Uncovering Cultural Representation Disparities in Vision-Language Models

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Datasets & Code

Abstract

Vision-Language Models (VLMs) have demonstrated impressive capabilities across a range of tasks, yet concerns about their potential biases persist. This work investigates the cultural biases in state-of-the-art VLMs by evaluating their performance on an image-based country identification task at the country level. Utilizing the geographically diverse Country211 (OpenAI, 2021) dataset, we probe VLMs via open-ended questions, multiple-choice questions (MCQs), and include challenging multilingual and adversarial task settings. Our analysis aims to uncover disparities in model accuracy across different countries and question formats, providing insights into how training data distribution and evaluation methodologies may influence cultural biases in VLMs. The findings highlight significant variations in performance, suggesting that while VLMs possess considerable visual understanding, they inherit biases from their pre-training data and scale, which impact their ability to generalize uniformly across diverse global contexts.

1 Introduction

VLMs have rapidly advanced, demonstrating exceptional capabilities in integrating visual and textual information for a wide array of tasks, from image captioning to visual question answering (Liu et al., 2024; Alayrac et al., 2022; Wang et al., 2024). These models are increasingly being deployed in diverse applications, impacting areas such as education, healthcare, and public services globally (Zhang et al., 2024).

However, as their influence grows, so do concerns regarding their potential to perpetuate and even amplify societal biases present in their training data (Zhao et al., 2017; Zhou et al., 2022; Cabello et al., 2023; Weng et al., 2024). Cultural and geographical biases are of particular concern because they can lead to unequal performance and representation across different populations and regions of the world (AlKhamissi et al., 2024; Manvi et al., 2024). Defining "culture" is inherently complex, encompassing a broad spectrum of social norms, values, practices, languages, and historical contexts that shape the lived experiences of individuals and communities (Kroeber et al., 1985) (Yadav et al., 2025a). Establishing culture in computational settings presents a persistent challenge due to its multifaceted and dynamic nature. Empirical studies employ tractable proxies such as demographic or geographic proxies to enable systematic analysis (Liu et al., 2021; Adilazuarda et al., 2024; Yadav et al., 2025b). While nation-level aggregation can mask sub-national heterogeneity, prior work in human–computer interaction and cultural analytics has demonstrated that country labels often serve as a practical proxy for coarse-grained cultural signals when large-scale analyses are required (Obradovich et al., 2022).

In order to quantify cultural disparities in VLMs, we adopt image-based country identification as a concrete proxy task in which a model must both infer an image's country of origin solely from visual cues and also provide a justification. Prior work has shown that geolocation tasks reveal representational imbalances in visual models, as performance often correlates with the prevalence of training data from different regions (Pouget et al., 2024).

The main contributions of this paper are:

1. We introduce a scalable framework to evaluate cultural biases in VLMs using an image-based country identification task over 211 countries, leveraging the geographically diverse and bal-

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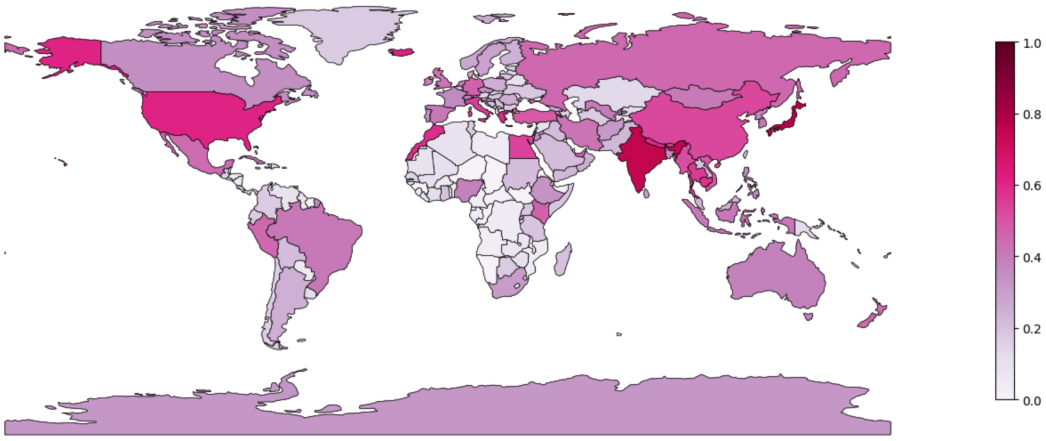

Figure 1: Visualization of the average country-wise recognition accuracy across the VLMs studied in this paper. VLMs perform well at recognizing images from North American and Western European countries, but there are clear disparities in performance for African and Central American countries.

anced Country211 dataset.

2. We systematically probe VLMs under varied settings—open-ended and multiple-choice questions (MCQs) with both random and culturally similar distractors—alongside multilingual prompts in five languages, to capture nuanced cultural and linguistic disparities.[1]

3. We examine model robustness to image perturbations and analyse performance across nine image categories (e.g. architecture, landscape, food etc), revealing the influence of image content on cultural bias.

4. Our findings show that VLM biases do not consistently favour Western countries; instead, biases often reflect over representation of certain popular countries (e.g., India, USA) in the training data[2], suggesting a more complex bias landscape.

