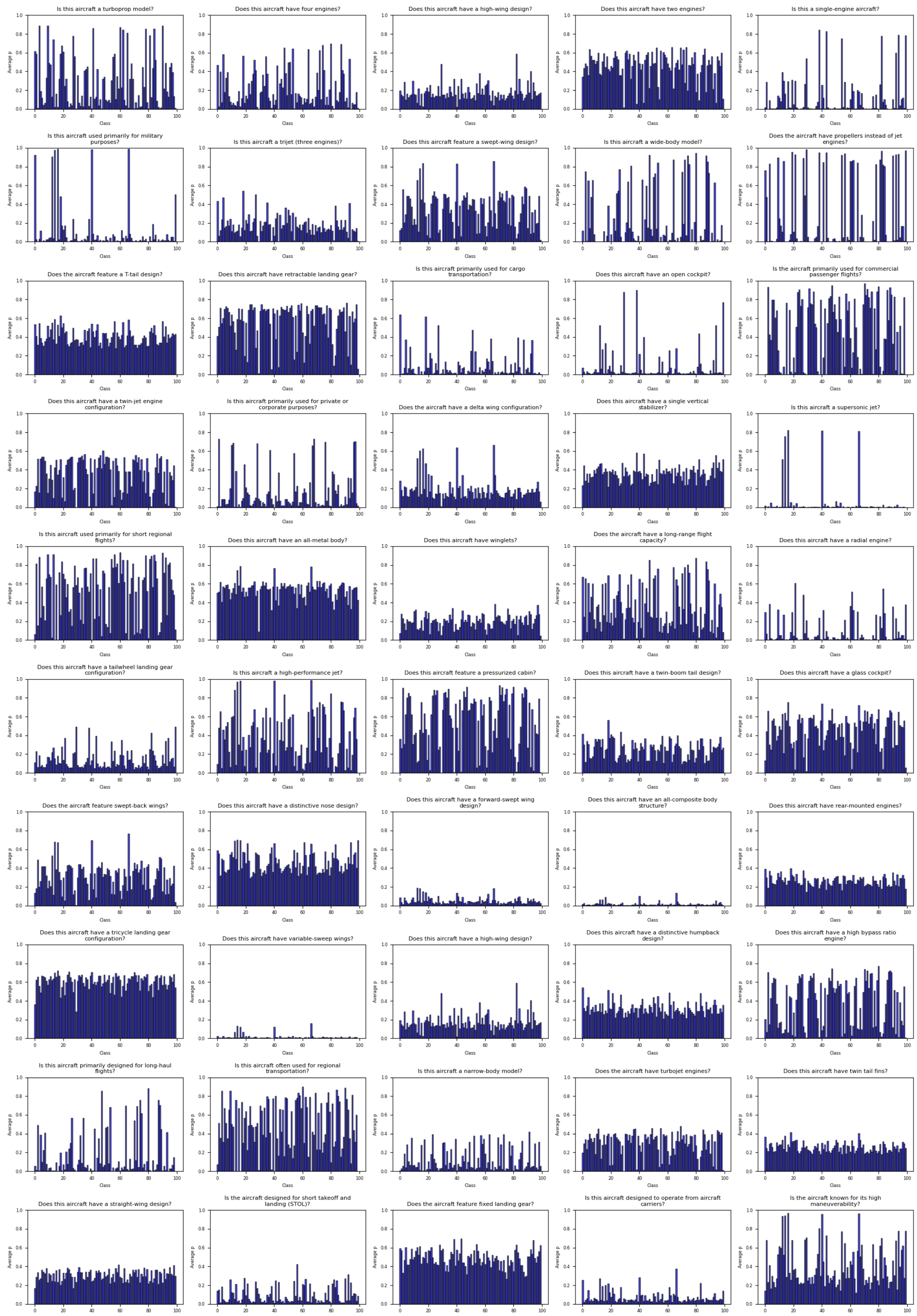

Figure 8: **Visualization of the average logit distribution for the multi-aspect of the FGVC-Aircraft.**

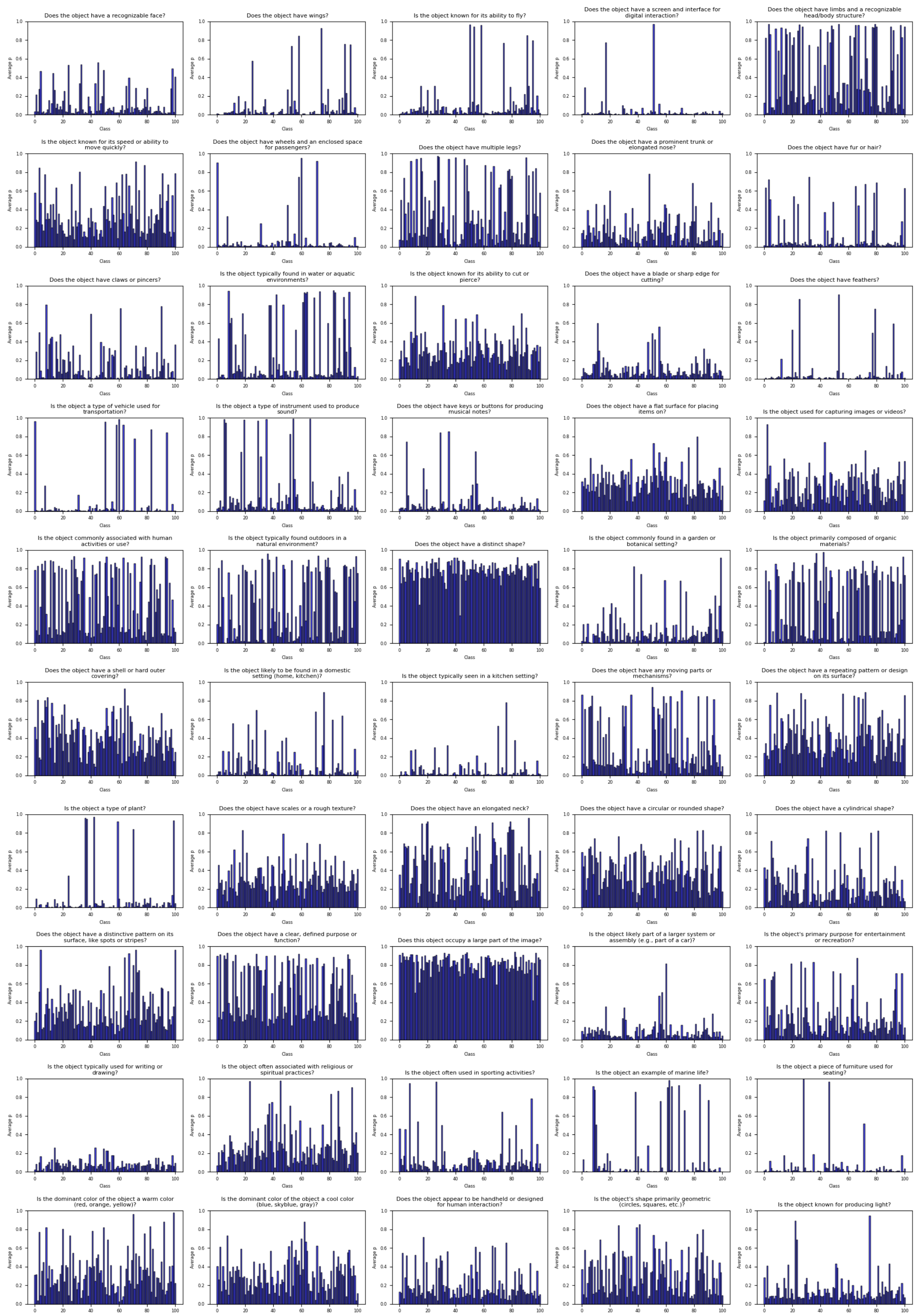

Figure 9: **Visualization of the average logit distribution for the multi-aspect of the Caltech101.**

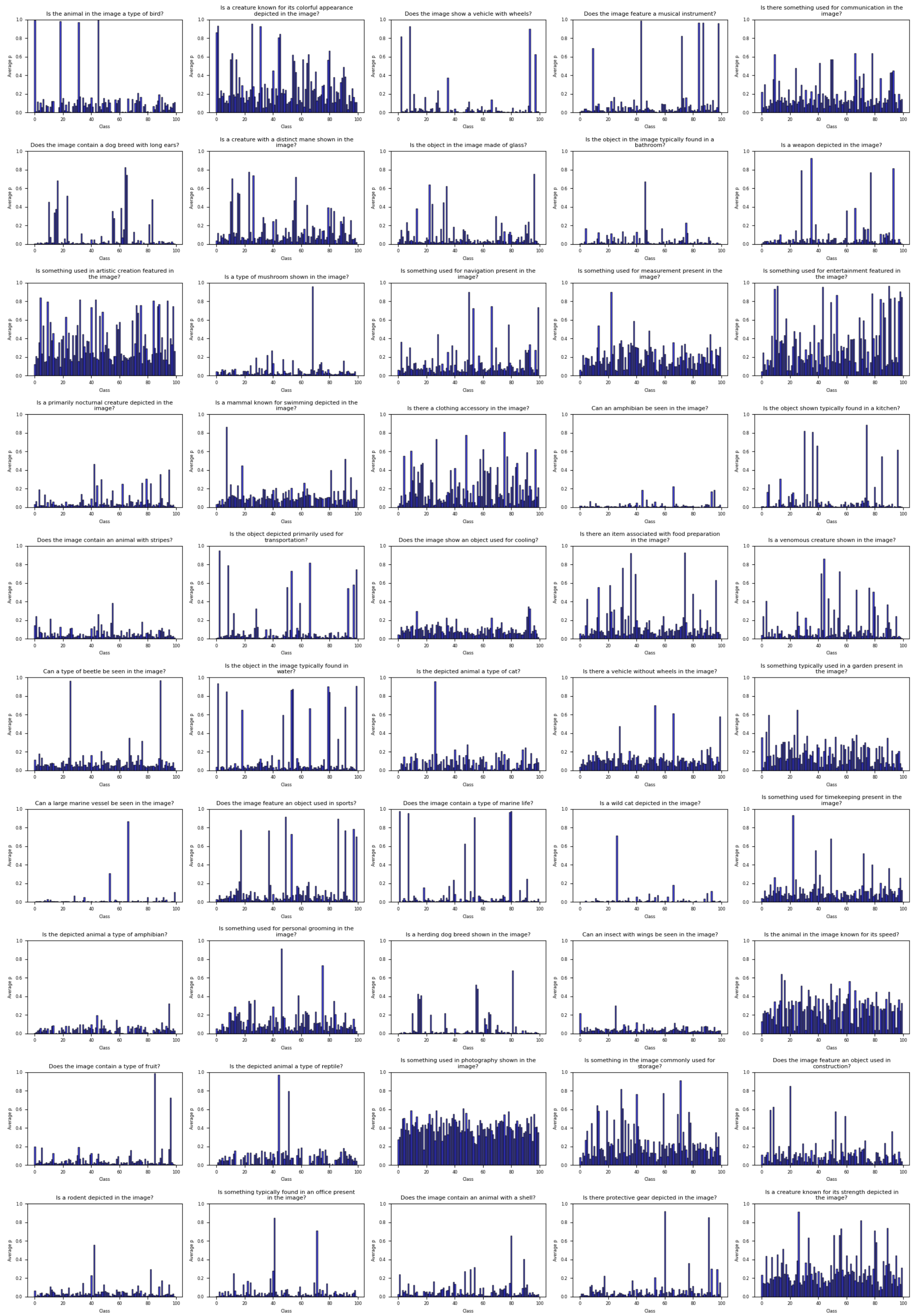

Figure 10: **Visualization of the average logit distribution for the multi-aspect of the Mini-ImageNet.**

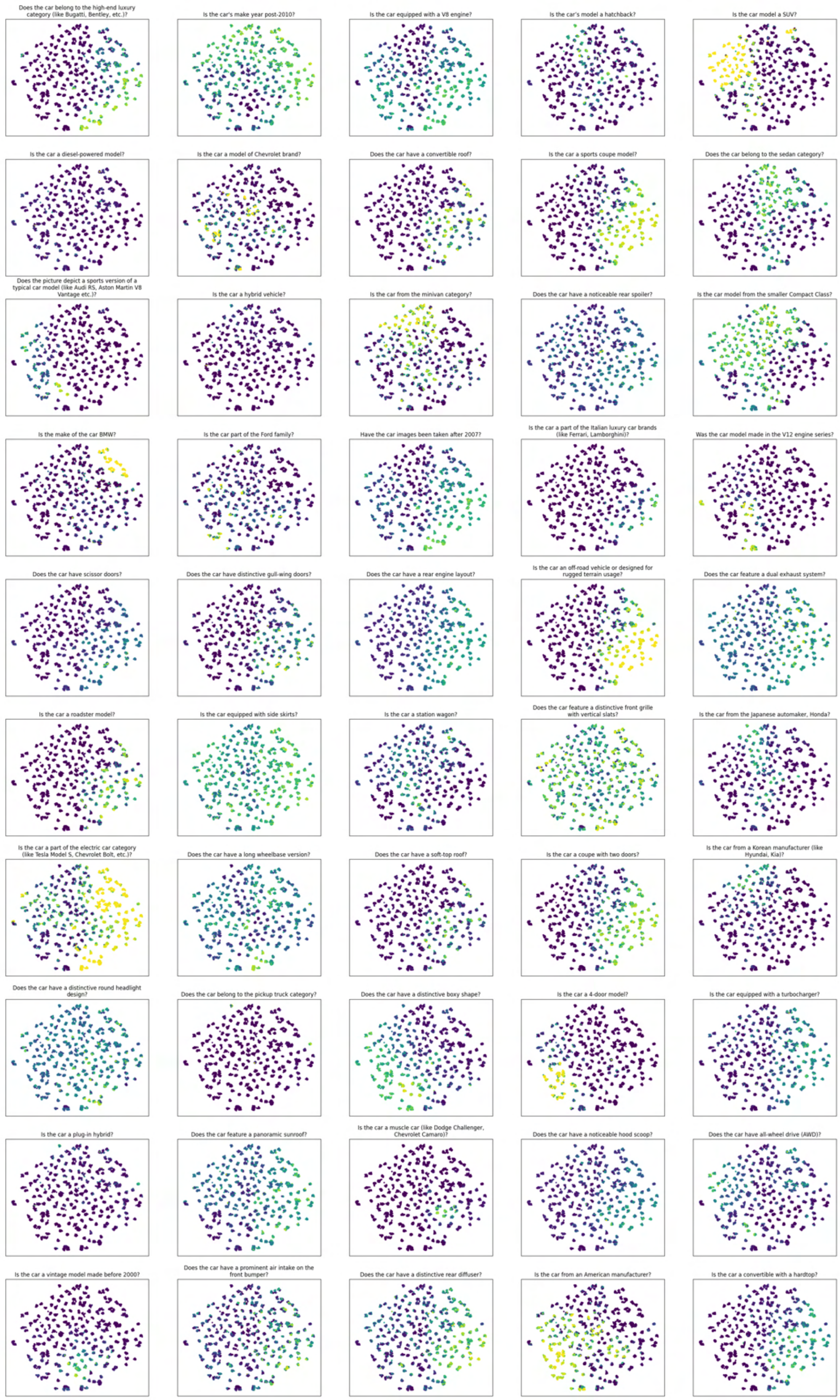

Figure 11: **Visualization of ground truth t-SNE embeddings for the multi-aspect of the StanfordCars.**