2 Related Work

Recent work has explored the socio-cultural dimensions of VLMs, including how they encode, express, and respond to culturally specific knowledge. Studies have examined value alignment (Choenni and Shutova, 2024), moral reasoning across languages (Agarwal et al., 2024), and cultural persona (AlKhamissi et al., 2024), while also uncovering strong Western biases in model outputs (Naous et al., 2024) which risk marginalizing cultural diversity if deployed in real world. There have also been efforts to address these concerns, like prompting based on ethnographic fieldwork (AlKhamissi et al., 2024) and fine-tuning culture-specific LLMs (Li et al., 2024a). Similar studies have been performed for Vision Language Models (VLMs) starting from (Liu et al., 2021) over cultural aspects, while (Nwatu et al., 2023) showed that CLIP (Radford et al., 2021) struggled in data for poor socioeconomic groups worldwide in the Dollar Street dataset (Gaviria Rojas et al., 2022). State-of-the-art off-the-shelf VLMs perform better when processing images depicting western scenes than equivalent East-Asian scenes for every vision task, such as identification, question-answering, and art emotion classification (Ananthram et al., 2025). It has also been shown that VLMs show stronger performance in Western concepts and weaker results in African & Asian contexts(Liu et al., 2025; Yadav et al., 2025b). These findings align with the fact that large pretraining corpora are dominated by high-resource languages. Of the samples that can be geolocated in the OpenImages dataset (Kuznetsova et al., 2020), 32% were from the USA, and 60% came from only six Western countries (Shankar et al., 2017). Such imbalance could lead to biases in VLM behavior (de Vries et al., 2019).

Datasets & Benchmarks : To probe these biases, a growing body of work has constructed specialized datasets and benchmarks with cross-cultural content, such as MOSAIC-1.5k (Burda-Lassen et al.,

[1]Due to cultural similarities, misclassification among similar countries is more likely than misclassification with an unrelated country. MCQ with random and similar distractors tested the VLMs in both scenarios as to whether misclassification would occur when all distractors are neither neighboring nor similar countries

[2]For deliberately under specified inputs without country names, the generated images most reflect the surroundings of the United States followed by India. (Basu et al., 2023)

	Evaluation	Languages	Adversarial	Regions	Samples	Categories
CulturalVQA (Nayak et al., 2024)	Open-Ended	1	No	11 Countries	2,328	5
WorldCuisines (Winata et al., 2025)	Both	30	Yes	189 Countries	6,045	Only Food
Food-500 CAP (Ma et al., 2023)	Open-Ended	1	Yes	7 Regions	24,700	Only Food
MOSAIC-1.5k (Burda-Lassen et al., 2025)	Open-Ended	1	No	N/A	1,500	3
See It From My Perspective (Ananthram et al., 2025)	Open-Ended	2	No	2 Regions	38,479	4
CVQA (Romero et al., 2024)	MCQ	31	Yes	39 Countries	5,239	10
GIMMICK (Schneider et al., 2025)	Both(MCQ)**	1	No	144 Countries	1,741**	-
This paper	Both	5	Yes	211 Countries	21,100	9

Table 1: Overview of prior datasets used in cultural recognition experiments. **: the values in brackets indicate the features in the Country recognition task subset.

Figure 2: Examples of the Country211 dataset, alongside automatically-predicted categories for each image, showcasing the visual diversity of the examples to be classified.

2025), CULTURAL-VQA (Nayak et al., 2024), and GlobalRG (Bhatia et al., 2024). Many works also opt for probing specific aspects of culture, such as food (Li et al., 2024b), race (tse Huang et al., 2025), art (Mohamed et al., 2024), etc., instead of providing an overall view for bias study. (Winata et al., 2025) introduced WorldCuisines for Food Vision Question Answering and country identification and found that VLMs often fail on adversarially misleading contexts or less-common cuisines. (Ma et al., 2023) introduced the Food-500 CAP dataset and observed that most models exhibited geographical culinary biases. Several studies have also treated country-of-origin or geolocation as a proxy for cultural provenance. WorldCuisines includes a country identification task to reveal failures on uncommon or misleading contexts (Winata et al., 2025), and Food-500 CAP finds systematic mismatches between predicted and actual countries of culinary images (Ma et al., 2023). Even in datasets like Dollar Street (Gaviria Rojas et al., 2022) or OpenImages (Kuznetsova et al., 2020), geographic metadata has been used to analyze representational imbalances across regions (Nwatu et al., 2023; Shankar et al., 2017), demonstrating that country-level annotations provide a practical signal for probing cultural and geographic bias in VLMs. Table 1 presents an overview of datasets used for cultural recognition experiments.

Impact of Evaluation: The format of evaluation also impacts bias measurement. Many of the above benchmarks use multiple-choice or binary questions, which can mask a model's true understanding. Since language choice can influence bias, benchmarks are often performed across multiple languages. (Romero et al., 2024) showed that the performance of LLaVA-1.5-7B dropped by 19.6% when prompted without multiple choices for CVQA. Models also showed lower performance when prompted in native language of the image's country of origin. However, (Ananthram et al., 2025) observed that prompting in a culturally closer language can reduce Western bias in some VLMs. It was also observed that people of different cultures are capable of differently capable of describ-

ing what they see in an image (van Miltenburg et al., 2017). We build on these insights by comparing open-ended vs. multiple-choice prompts (including "hard" questions with challenging distractors) and by evaluating in both English and native languages, to see how the prompting strategy affects cultural bias in VLMs.

3 Dataset Used

The dataset used for the experiments is the Country211 (Radford et al., 2021) dataset, which is a subset of images from YFCC100M (Thomee et al., 2016) that has GPS coordinates associated with them. The images cover several domains including but not limited to - exterior architecture, interior architecture, landscape (vegetation, nature, sky view), people's appearance, attires, scripts, texts, posters, etc. The GPS coordinates associated with the images were then used to map them to individual countries. ISO-3166 codes representing each country were used as labels for each image. ISO labels were used for consistency as country names used by the VLMs were not deterministic e.g. Britain was also used simultaneously in place of Great Britain or UK or its constituents, proving that the list of tags and corresponding country names led to the models responding consistently with no observable difference in performance. For our experiments, we utilized this dataset, which consists of 21.1 K images i.e., 100 images each from 211 countries.

Key Differences: Existing benchmarks highlight cultural blind spots in VLMs, but they generally either cover fewer categories or countries or are restricted to specialized domains. Our work differs by using an image-based country-identification task covering 211 countries, providing a broader geographic coverage, and adversarial probing. Furthermore, the datasets used in prior work contain images that might be easier to classify, including but not limited to close-up shots of food items, popular monuments being the primary object in an image, etc. The Country211 dataset consists of images with verified location information that were randomly selected from each country. The dataset was chosen to evaluate VLMs in realistic and practical scenarios rather than curated/idealized conditions. The issue of the representativeness of countries is already taken into account by our experiments, which test the VLMs with both culturally similar and random distractors in the multiple-choice questions, as well as in open-ended experiments.[3]

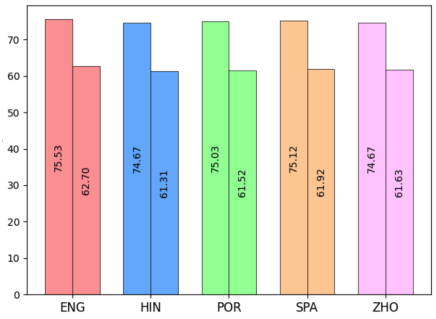

Figure 3: Model-wise averaged accuracy when varying the prompt language or selection of MCQA alternatives (left: random; right: similar). Overall performance is consistent across conditions.

4 Experiments

Prompt Variations: We probed each VLM under three complementary prompting paradigms.

1. Open-ended questions
2. MCQs (with random distractors)
3. MCQs (with similar distractors)

The open-ended experiments pose challenges for objective scoring due to semantic variability. The MCQs with random distractors may over-estimate model performance because the distractors can be easily ruled out by the model. The more challenging MCQs with similar distractors are expected to force models to discriminate between culturally proximate options, thus exposing fine-grained bias patterns. The MCQs are designed as part of discriminative probing and to assess the disparity in the model's cultural knowledge.

Linguistic Variations: We further extend discriminative proving to a multilingual setting, prompting models in five languages: English (ENG), Hindi (HIN), Chinese (ZHO), Portuguese (POR), and Spanish (SPA) to assess the intersection of cultural and linguistic biases.

Image Perturbations: In addition to linguistic variations, the open-ended experiments were performed with these adversarial changes:

[3]The images are part of OpenAI's YFCC100M dataset and come with pre-verified country labels. Although some samples might be difficult to classify, even for local experts, the primary goal was to uncover cultural biases using the features that the VLMs could probably misclassify with a culturally similar or neighboring country, but frequently misclassify with a very dissimilar country.

1. Rotation by 90° clockwise,
2. Rotation by 90° counterclockwise
3. Flipping the image
4. Gray-scaling the image

Model Variations: A diverse set of VLMs were tested including both proprietary and open-weight models of varying sizes: Gemini-2.5-Flash, Gemma-3-12B and 27B (Team et al., 2025), Aya-Vision-8B, Aya-Vision-32B (Dash et al., 2025), GPT-4o-Mini (OpenAI et al., 2024), (etal, 2025).

The experiments are repeated with each permutation of features, resulting in a total of 168.8 K samples tested. Inference was done in JSON format with the default hyperparameters for each of the models tested through Cohere[4] and OpenRouter's API[5]. More on the JSON formatting and prompts used can be found in Appendix D.

4.1 Open-Ended Evaluation

For the open-ended experiments, we asked each model to respond to four questions: (1) name of the country; (2) country selection rationale in a few sentences; (3) a score from 0 to 100 that represents the model confidence in the classification; and (4) up to 6 features from the image listed that had an influence on the decision. The accuracies of each country obtained using each of the VLMs used can be seen in Figure 17. The accuracies of many countries were far lower especially in Eastern Europe, South America, Africa and Central Asia. This gap between country level accuracies was higher in open ended experiments compared to the multiple-choice experiments.

4.2 MCQA with random distractors

For these experiments, we asked each model to provide information on 4 areas: (1) name of the country, (2) label of the chosen country from the choices provided (3) country selection rationale in a few sentences, and (4) a score from 0–100 representing the model confidence in the classification. For these experiments, 4 countries were chosen at random from among the other 210 countries for each sample as distractors. The order of options were then shuffled such that the distribution of correct answer choice is uniform. Compared to other settings, this setting led to the highest average accuracies performance. We expect this is due to the clearly contrasting nature of the distractors used. However, many central African nations still face a recognition bias likely due to low representation in training data. This was observed across all VLMs that were tested, as show in Figure 18.

[4] https://docs.cohere.com/cohere-documentation
[5] https://openrouter.ai/docs/quickstart

		MCQA	
Region	**Open-Ended**	**Similar**	**Random**
North America	41.9	73.7	80.2
Central America	11.1	69.7	68.0
Caribbean	13.6	50.5	71.4
South America	20.4	70.9	68.7
Oceania	19.0	57.5	68.9
Western Europe	30.9	57.9	77.5
Northern Europe	25.3	60.6	79.4
Eastern Europe	26.6	53.4	75.9
Middle East	29.3	68.4	77.1
Central Asia	26.7	53.5	78.1
East Asia	43.6	71.6	83.8
Southeast Asia	41.7	67.5	81.7
South Asia	49.1	69.0	85.5
North Africa	31.9	54.3	78.9
Central Africa	11.8	57.0	68.2
Southern Africa	20.4	74.2	74.2
Overall	27.7	63.1	76.1

Table 2: Region-wise averaged accuracy across models. There are consistent disparities in performance across different regions, regardless of the prompting method.

4.3 MCQA with similar distractors

Similar to the prior experiments with MCQs using random distractors, in this setting we use similar nations as distractors. These were chosen from among the bordering nations. Any countries with high similarity in culture ,if any, were added manually. (e.g. : Spain -> Mexico). This led to the average of accuracies dropping considerably due the challenging nature of the options presented to the models. However, the drops were observed for only a few countries where choosing similar distractors led to these countries' images being classified as belonging to one of their popular neighbors. This can be observed in Figure 18 and Figure 19.