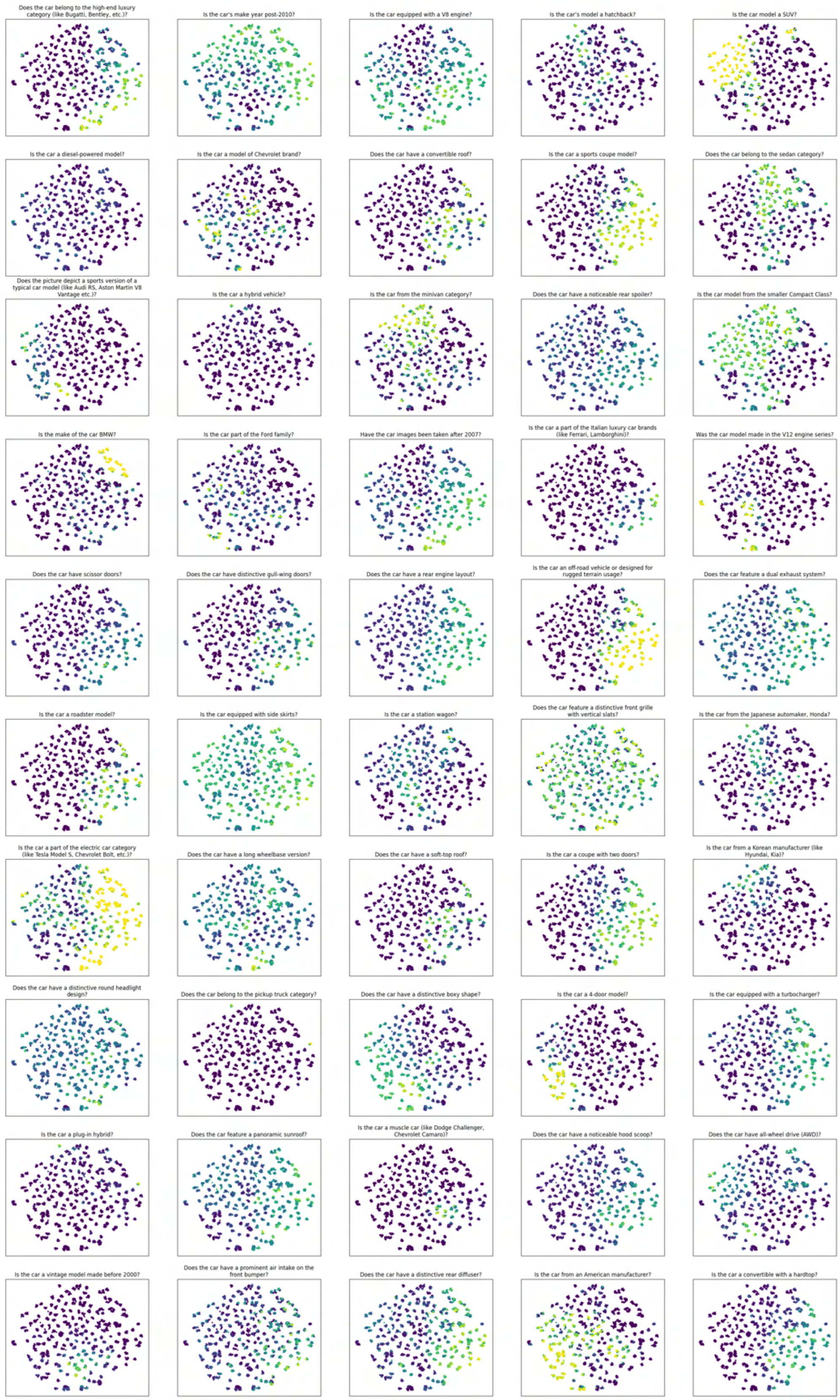

Figure 12: **Visualization of predicted result t-SNE embeddings for the multi-aspect of the StanfordCars.**

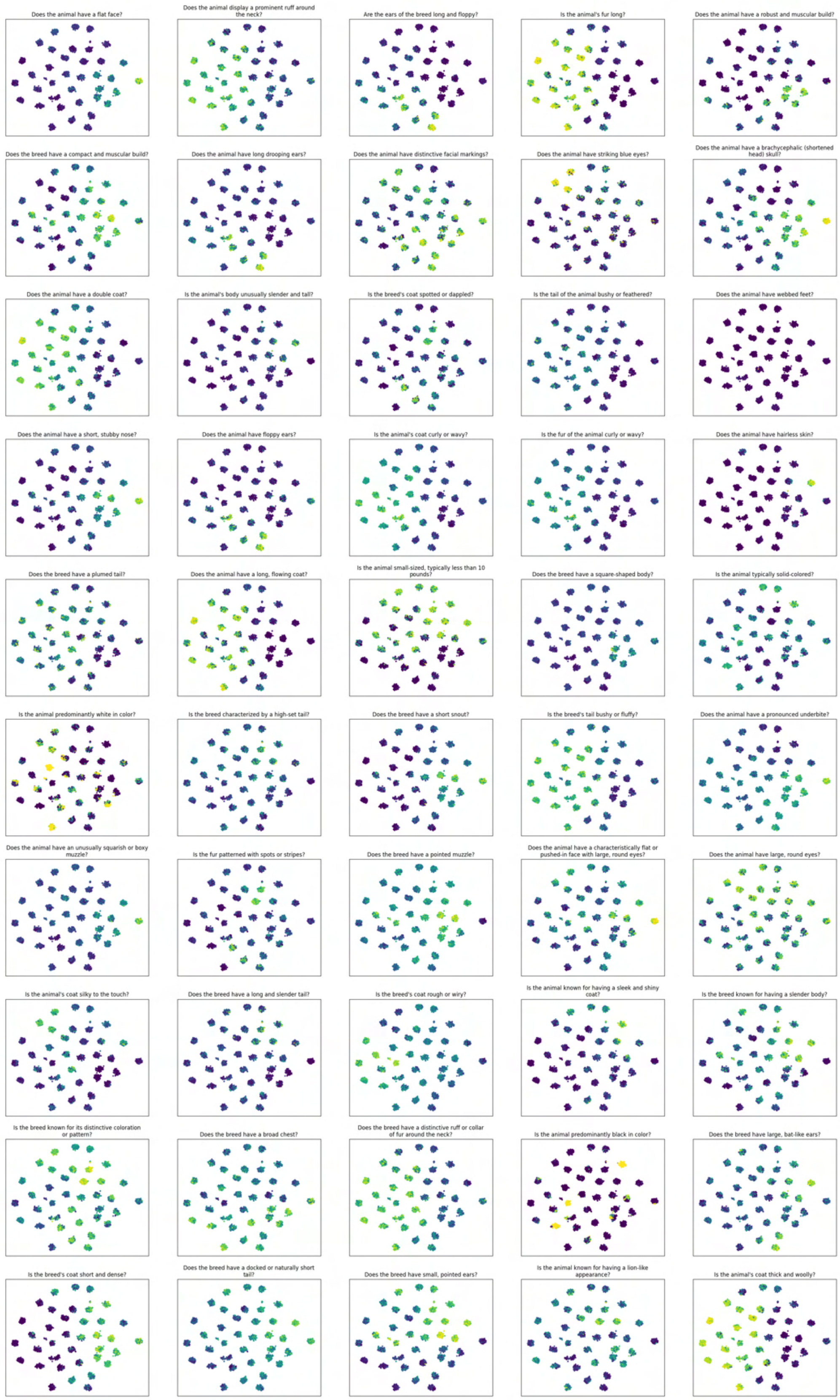

Figure 13: **Visualization of ground truth t-SNE embeddings for the multi-aspect of the Oxford-Pets.**

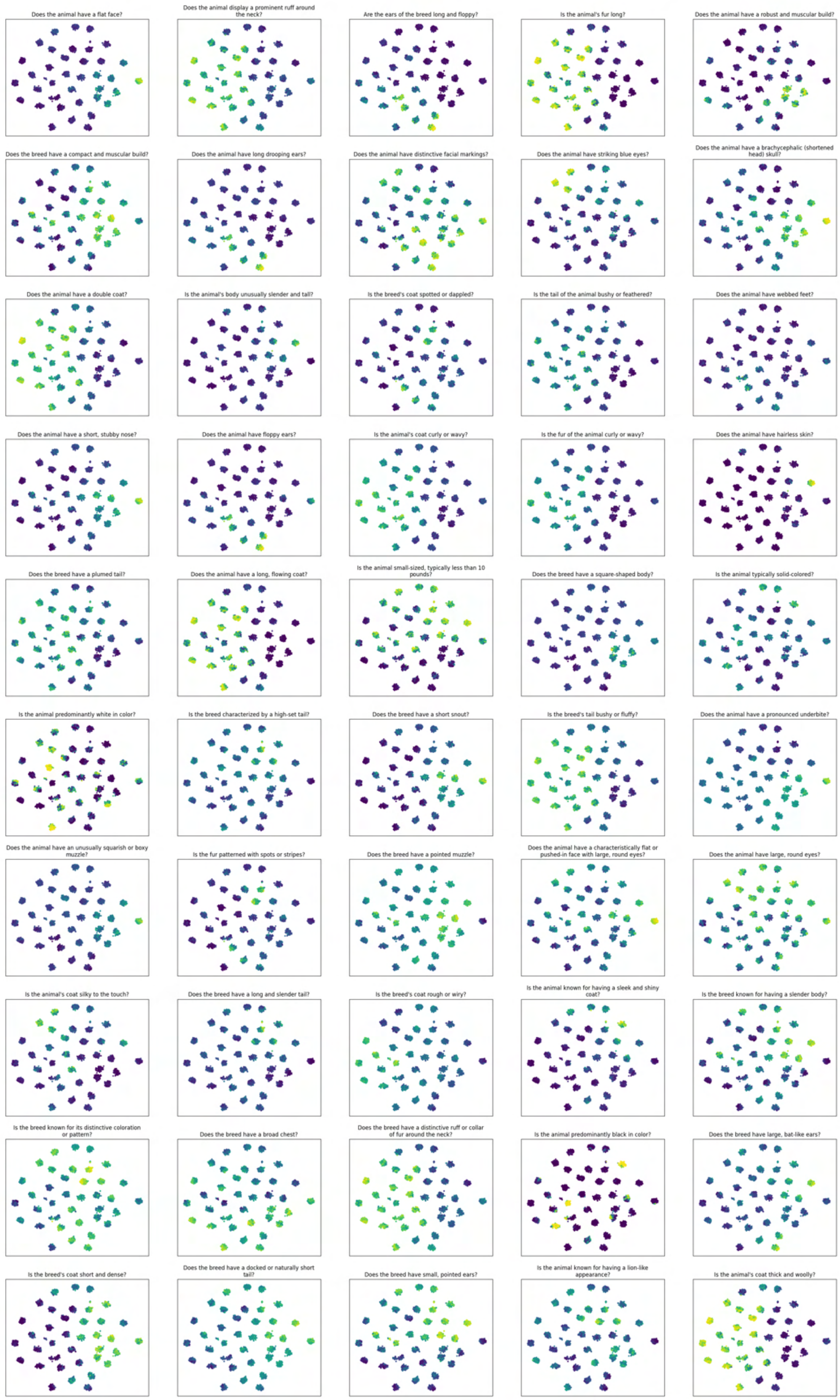

Figure 14: **Visualization of predicted result t-SNE embeddings for the multi-aspect of the OxfordPets.**

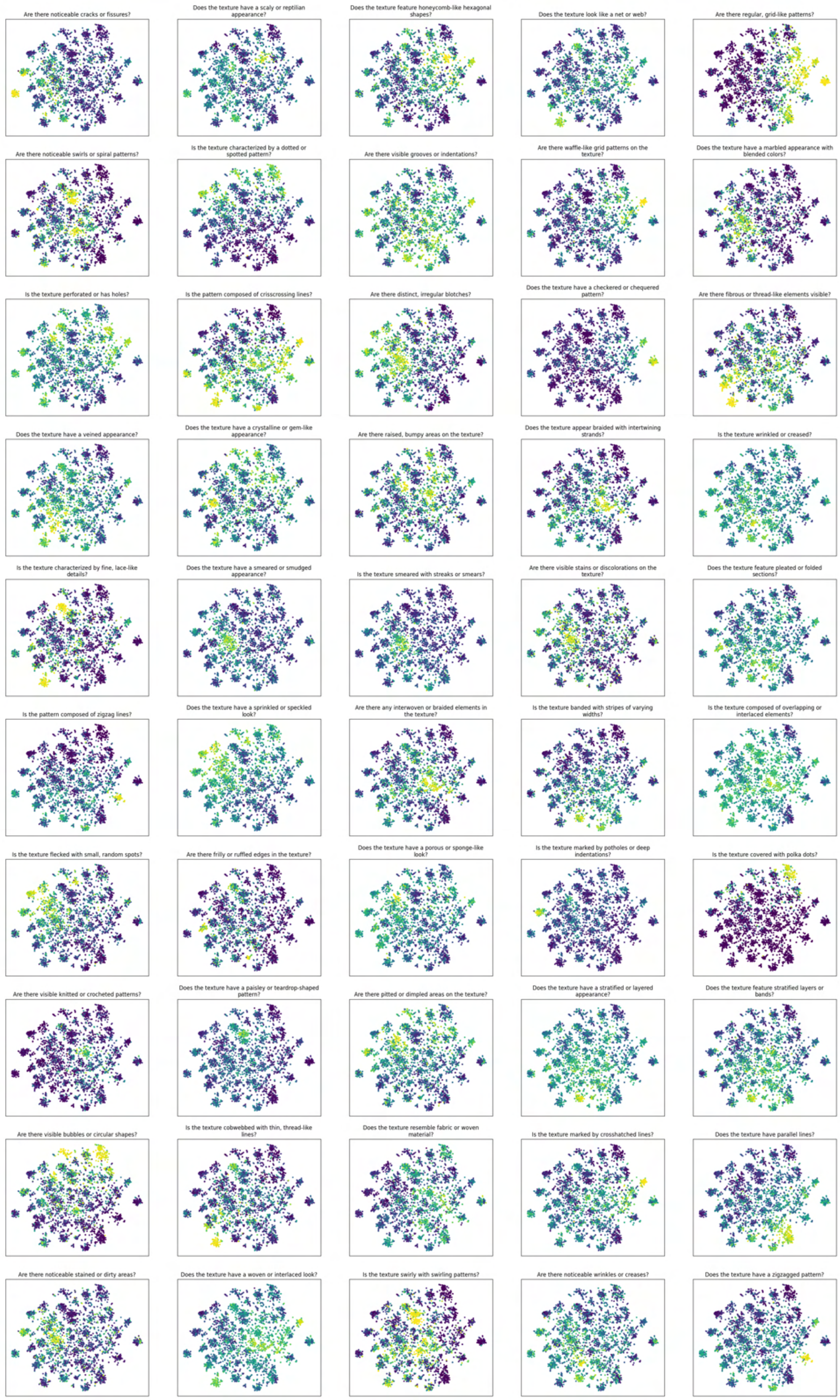

Figure 15: **Visualization of ground truth t-SNE embeddings for the multi-aspect of the StanfordCars.**