5 Results

The results for experimental setting over countries of each region can be seen in Table 2.

5.1 Effect of Prompt Language on Accuracy

The average of country level accuracies compared to each prompt language can be seen in Figure 3. The language used in the prompt had a minor effect i.e. <2% for all languages. However, at a country level, most countries remained unaffected by language of the prompt, with the change in accuracy <0.1%. The only cases with a noticeable change in accuracy are (some but not all of the) countries that speak the target language predominantly. For example, changing the input language from English to Spanish improved accuracy for Spain but the change to Latin-American countries was negligible. Similarly, while switching to Portuguese had improved the accuracy for Brazil, it lead to a drop in accuracy for Portugal. Overall, the input language improves performance for some countries primarily associated with the language used. The results also partially contradict prior findings that prompting in culturally similar languages reduces western bias (Ananthram et al., 2025).

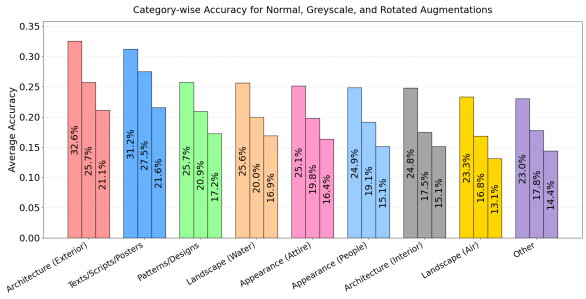

Figure 4: Model-wise averaged accuracy across the nine image categories, as a function of the image perturbations. There is a clear trend of models performing better with the original images (left), compared to the grayscale images (middle) , or rotated images (right).

5.2 Effect of Image Perturbations

Figure 4 and Figure 7 show the changes in accuracy due to gray-scaling and rotating the images. Input image perturbations can have a large impact on the country-level biases in VLMs. Further, it can be assumed that the VLMs tested are not robust enough to image perturbations, with each country being affected at a different scale between each model/perturbation. The overall averages can also be seen in Figure 10, Figure 11 and Figure 12.

Figure 18 shows how perturbations affect model performance across different semantic image categories. For all nine categories, models perform best on the original images, with decreasing accuracy for gray-scaled and rotated versions. The exterior architecture, text/scripts/posters, and attire/patterns categories are especially impacted by perturbations. We hypothesize that it is likely because they contain fine-grained, orientation-sensitive, or highly color-dependent details.

We also look at geographical disparities of these changes in orientation in Figure 5 and Figure 6. We also observe the disparity in model robustness. For example, models such as Aya Vision 32B, GPT-4o-mini and Gemini 3 12B show very different sensitivity across both a) perturbations and b) regions which were affected. We hypothesize that architectural and training differences might be influencing how models process image orientation and color. While gray-scaling may reduce performance due to the loss of visual detail or color-dependent cues, rotation disrupts spatial reasoning and object orientation, which are critical for geographic or cultural recognition.

These findings highlight the importance of evaluating model performance under realistic image distortions, especially for applications where images may not be clean or consistently formatted as image characteristics can vary widely.

5.3 Effect of Input Variations on Confidence

Despite the drop in overall accuracy due to the image perturbations, the model-estimated confidence of the open-weight models did not significantly change, whereas there was a larger drop in confidence for the proprietary models. Compared to rotation of images, gray-scaling had a larger impact on the response accuracies. The average confidence of each VLM with each adversarial setting compared to the original can be seen in Figure 7. The models with closed-weights exhibited a drop in confidence when a perturbed image was provided, in contrast to the tested open-weight models.

5.4 Image Feature categories VS accuracy

Apart from the experiments, the original 21.1k images were also labeled multi-way based on the key features they contain using larger VLMs like Gemini-2.5-Pro, o4-mini, Grok-2-Vision. Later a majority vote of each label was considered. The quality was later manually verified over a subset by multiple people.[6] We have used 9 sub-categories

[6]Feature category labels were verified on a subset of 10% samples equally distributed over all countries, with 2 people verifying labels, in cases with no consensus between the two, the third annotator was used.

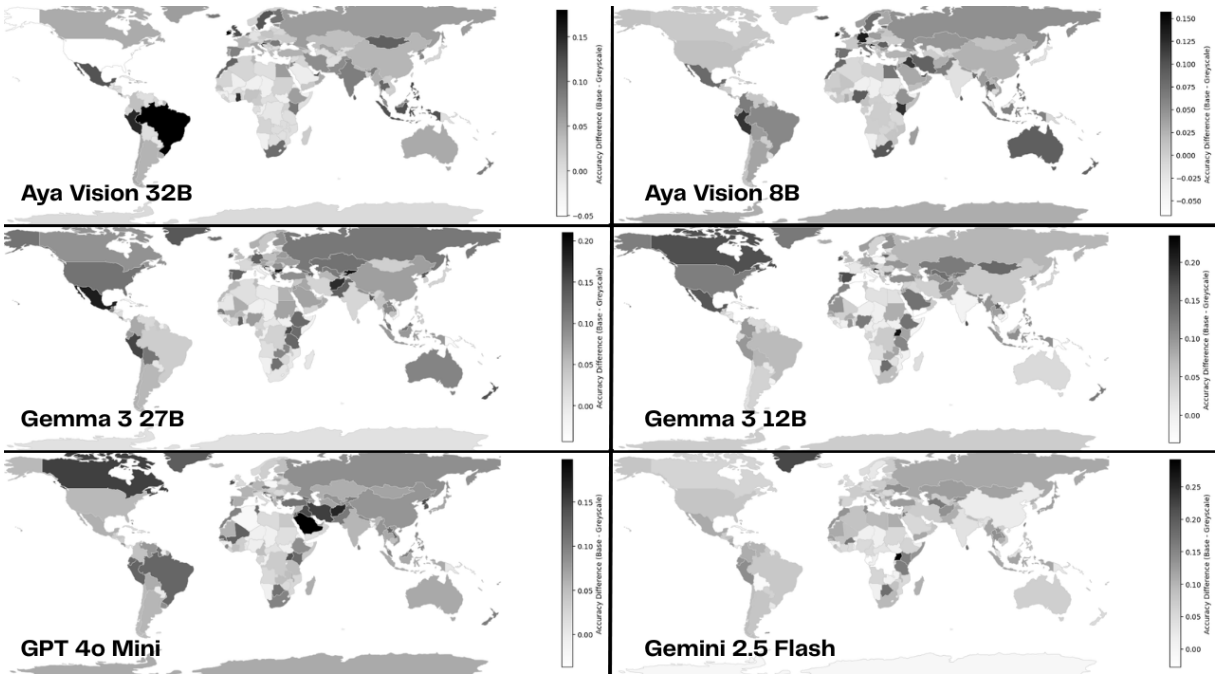

Figure 5: Effect of Gray-scaling VS change in country wise accuracies. **The effect of greyscaling images on overall performance varies significantly between each model, even those of the same model family (ex: Aya-8b and Aya-32b)**. Higher Contrast indicates a larger drop in accuracy from using greyscaled images)

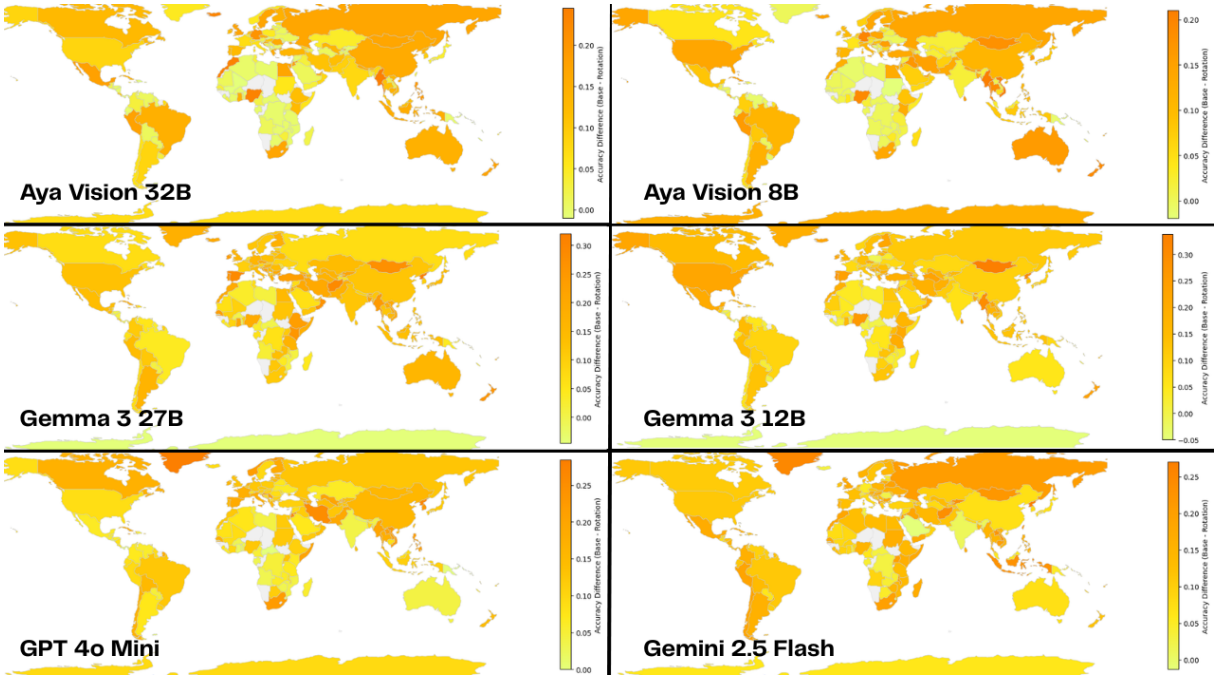

Figure 6: Effect of Rotation VS change in country wise accuracies. **The effect of rotating images on overall performance varies significantly between each model, but the effect is not as much as greyscaling of images**. (Higher Contrast indicates a larger drop in accuracy from using rotated images)

Category	Description
Appearance (Attire)	Attires of some people from the image, clothes being hung in the background, etc.
Appearance (People)	Appearance / visual perception of people's ethnicity, presence of any celebrities, etc.
Architecture (Exterior)	Building facades, monuments, bridges, outdoor structures, and any external architectural elements visible in the scene.
Architecture (Interior)	Indoor environments e.g. rooms, corridors, staircases, furniture, and interior design details.
Landscape (Water)	Bodies of water such as oceans, rivers, lakes, waterfalls, ponds, and any aquatic scenery.
Landscape (Air)	Aerial / bird's-eye views, landscapes captured from above, clouds, sky scenes, and horizon vistas.
Landscape (Vegetation)	Forests, grasslands, gardens, crops, shrubs, foliage patterns, plant life, or visible greenery.
Texts/Scripts/Posters	Signs, banners, billboards, labels, handwritten or printed text, posters, and any other written or graphic messaging.
Patterns/Designs	Decorative motifs, surface textures, fabric prints, wallpaper or tile patterns, abstract designs, and repetitive graphical elements.

Table 3: Overview of the image categories used to analyse model performance as a function of the type of image.