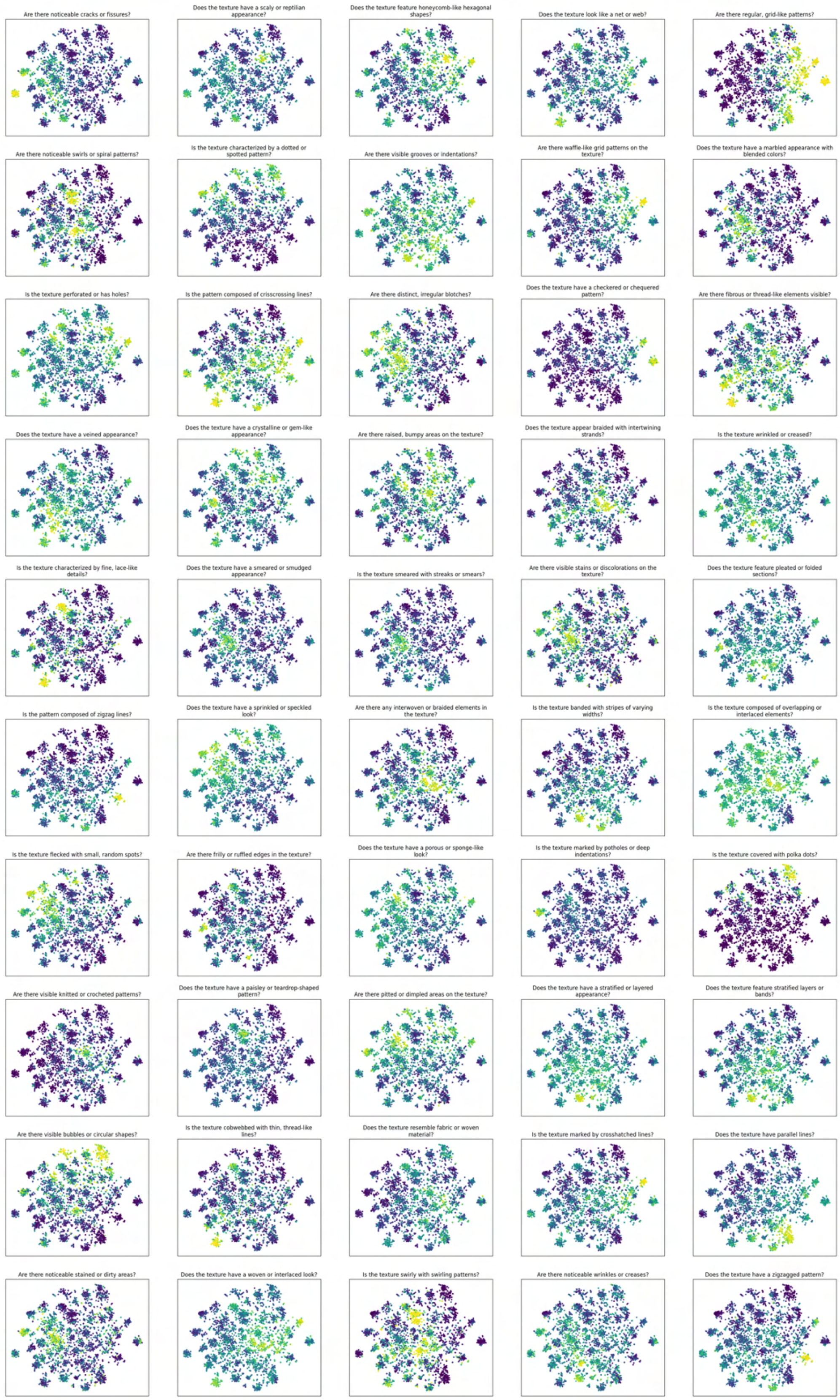

Figure 16: **Visualization of predicted result t-SNE embeddings for the multi-aspect of the StanfordCars.**

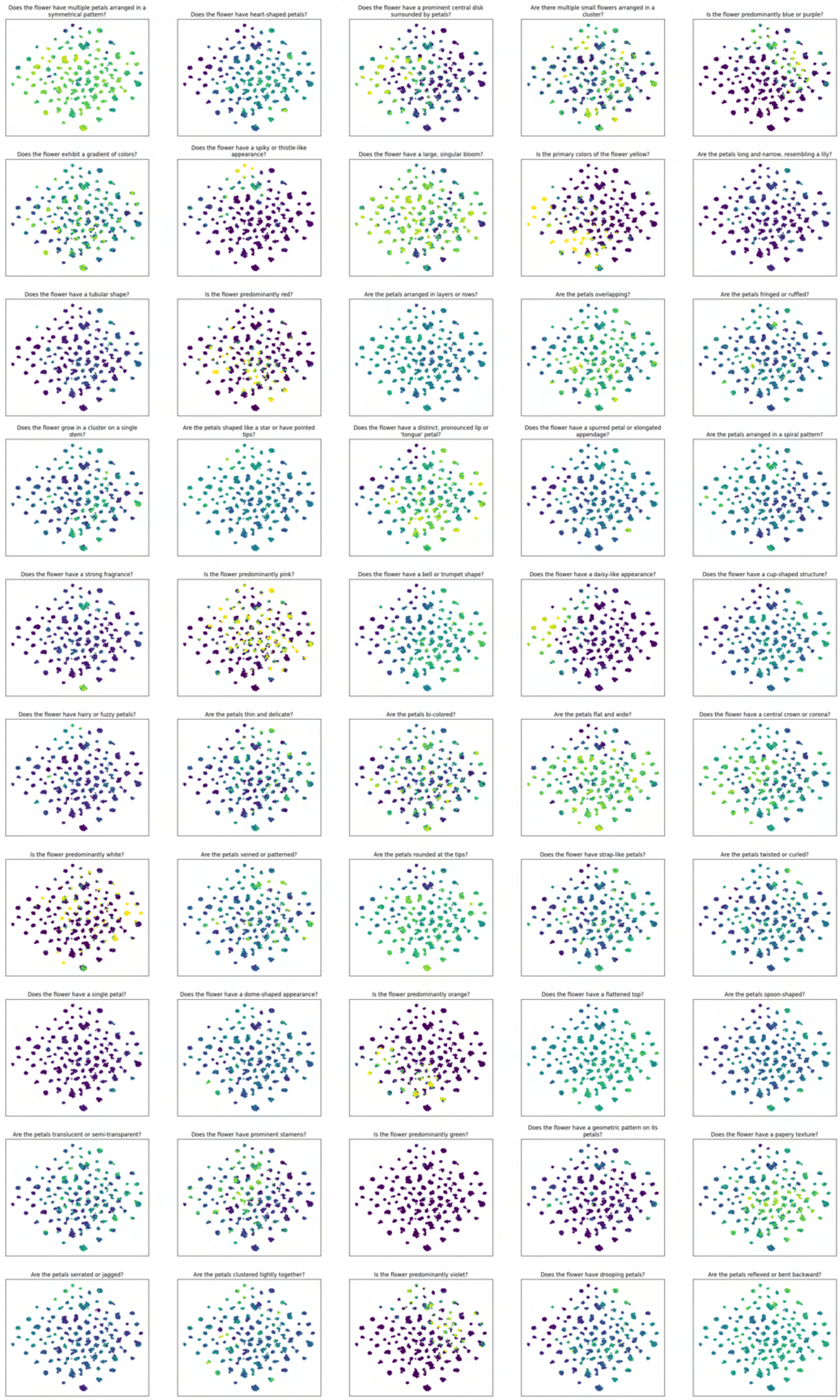

Figure 17: **Visualization of ground truth t-SNE embeddings for the multi-aspect of the DTD.**

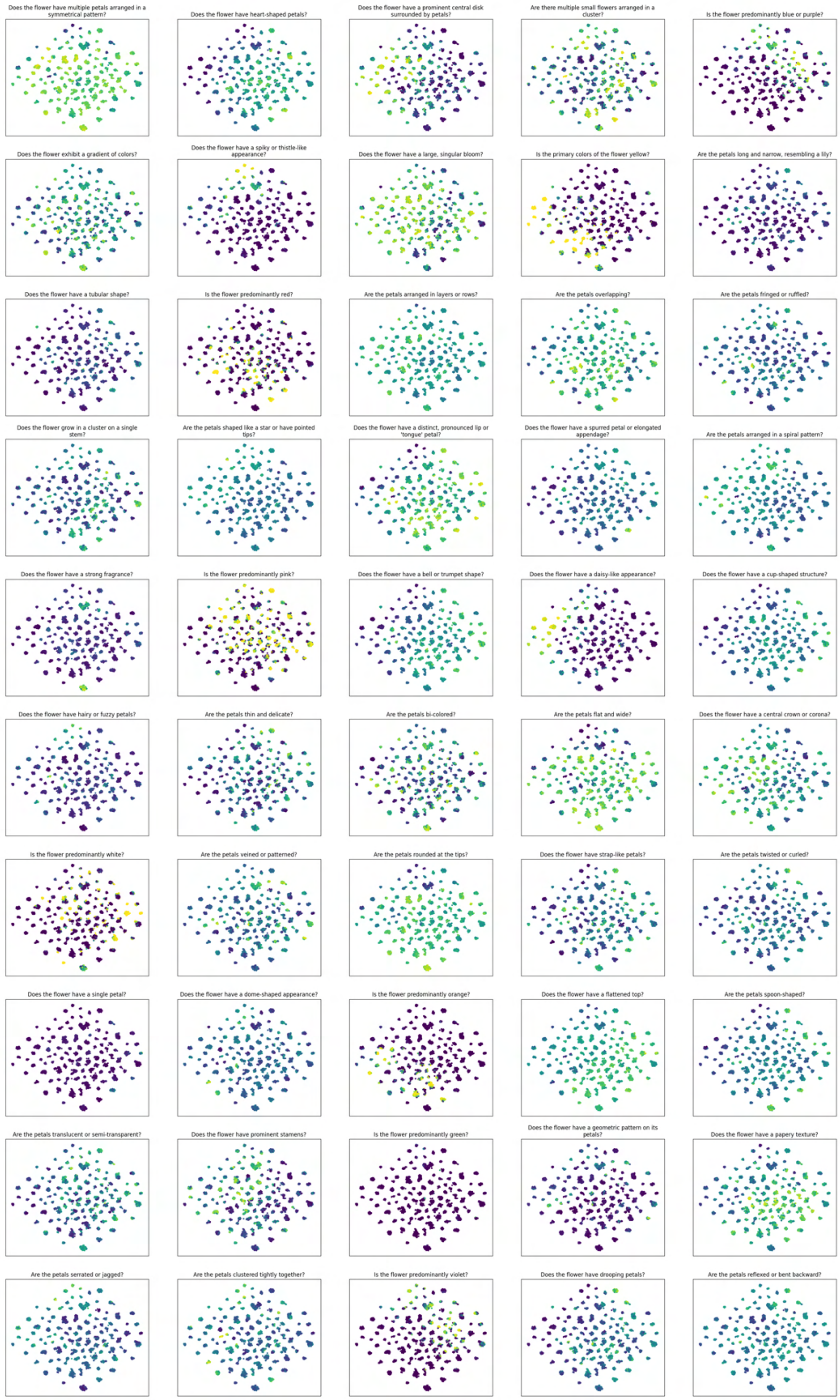

Figure 18: **Visualization of predicted result t-SNE embeddings for the multi-aspect of the DTD.**

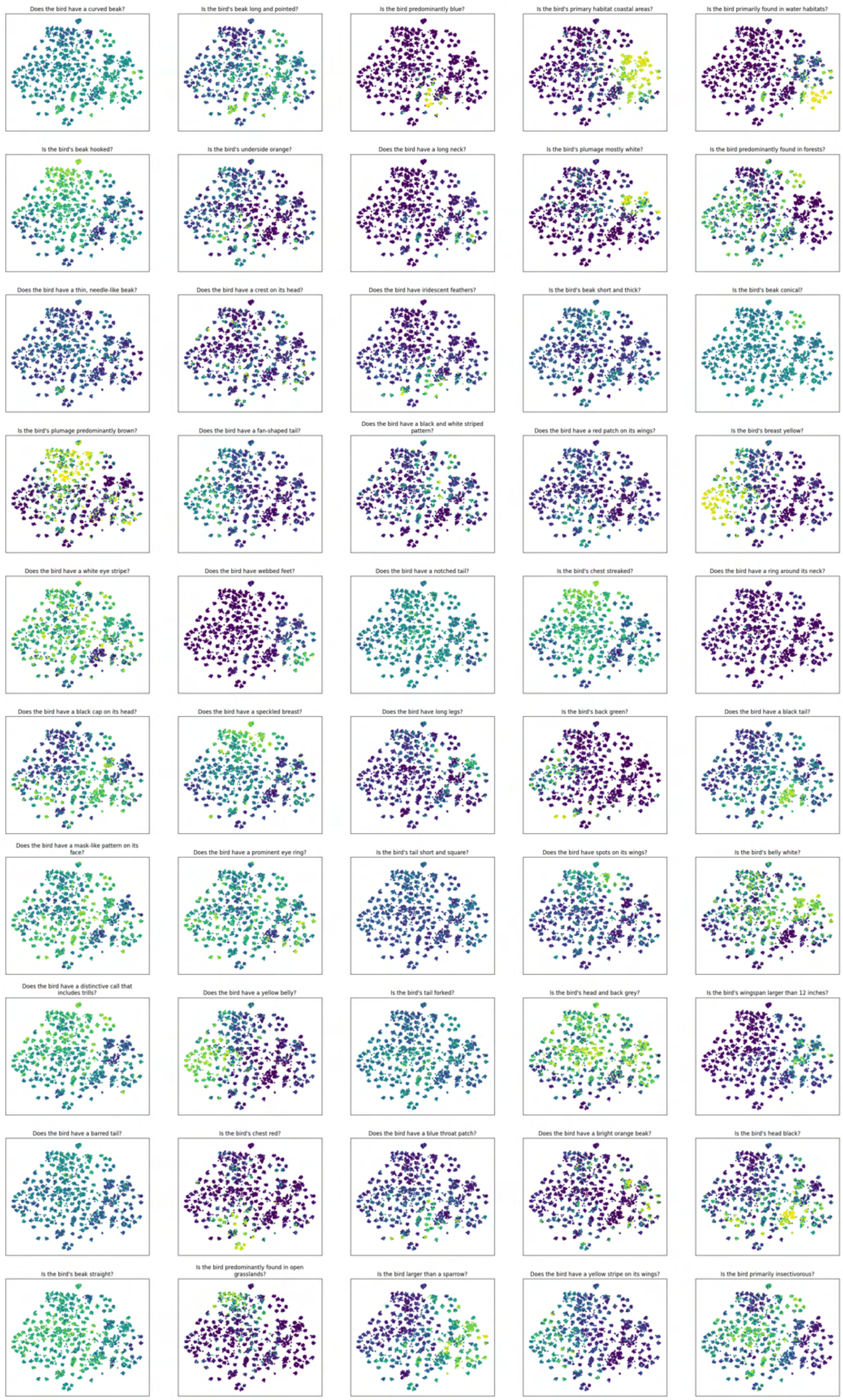

Figure 19: **Visualization of ground truth t-SNE embeddings for the multi-aspect of the CUB200.**

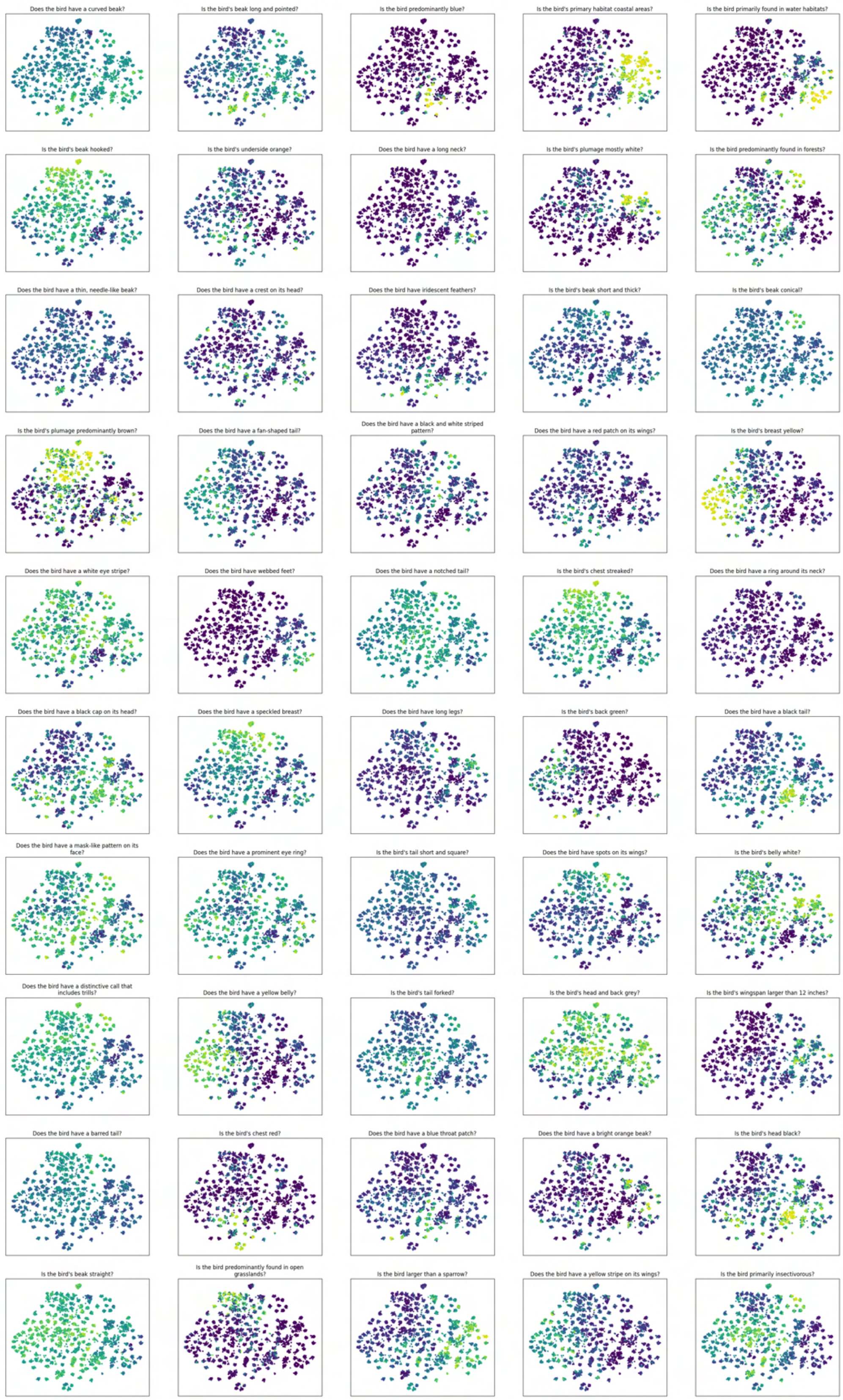

Figure 20: **Visualization of predicted result t-SNE embeddings for the multi-aspect of the CUB200.**

Figure 21: **Visualization of ground truth t-SNE embeddings for the multi-aspect of the FGVC-Aircraft.**

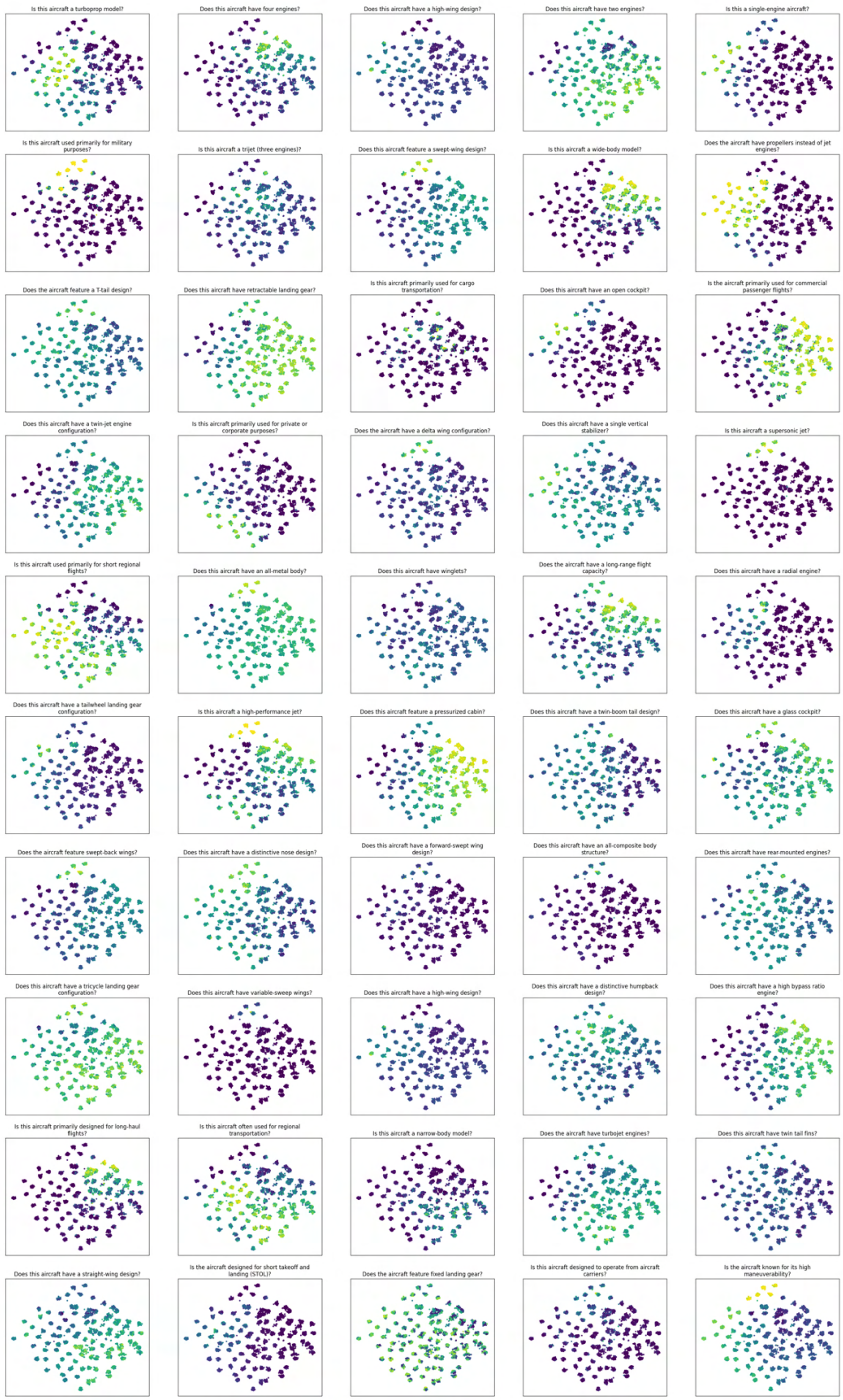

Figure 22: **Visualization of predicted result t-SNE embeddings for the multi-aspect of the FGVC-Aircraft.**

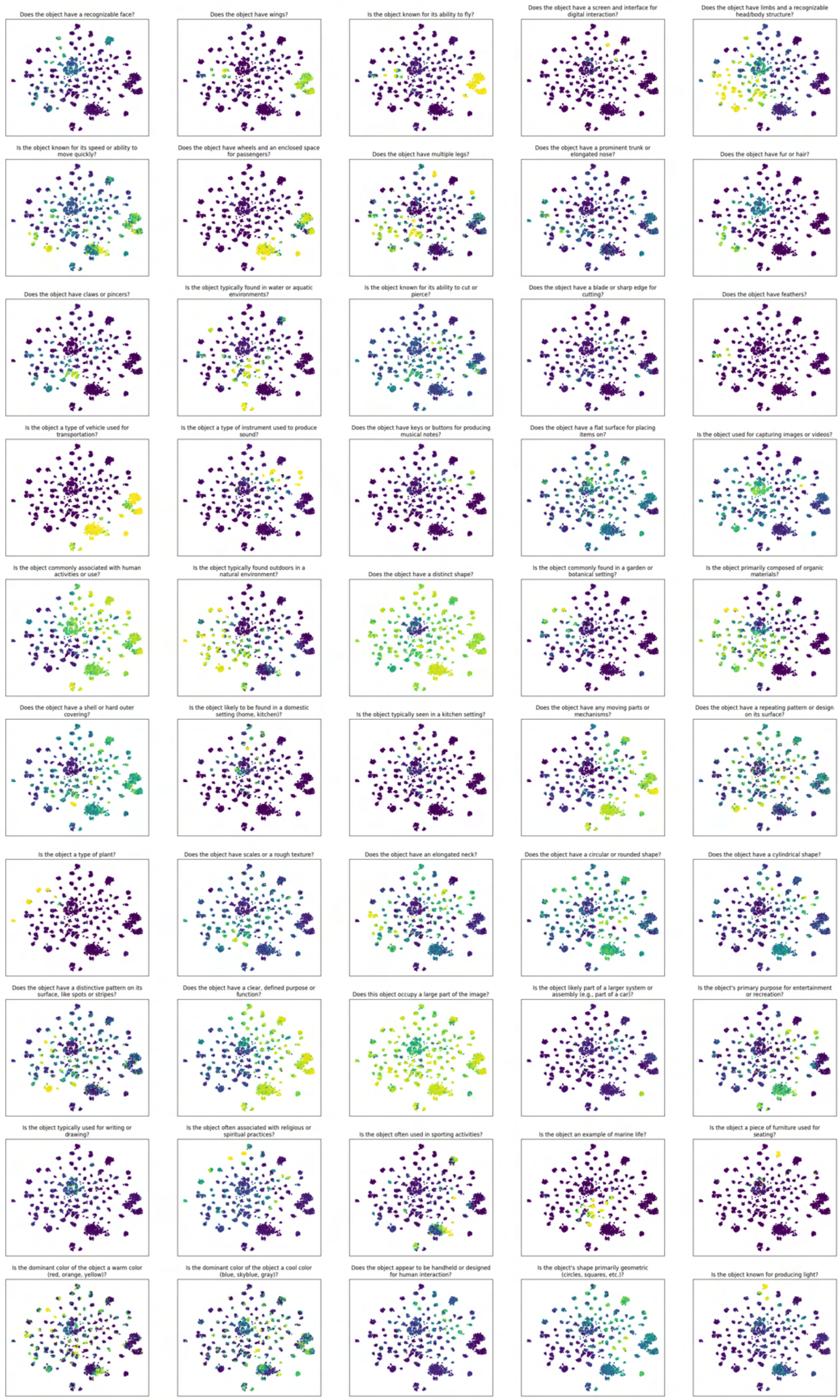

Figure 23: **Visualization of ground truth t-SNE embeddings for the multi-aspect of the Caltech101.**

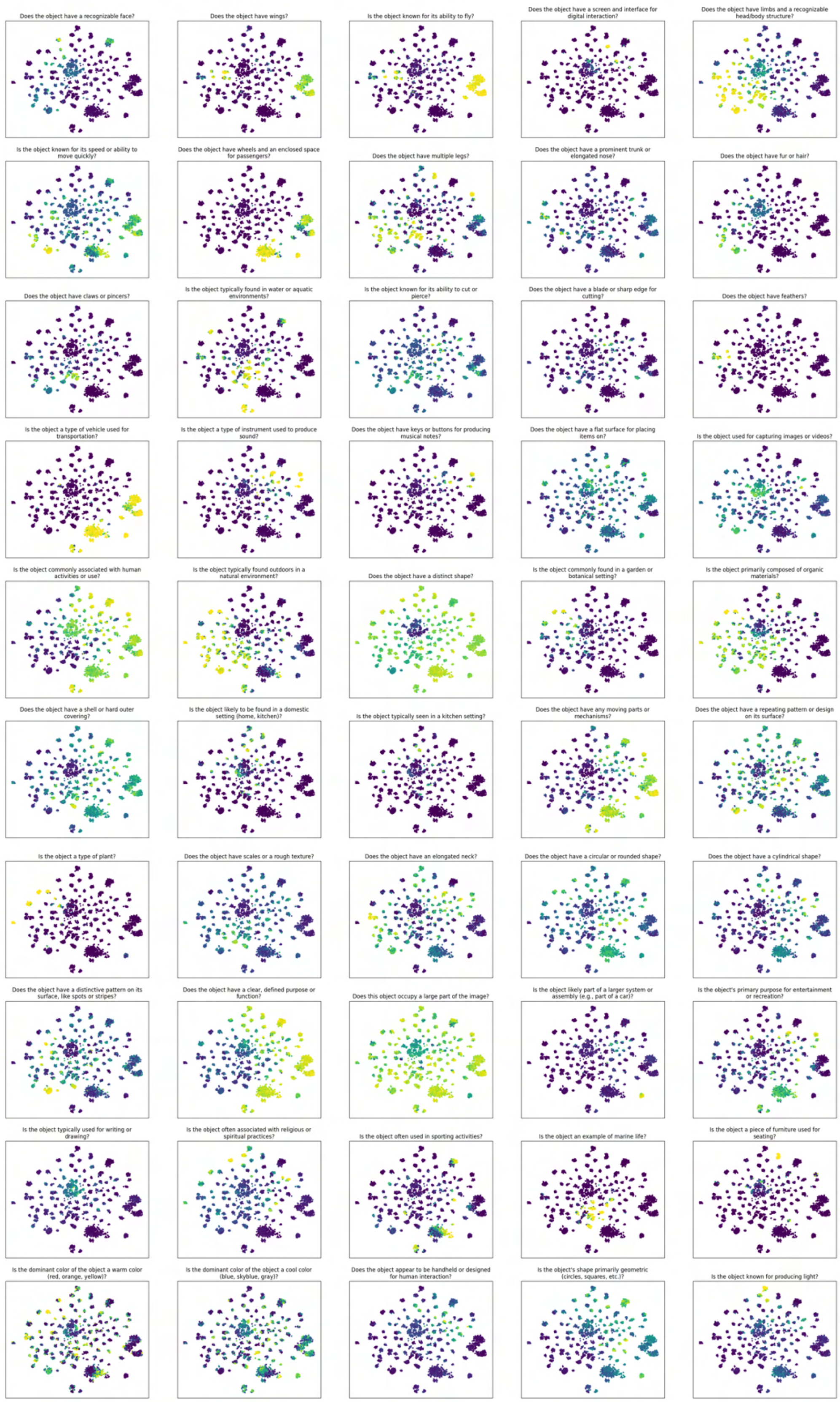

Figure 24: **Visualization of predicted result t-SNE embeddings for the multi-aspect of the Caltech101.**