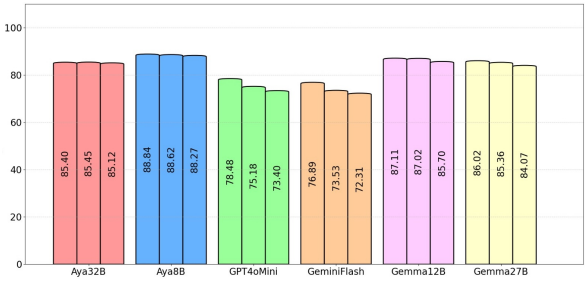

Figure 7: Average model confidence, given the original images (left), grayscale images (middle), and rotated images (right). GPT4o, Gemini-Flash, and Gemma-27B are most sensitive to image perturbations.

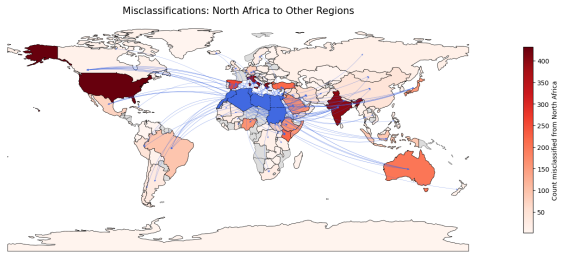

Figure 8: Mis-classification map for North African countries. There is a clear trend of models predicting USA, India, Australia, or geographically close countries in Europe and the Middle East.

for this categorization. The descriptions of each of these categories can be seen in Table 3. A large variance was observed between each feature category and the country level accuracies obtained. Additionally there was also a large variation between how accuracy was affected for each country/feature based on model/perturbation used. This can be also be seen in Figure 15. The extent to which each category's images were recognized by VLMs can be seen in Figure 4. External architecture and native language texts' presence in the background helped VLMs recognize culture better compared to the other features.

5.5 Distribution of Predicted countries

The distribution of responses in an open ended approach can be seen in Figure 9. The output distributions varied largely among models, even those within the same family (i.e between Gemma-3-27B, Gemma-3-12B and Aya-vision-32B, Aya-vision-8B). The results obtained contradict the usual assumption about western biases in generative models, and was observed over a few nations with likely high training data proportion.

Notably, all models consistently over-predict certain countries,particularly USA, India, and Brazil, regardless of the actual ground truth. We hypothesize that these countries are likely overrepresented in the models' pretraining data or benefit from more visually distinctive cues. Biases seem to cluster around a few highly represented or visually salient countries rather than reflecting broader geopolitical landscape.

These results show that model predictions are likely to be influenced by data availability and image characteristics rather than a generic global bias. It also underscores the need for better interpretability regarding the geographic composition of VLM training datasets to fully understand such biases.

5.6 Misclassification Analysis

The mapping of misclassification of samples was not limited to similar or neighboring nations. This can be observed in Figure 20 to Figure 34. These misclassifications varied by each individual feature and provide a better fine-grained insights of cul-

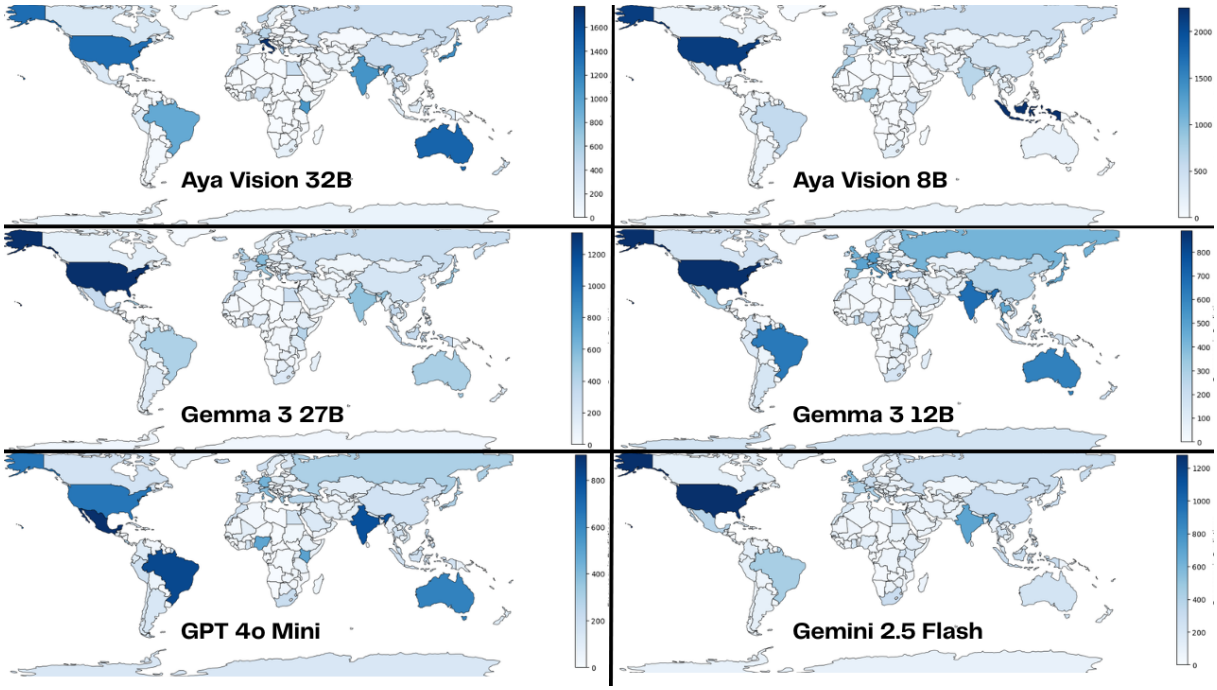

Figure 9: Country-wise response distribution in the open-ended prompt format. **There is a consistent trend of models predicting USA, but otherwise, no clear bias towards predicting Western countries.** (Higher contrast over a country indicates higher proportion of responses from a model)

tural biases. For instance, apart from neighboring or similar countries, most images from Africa and rural regions of South America were classified as India. A specific example is shown in Figure 8 where out of the 600 images, roughly 80-120 belong to this category for most countries, while many countries had most of their misclassified samples as originating from India.