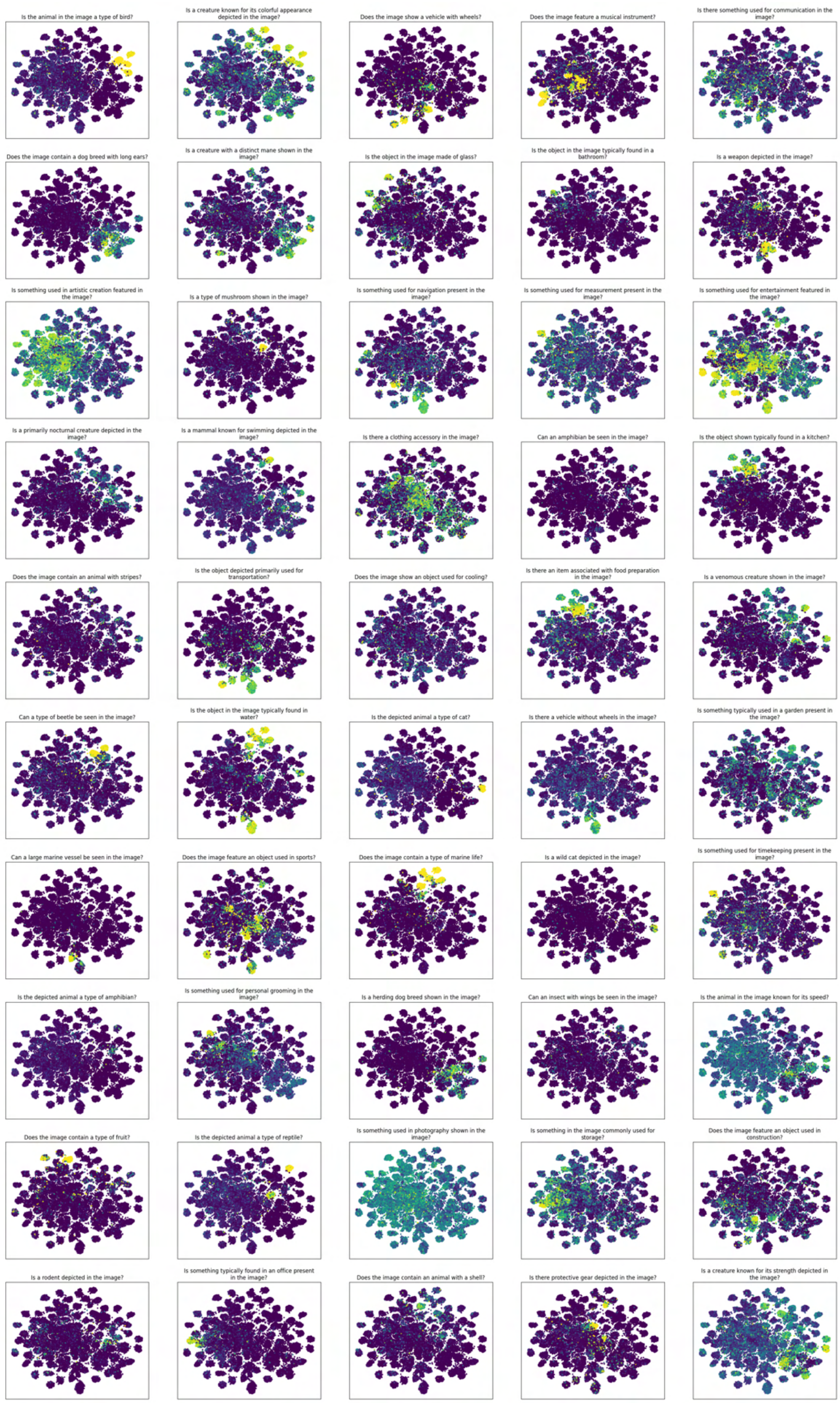

Figure 25: **Visualization of ground truth t-SNE embeddings for the multi-aspect of the Mini-ImageNet.**

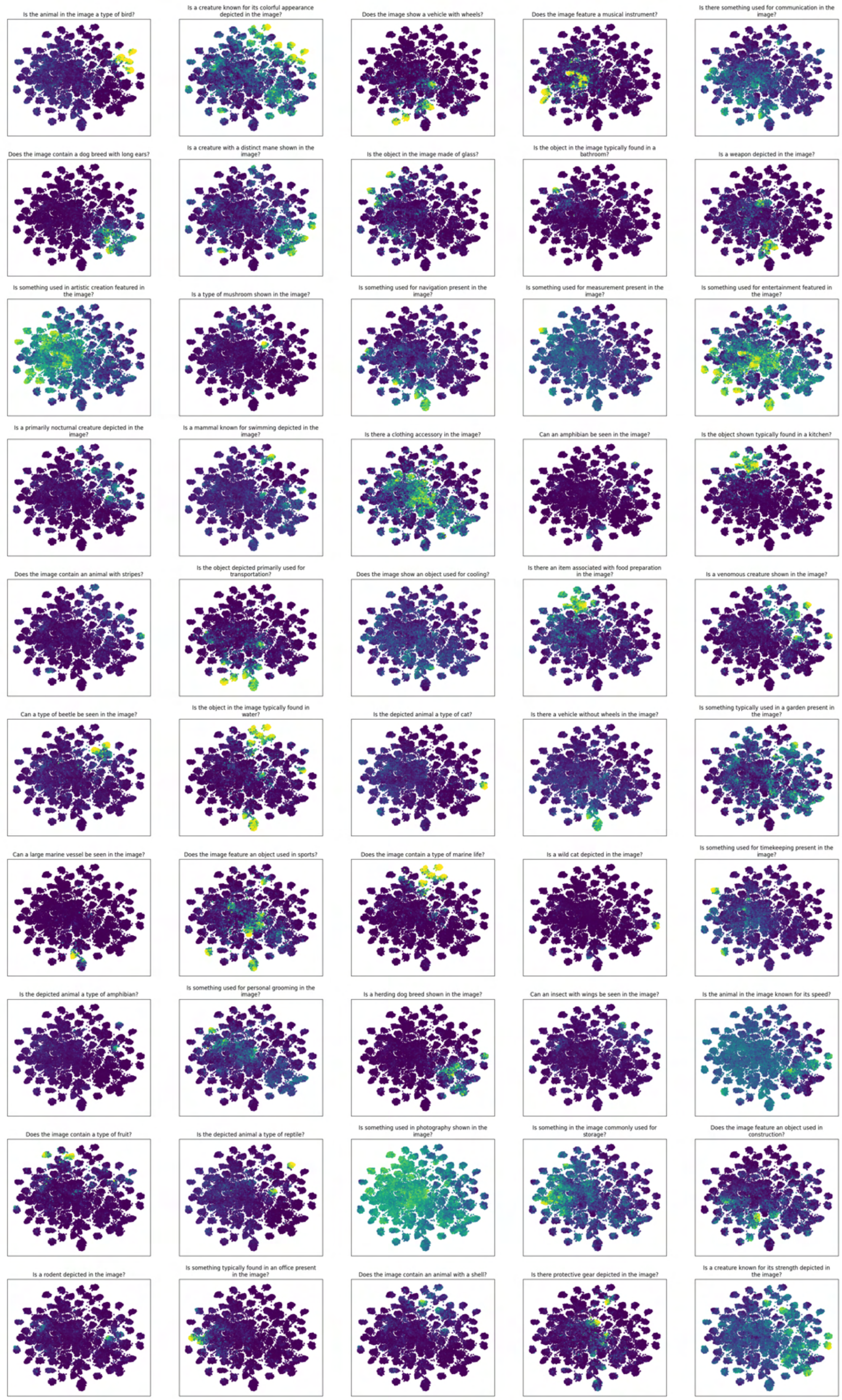

Figure 26: **Visualization of predicted result t-SNE embeddings for the multi-aspect of the Mini-ImageNet.**

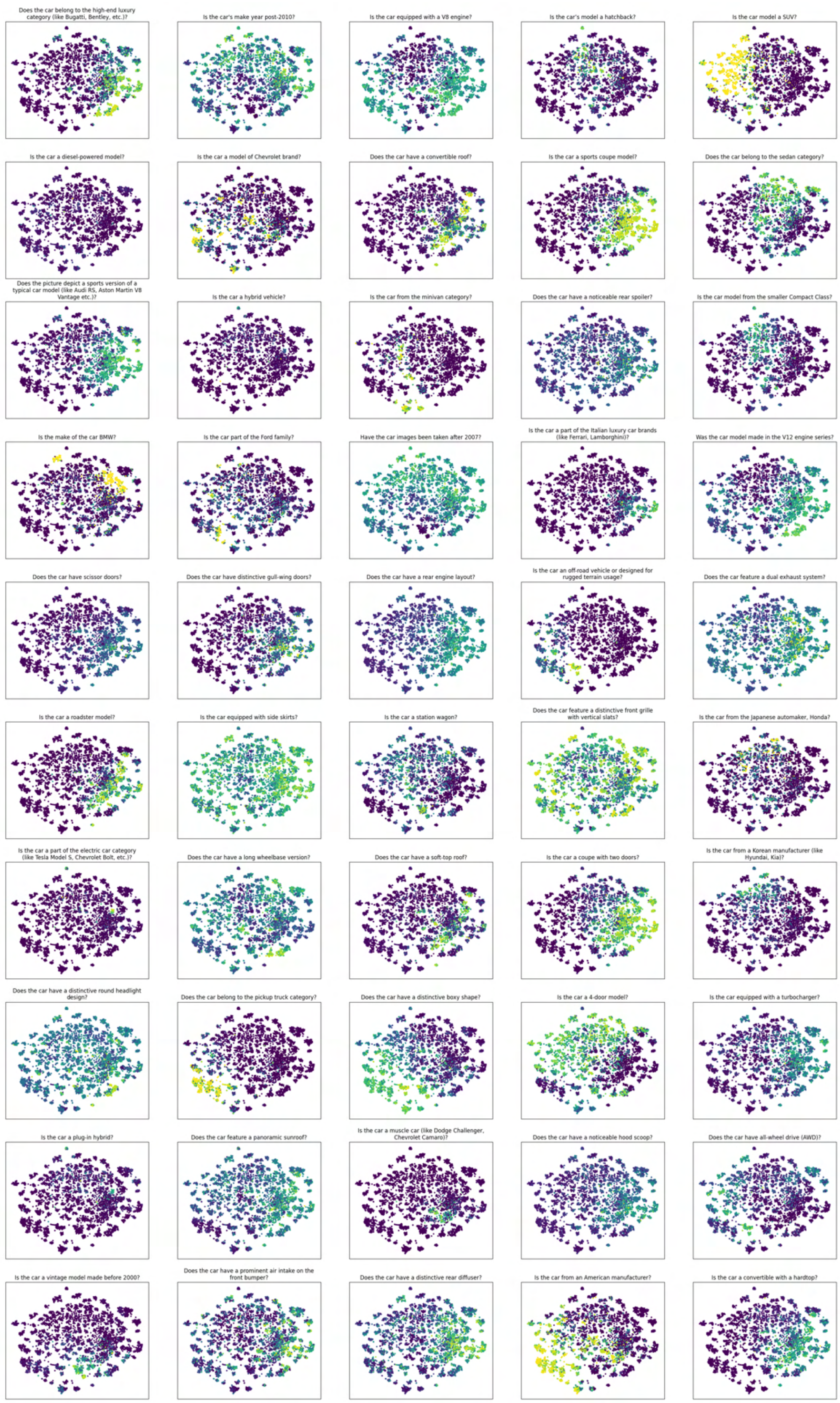

Figure 27: **Visualization of ground truth t-SNE embeddings for the multi-aspect of the StanfordCars testing dataset.**

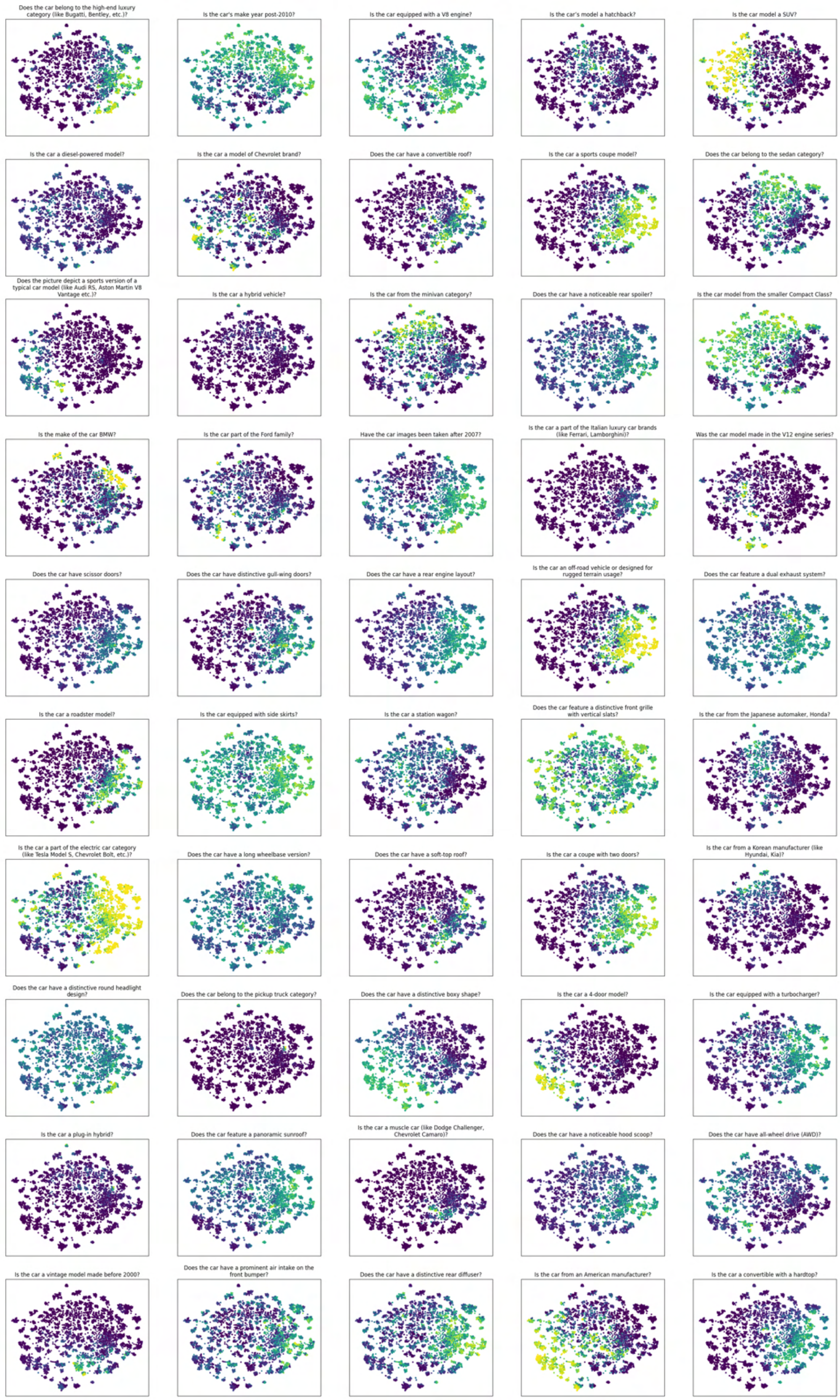

Figure 28: **Visualization of predicted result t-SNE embeddings for the multi-aspect of the StanfordCars testing dataset.**

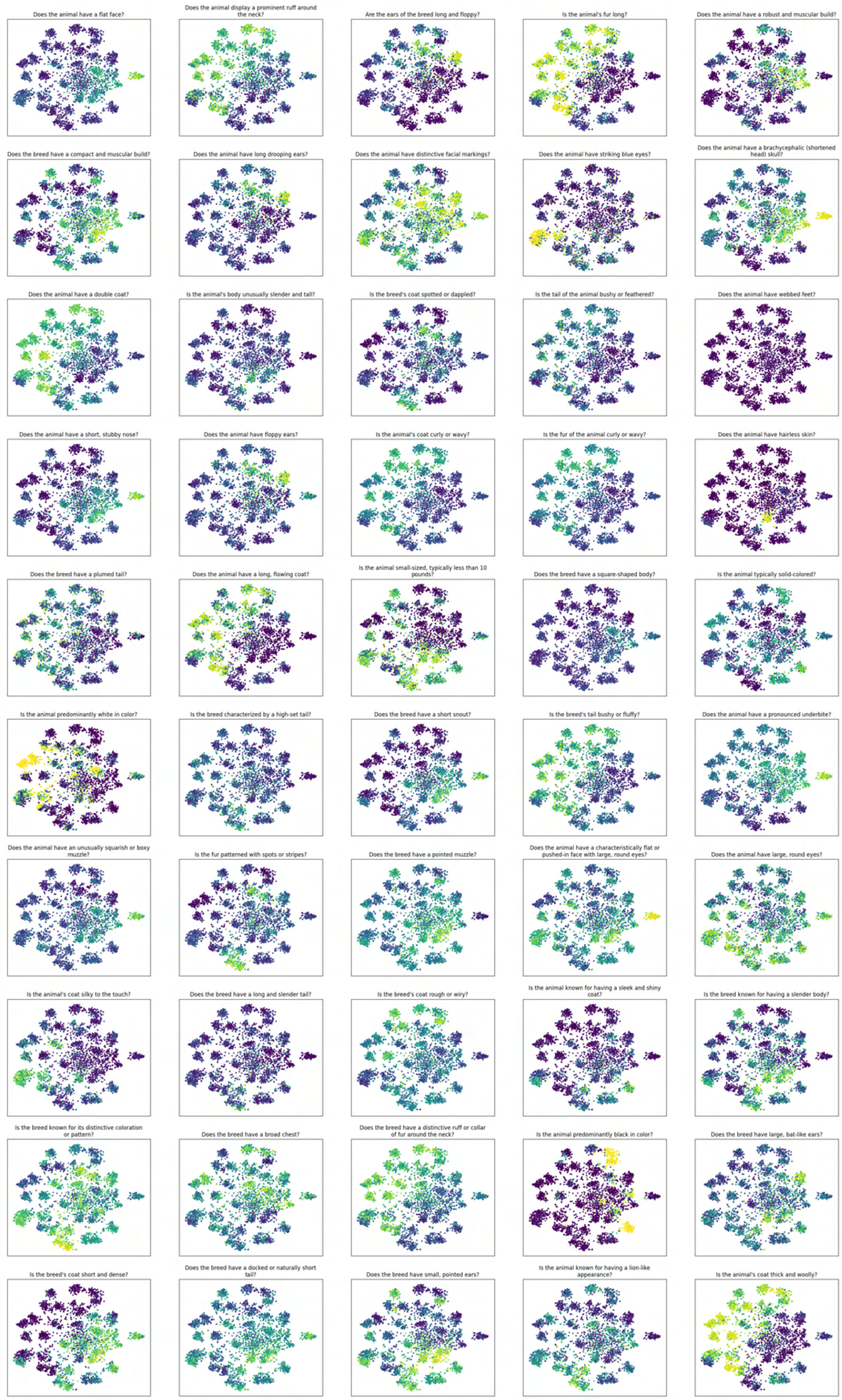

Figure 29: **Visualization of ground truth t-SNE embeddings for the multi-aspect of the Oxford-Pets testing dataset.**

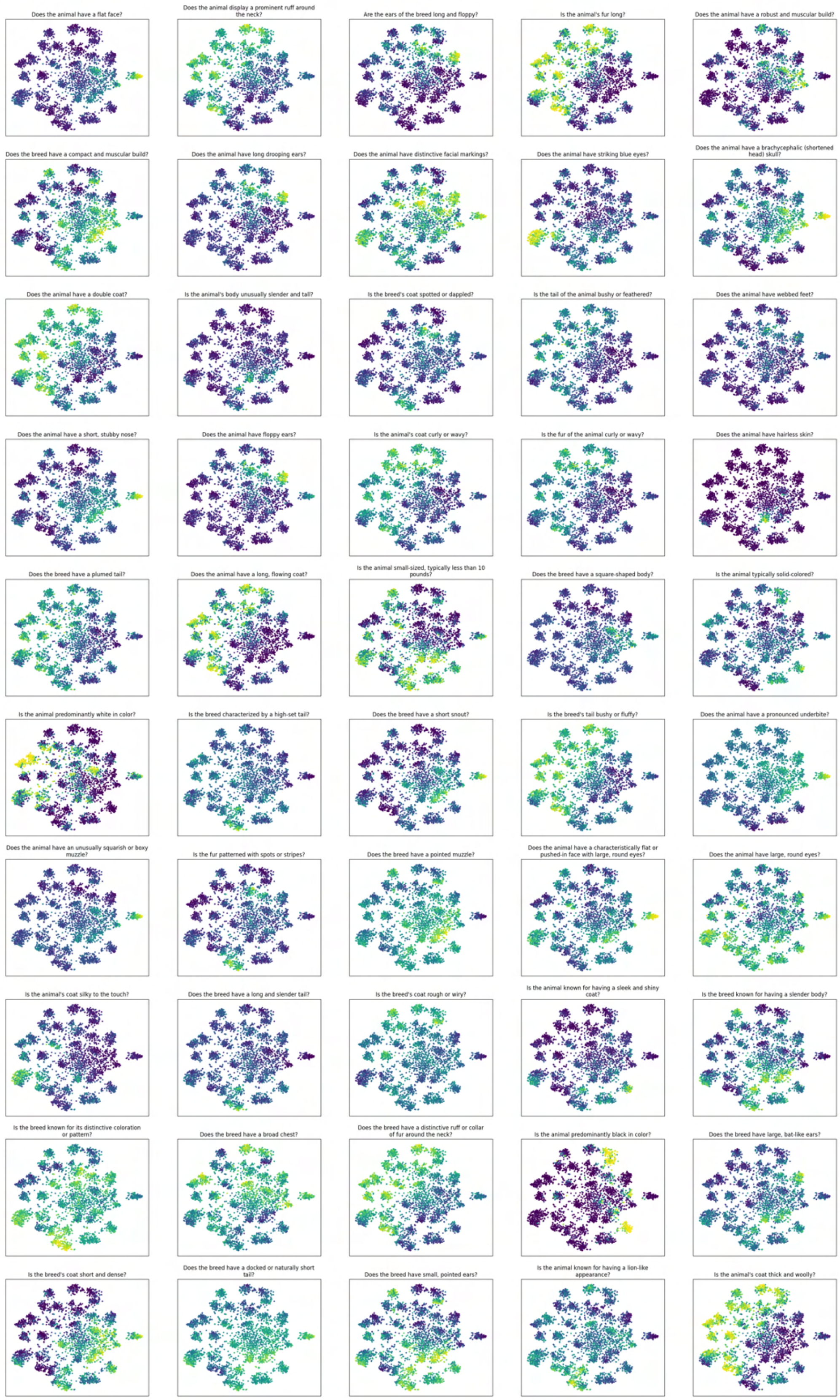

Figure 30: **Visualization of predicted result t-SNE embeddings for the multi-aspect of the OxfordPets testing dataset.**

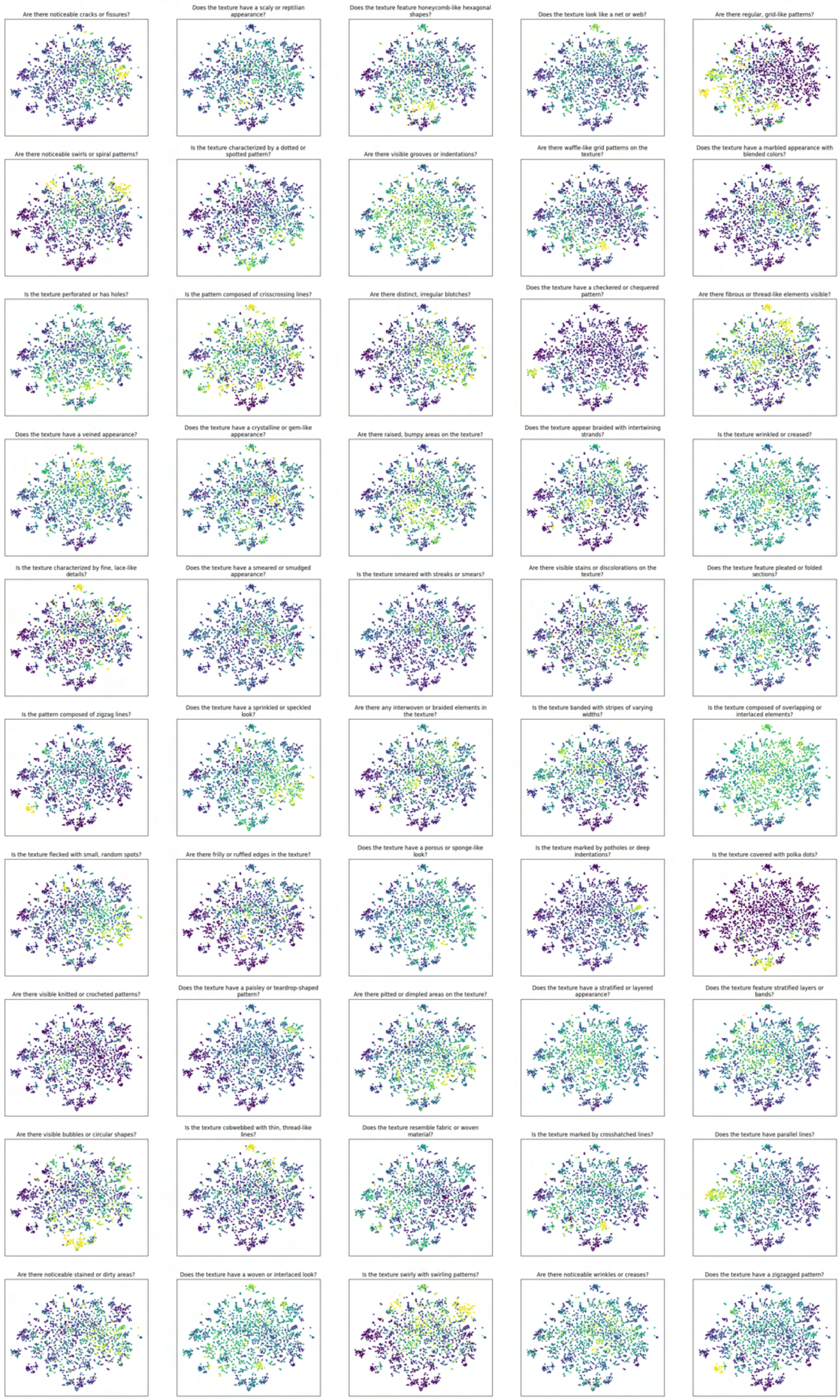

Figure 31: **Visualization of ground truth t-SNE embeddings for the multi-aspect of the DTD testing dataset.**

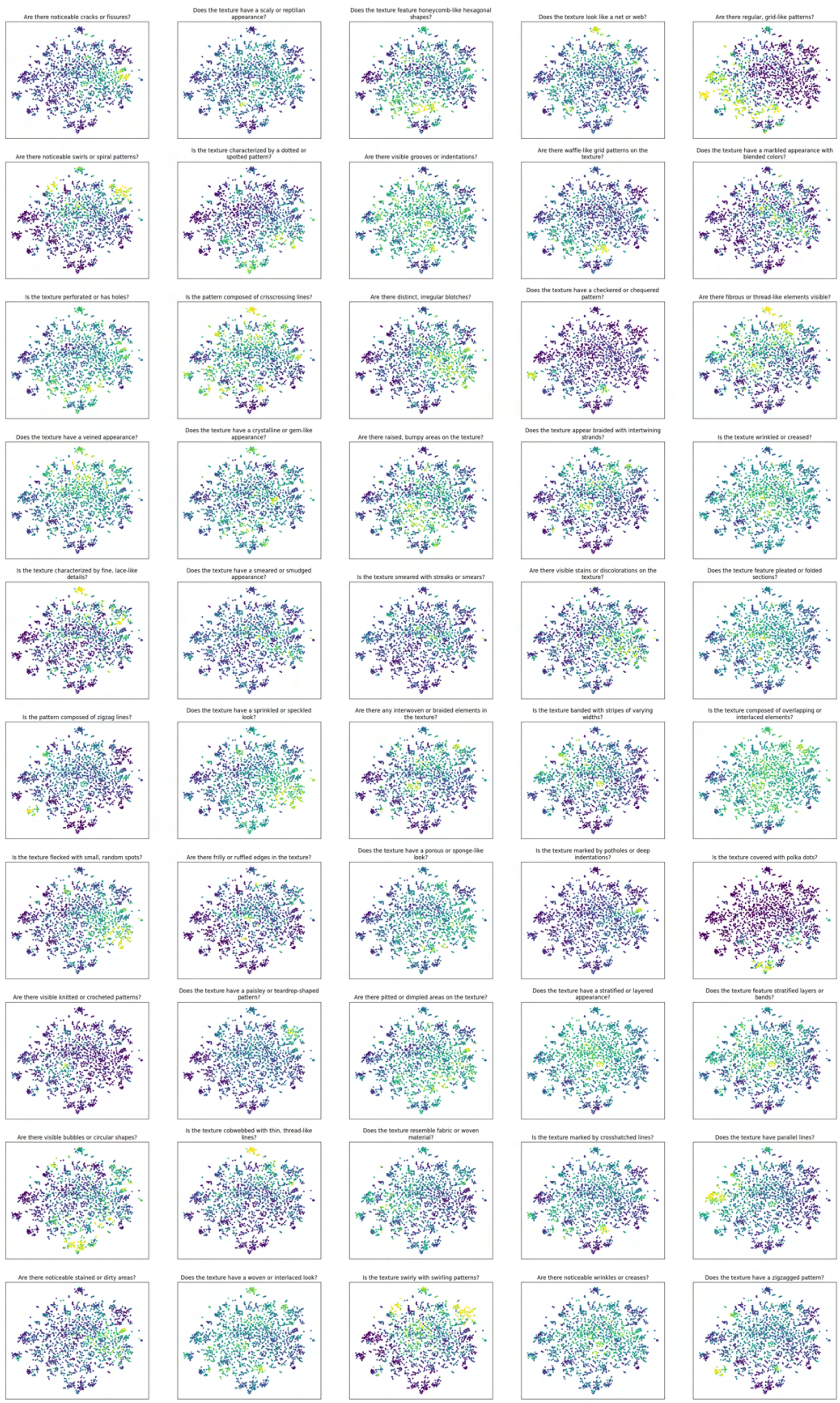

Figure 32: **Visualization of predicted result t-SNE embeddings for the multi-aspect of the DTD testing dataset.**

Figure 33: **Visualization of ground truth t-SNE embeddings for the multi-aspect of the 102Flowers testing dataset.**