6 Discussion

Our study presents a comprehensive analysis of cultural biases in Vision-Language Models (VLMs) using a geographically balanced dataset across 211 countries. We evaluated popular models across multiple prompting strategies, e.g. open-ended, multiple-choice (random and similar distractors), and multilingual settings. Open-ended formats showed the greatest disparities in country-level accuracy, particularly in underrepresented regions such as Central Africa and parts of South America. The use of culturally similar distractors proved to be the most effective in revealing fine-grained errors, highlighting limitations in models' cultural discrimination abilities.

We further assessed the models' robustness to image perturbations like gray-scaling and rotation. While gray-scaling affected only a few specific countries, rotation led to a broad and uniform drop in performance, confirming that VLMs rely heavily on image orientation. We further observed that performance also varied by semantic image content—categories like architecture, textual cues, and attire were more predictive of cultural origin, especially in unaltered images. Language variation in prompts had minimal impact on average accuracy, though countries closely tied to the input language (e.g., Spain with Spanish, Brazil with Portuguese) showed slight gains. However, this trend was inconsistent and did not generalize across all culturally linked regions. Finally, our misclassification analysis shows that models frequently confuse images from low-resource or visually ambiguous countries with a few dominant nations, reinforcing the role of training data bias.

7 Conclusion

Our findings show that biases are not uniformly Western but instead reflect over representation of certain countries in training data. Model performance varied across prompt types, languages, image features, and perturbations, highlighting limitations in robustness and cultural generalization. These results call for greater transparency in dataset composition and the need for more culturally inclusive evaluation methods to ensure fairer and more globally representative VLMs.

Limitations

Our study has an important limitations. The use of country-level labels as a proxy for culture, while common for large-scale analysis, inherently overlooks intra-country cultural diversity and multicultural populations, potentially obscuring subnational or regional nuances. The country labels used don't account for political complexities like disputed territories.

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A Overall Accuracies Before and After Image Perturbations

Figure 10, Figure 11, Figure 12 display the accuracy obtained for each image perturbation used compared to the original through each of the VLMs tested.

B Overall Accuracy VS Models used : In each MCQ setting

Figure 13, Figure 14 display the accuracy obtained through each model in each MCQ experiment.

C Reproducibility

Inference was done through Cohere's API for Aya-Vision-8B and Aya-Vision-32B through the default hyperparameters with a seed value of 1024. The rest of the models were used through OpenRouter's API through the default hyper-parameters with a seed value of 1024. The experiments were repeated thrice and the overall accuracy varied between 1-1.2%, with some countries' accuracy varying up to 1.5%. The costs associated with all experiments combined were 850$ through OpenRouter and 250$ Cohere API credits. The experiments were run on TPUs costing 0.35$/hr with the costs reaching 60$.

D Prompt Usage

The prompts used for each experiment setting can be seen below.

```
## OPEN ENDED
Respond in the following format :
{
  "Country": {
  "type": "string",
  "description": "Just Country Name, Nothing
      else."
  },
  "Reasoning": {
  "type": "string",
  "description": "Why you feel the image is
      from that particular country. Explain
      what features/objects/items/visuals
      of the image made you think so.
      Should be fine-grained and clear, but
      in just 2-3 sentences."
  },
  "Confidence": {
  "type": "integer",
  "description": "A integer score on a scale
      of 0 to 100 on how confident you are
      about the classification."
  },
  "Features": {
  "type": "string",
  "description": "Which of the features of
      the image were primarily used for
      determining the country labels,
      separated by commas, ordered with
      primary feature in the beginning."
  }
}
```

```
## MCQ
prompt_header="Respond with a label from the
    choices : What country is this image
    likely from ?\n"
for l,c in
    zip(labels,choices):prompt_header+=f"{l})
    : {c}\n"
fixed_prompt=prompt_header+"""Respond in the
    following format :
{
```

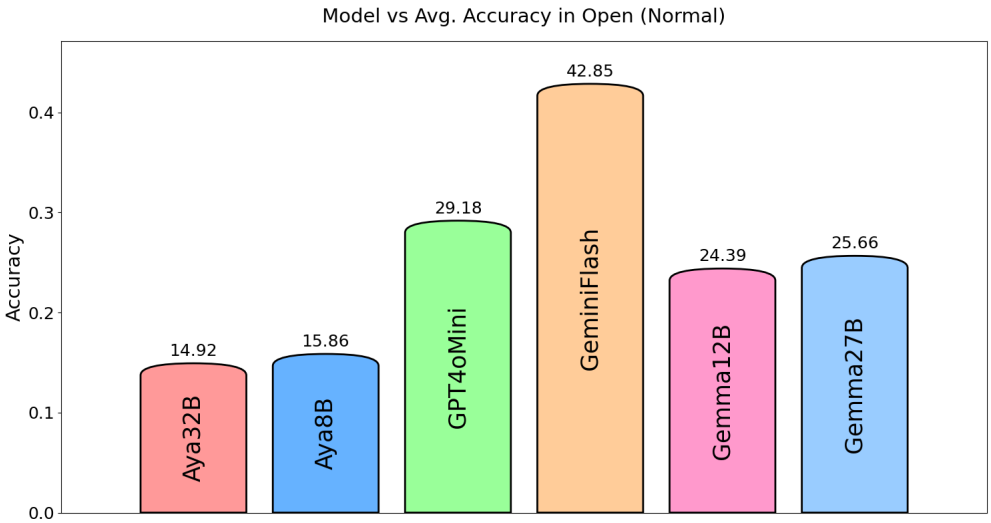

Figure 10: Overall Accuracy : Open Ended (Normal)