Figure 34: **Visualization of predicted result t-SNE embeddings for the multi-aspect of the 102Flowers testing dataset.**

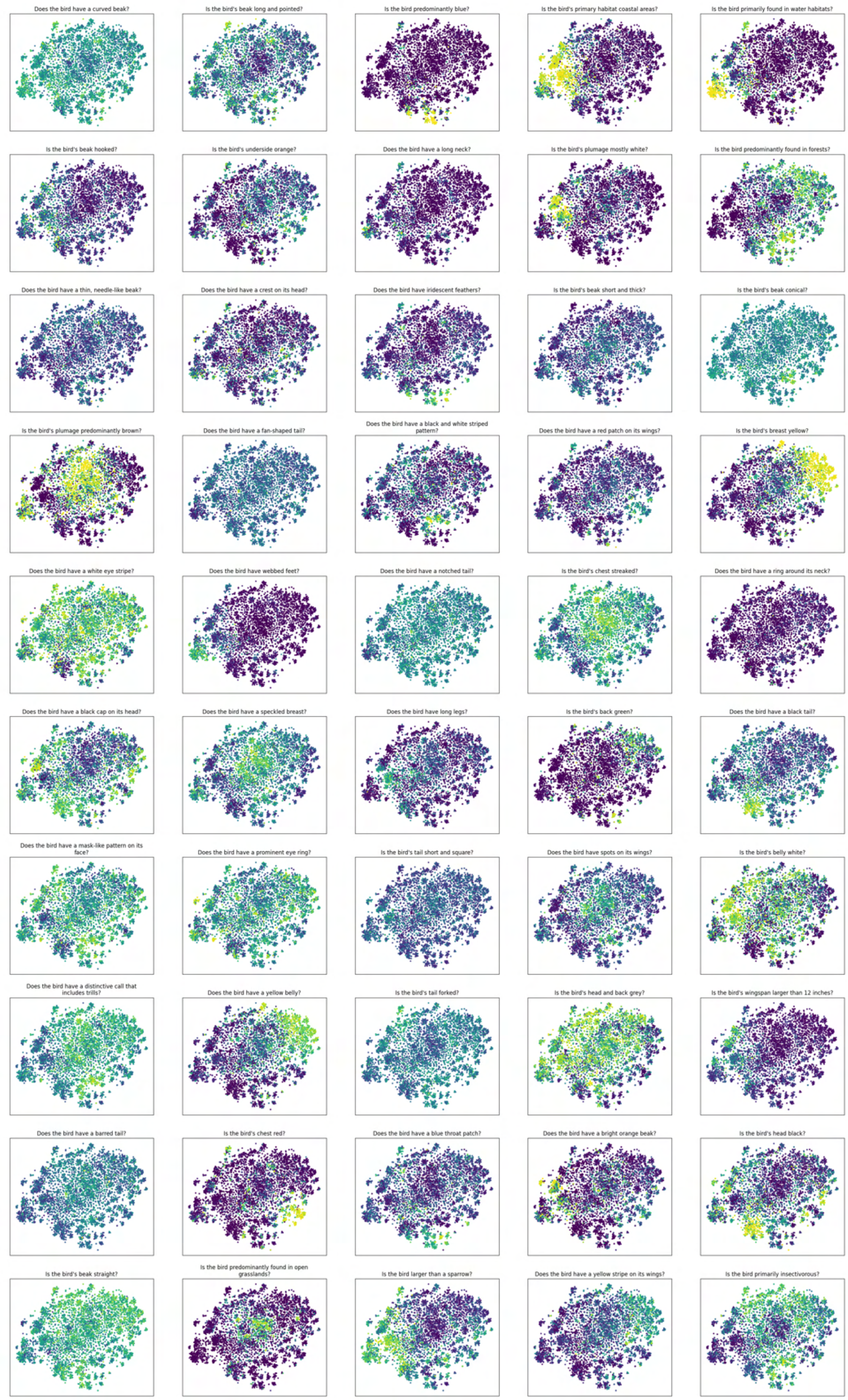

Figure 35: **Visualization of ground truth t-SNE embeddings for the multi-aspect of the CUB200 testing dataset.**

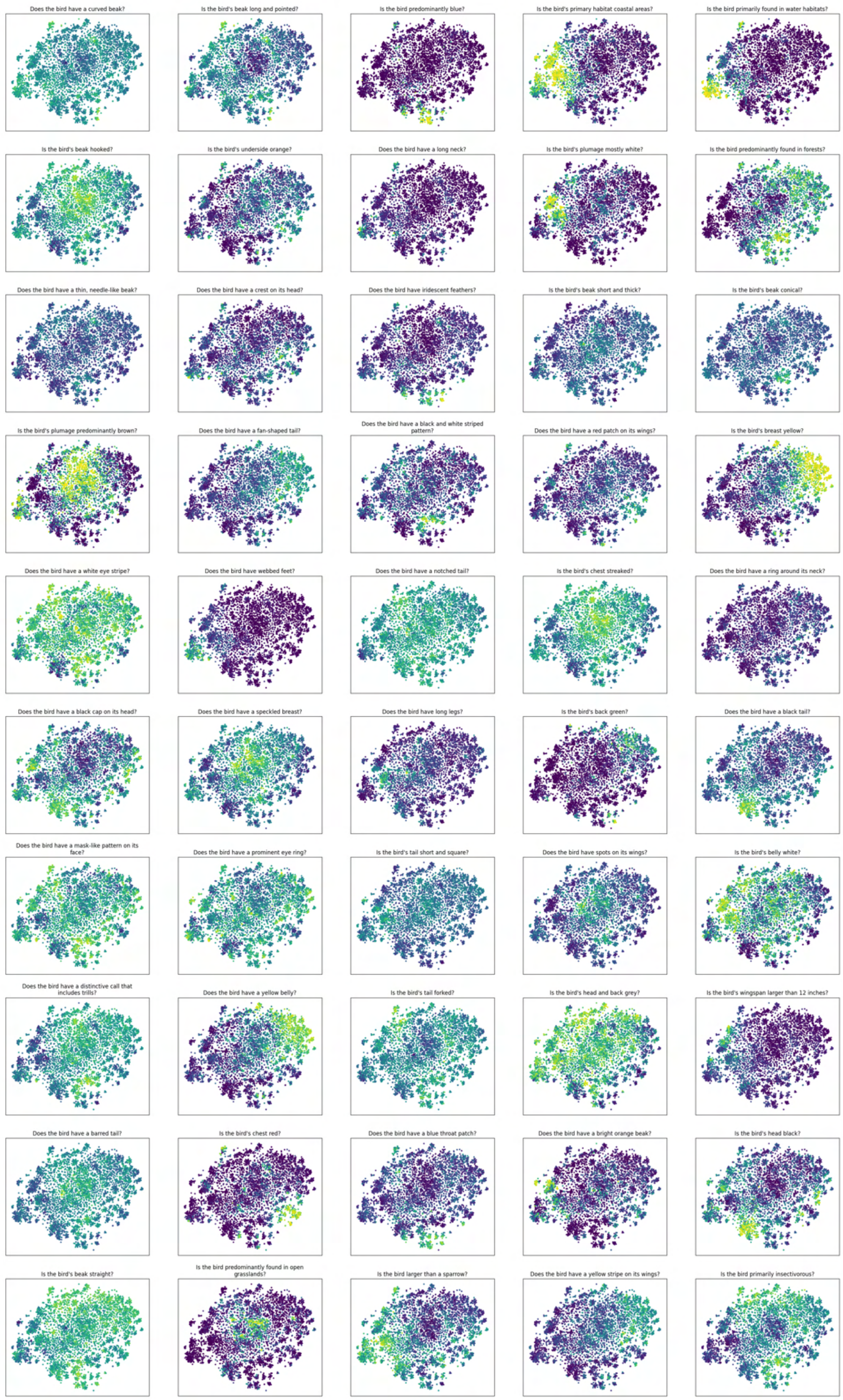

Figure 36: **Visualization of predicted result t-SNE embeddings for the multi-aspect of the CUB200 testing dataset.**

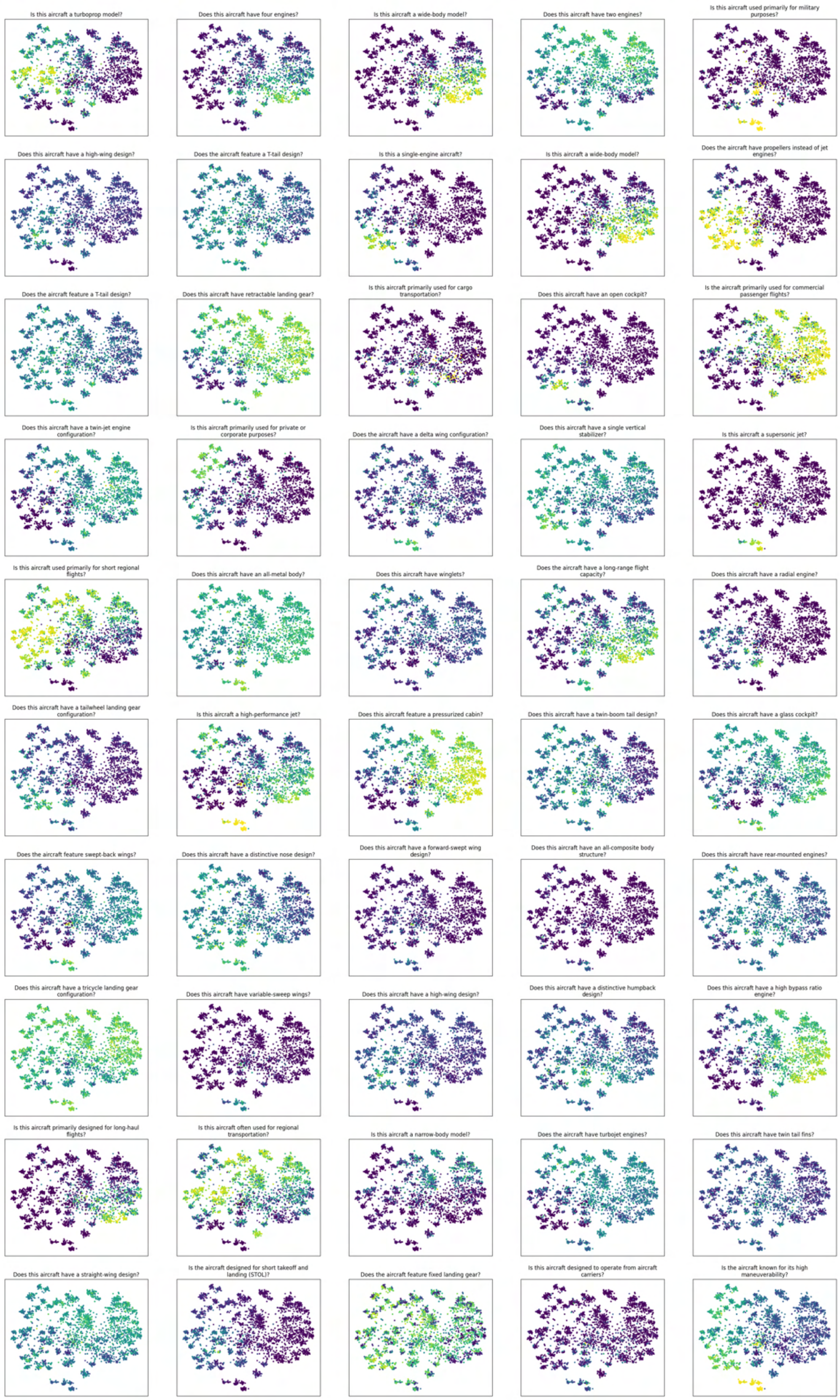

Figure 37: **Visualization of ground truth t-SNE embeddings for the multi-aspect of the FGVC-Aircraft testing dataset.**

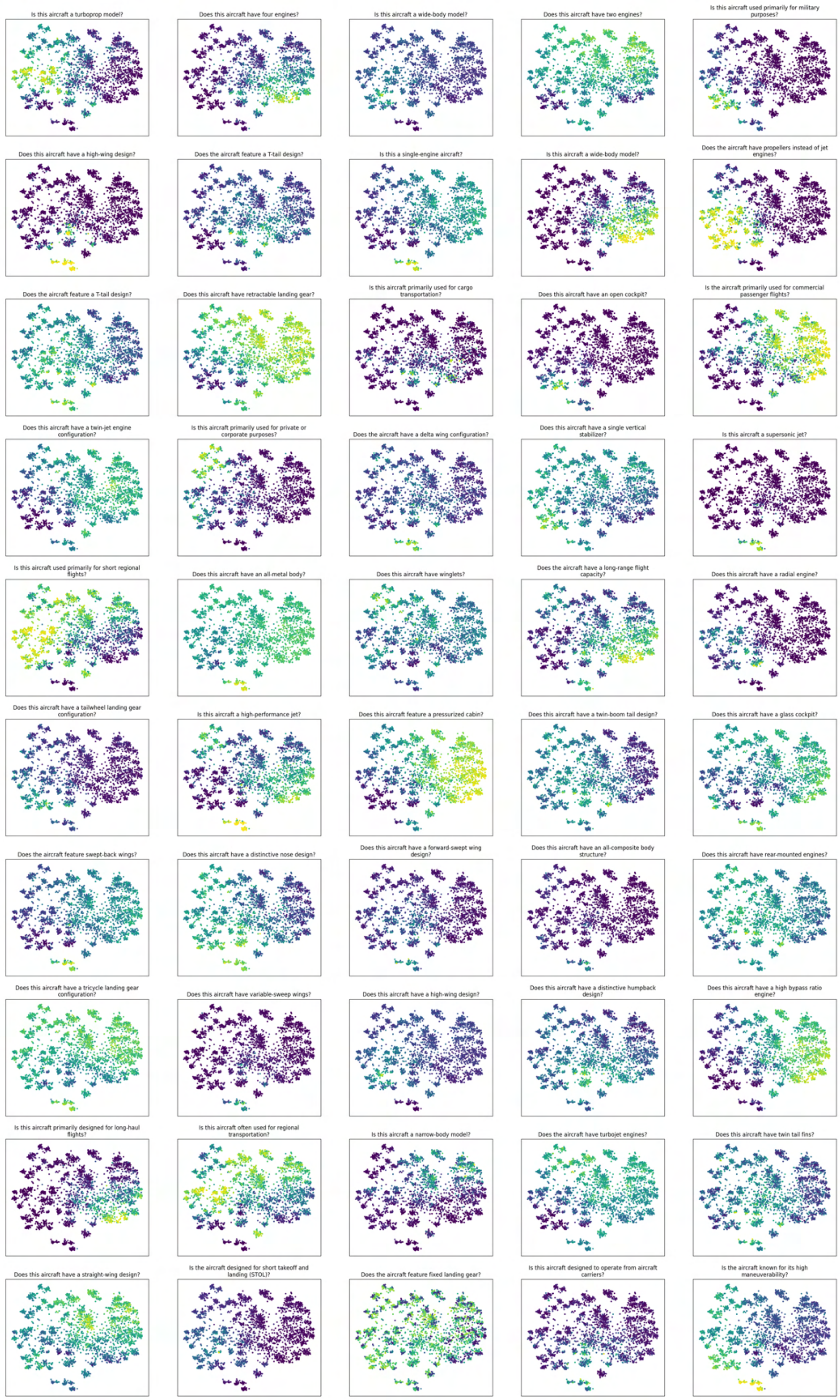

Figure 38: **Visualization of predicted result t-SNE embeddings for the multi-aspect of the FGVC-Aircraft testing dataset.**

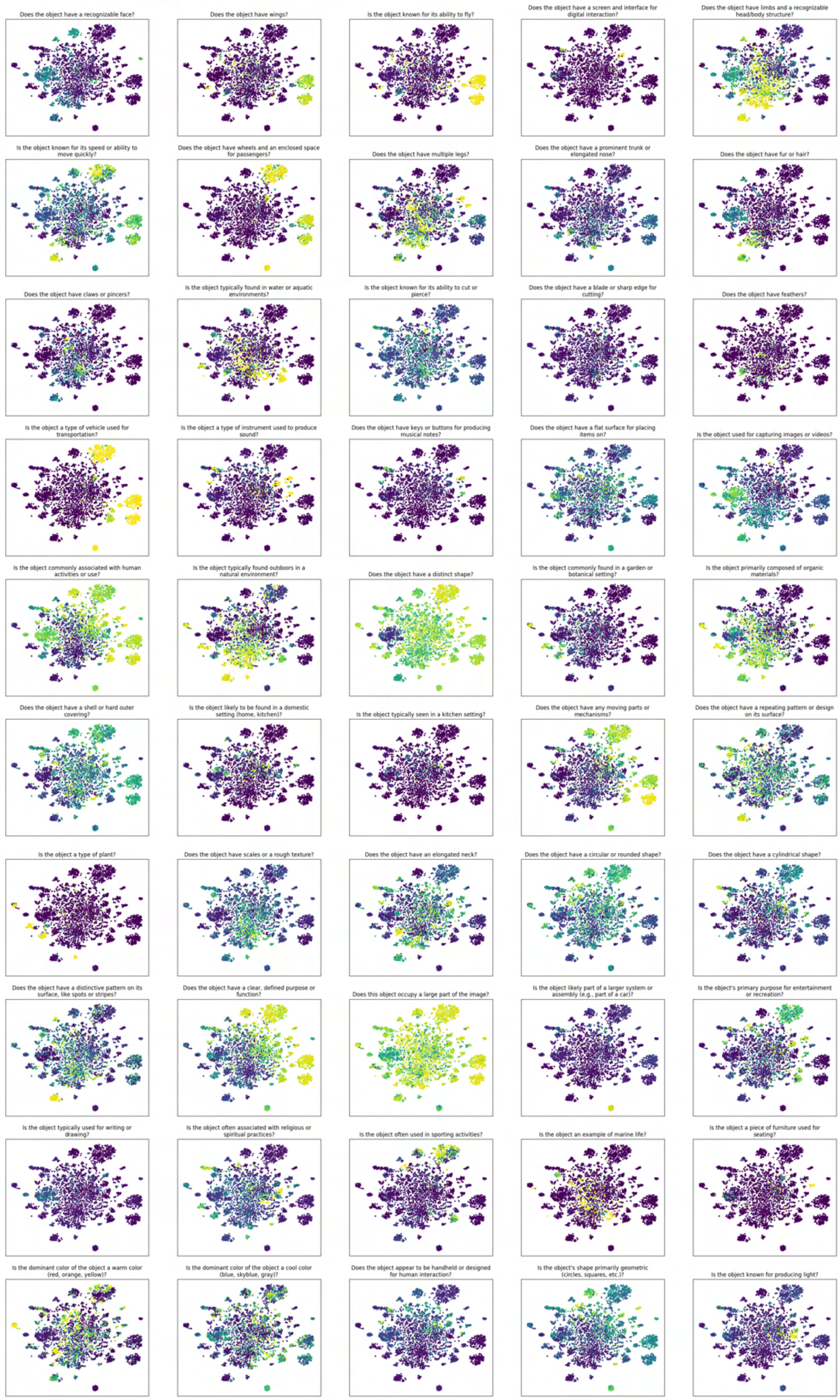

Figure 39: **Visualization of ground truth t-SNE embeddings for the multi-aspect of the Caltech101 testing dataset.**

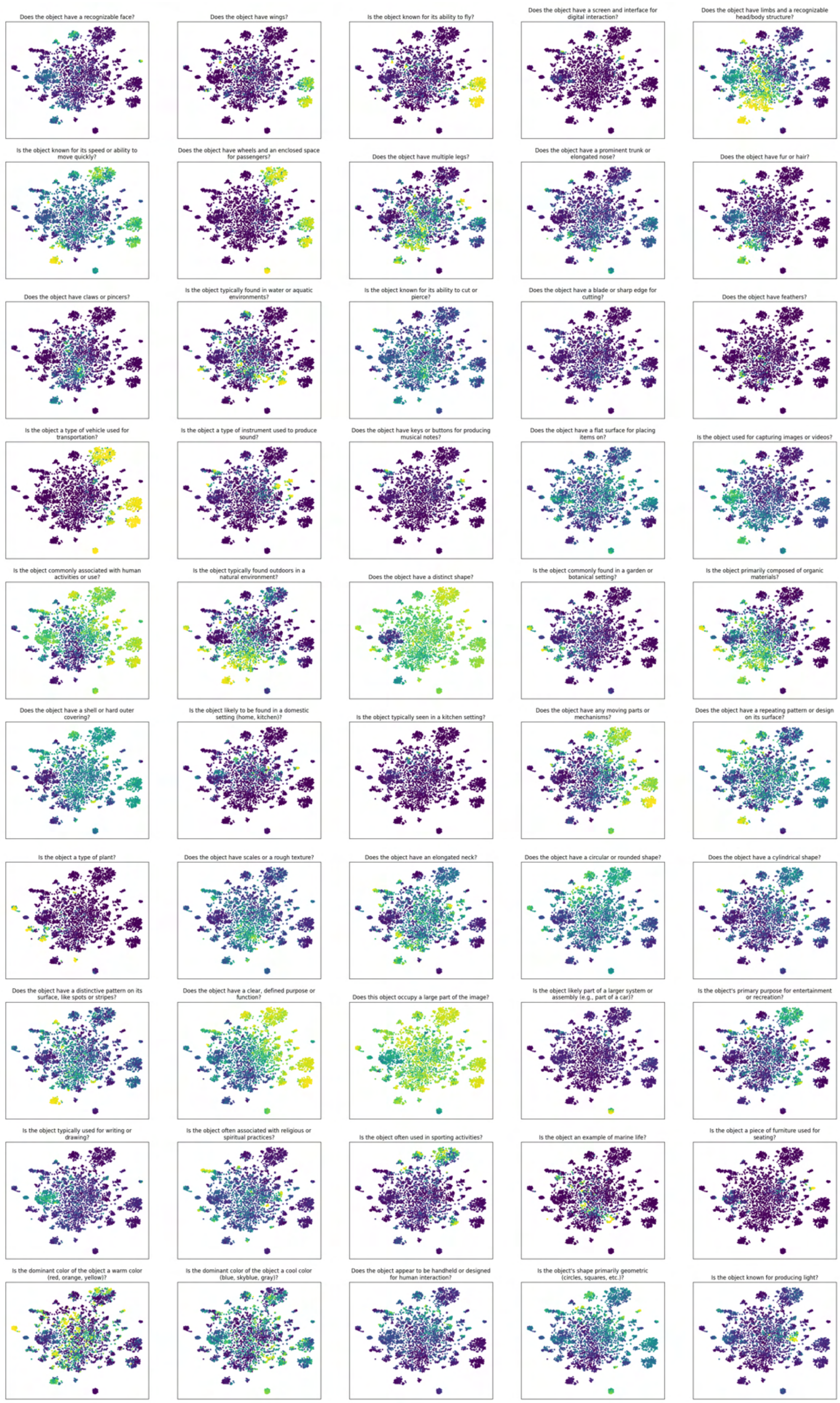

Figure 40: **Visualization of predicted result t-SNE embeddings for the multi-aspect of the Caltech101 testing dataset.**

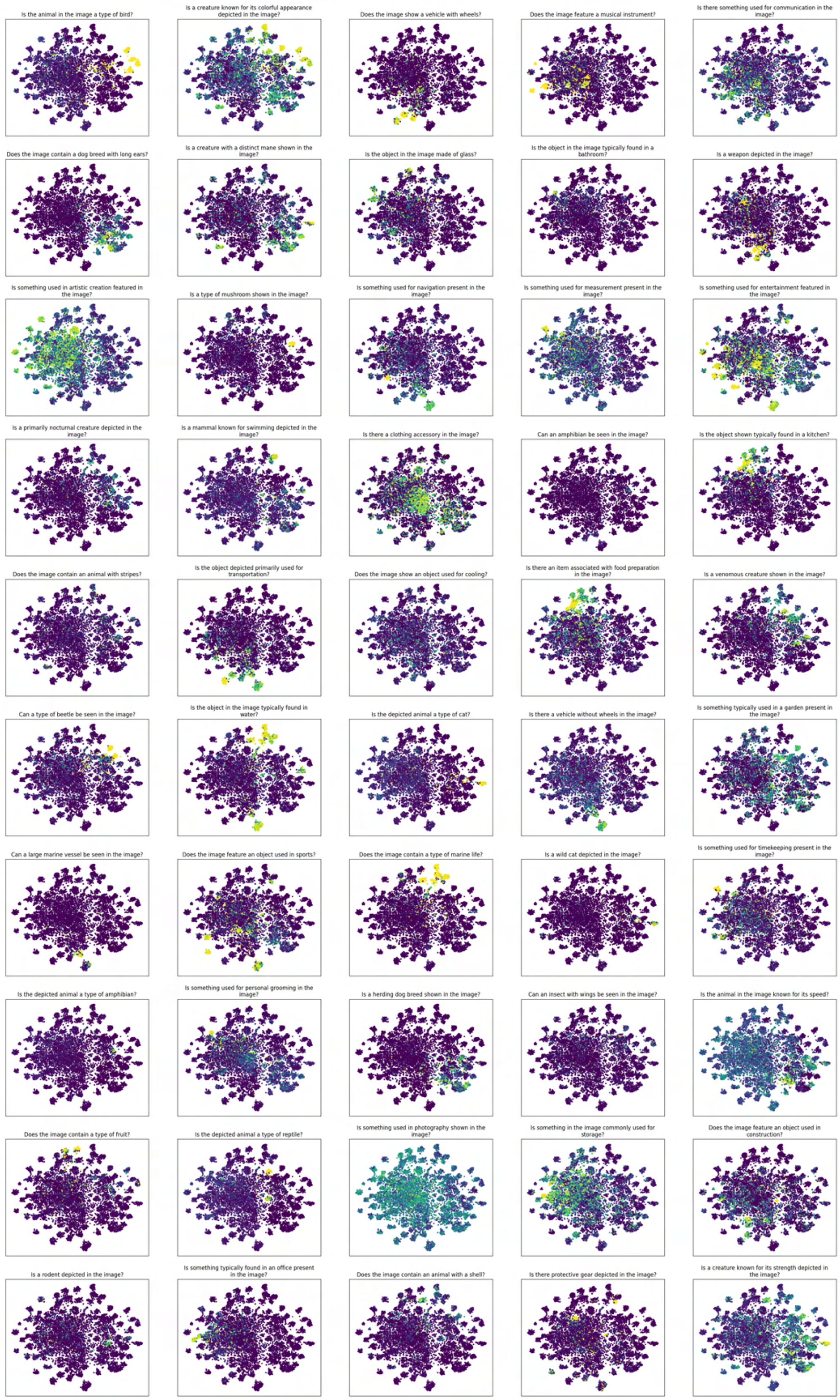

Figure 41: **Visualization of ground truth t-SNE embeddings for the multi-aspect of the Mini-ImageNet testing dataset.**

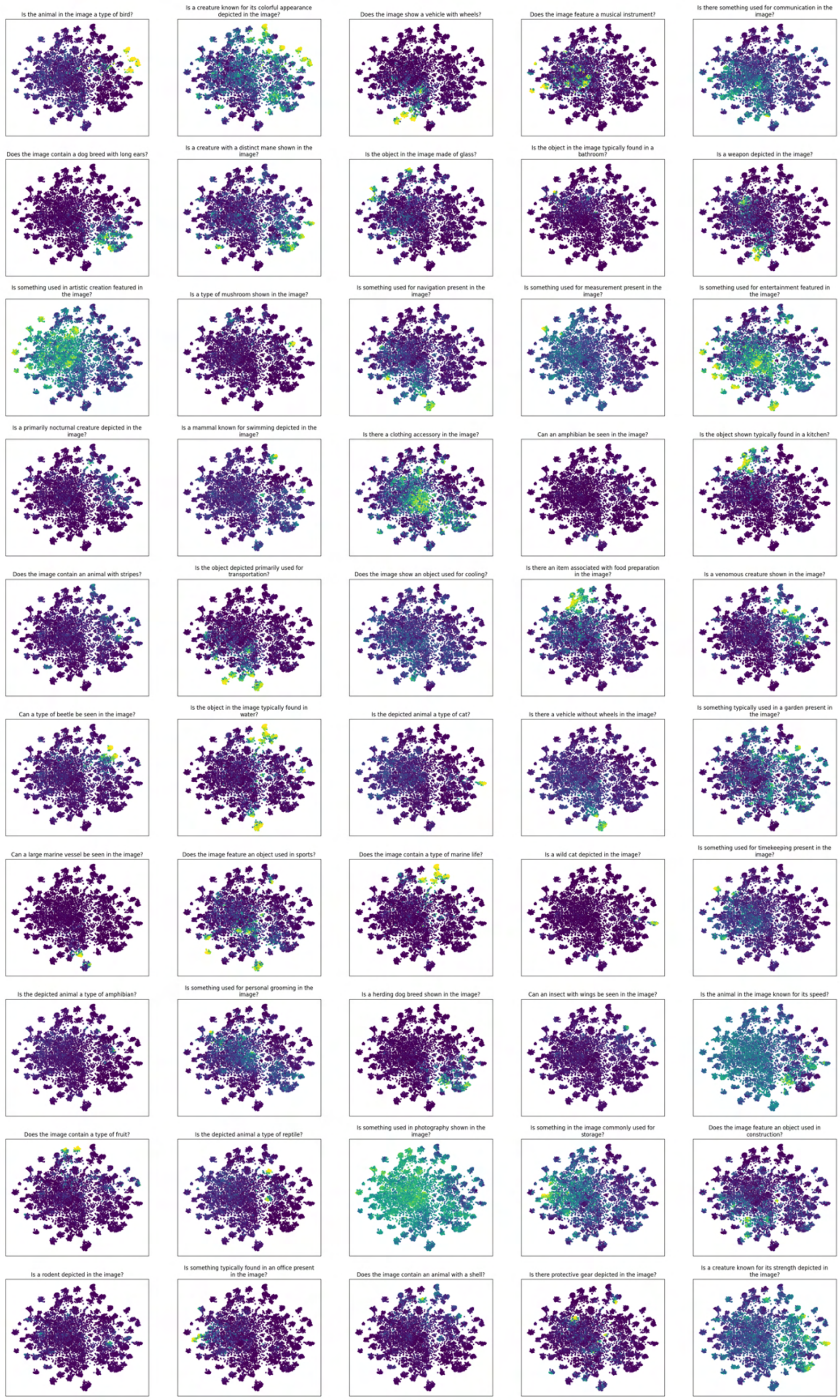

Figure 42: **Visualization of predicted result t-SNE embeddings for the multi-aspect of the Mini-ImageNet testing dataset.**