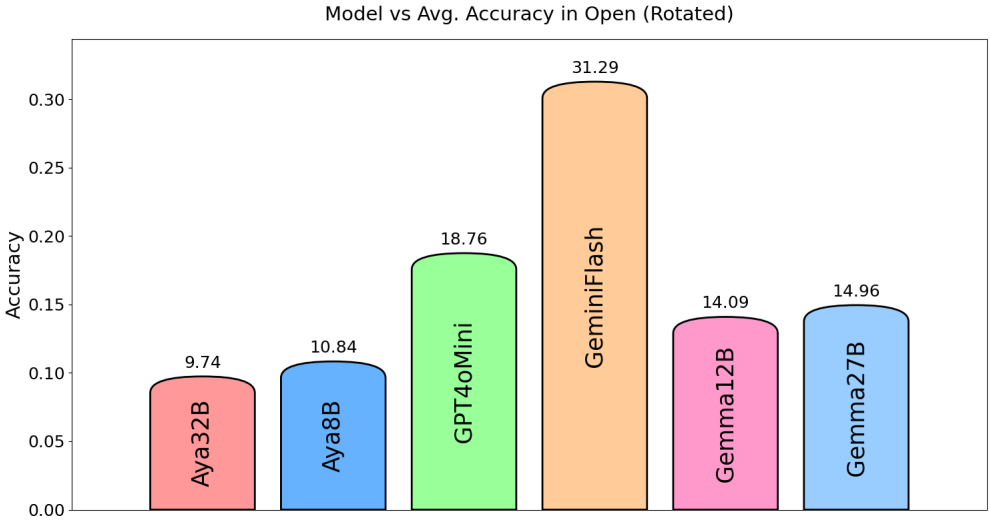

Figure 11: Overall Accuracy : Open Ended (Rotated)

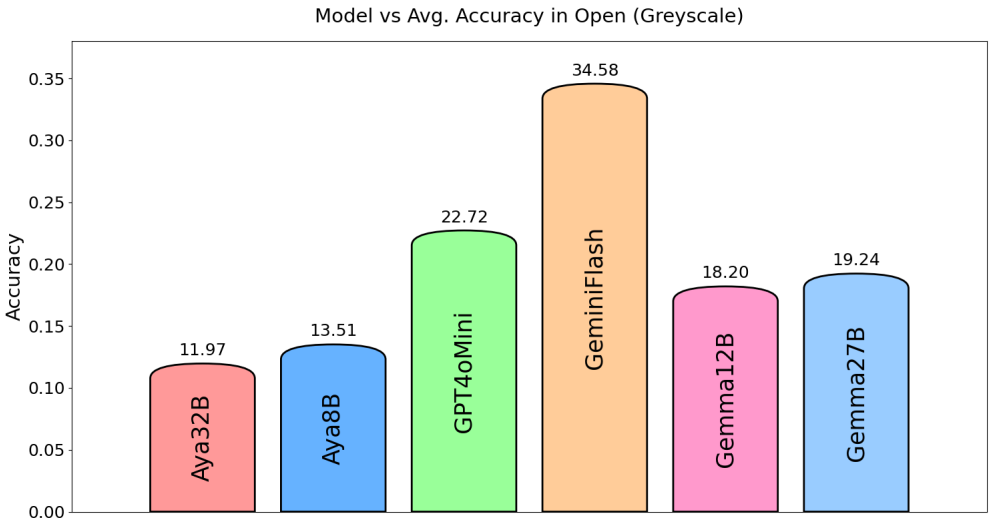

Figure 12: Overall Accuracy : Open Ended (Grayscale)

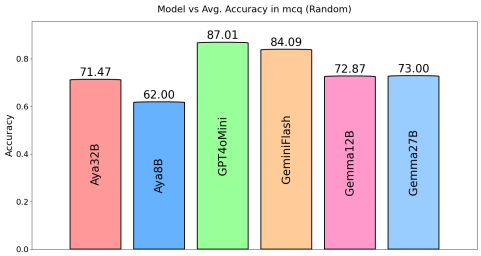

Figure 13: Overall Accuracy : MCQ-Random : Model wise

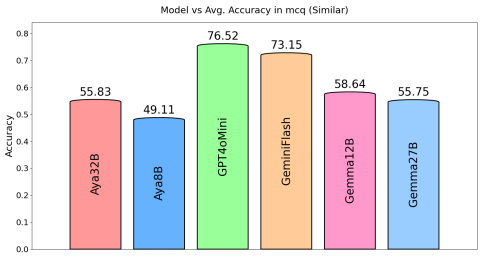

Figure 14: Overall Accuracy : MCQ-Similar : Model wise

```
    "Label": "Uppercase Alphabet",
    "Country": "The chosen label's country
        name exactly as it was",
    "Confidence": "Integer between 0 to 100 in
        numeric format"
}"""
```

E Other Plots

F Mis-Classification Map : Region-wise

The mis-classifications from one region to countries outside the region can be seen fro each region in Figure 20 to Figure 34 respectively.

G Country wise accuracies in each experimental setting

The accuracies obtained over samples of each country through each experimental setup can be seen in Table 4 to Table 8.

H Chord Diagrams of Mis-classifications

The chord diagrams representing the mis-classifications between each region can be seen in Figure 36. The mis-classifications between countries of each region can be seen in Figure 37 to Figure 52 respectively.

Country name	Open-Ended	MCQs with Similar choices	MCQs with Random choices
Afghanistan	41.33	68.90	81.56
Albania	20.00	42.80	67.64
Algeria	10.50	29.73	65.71
Andorra	12.00	59.63	72.41
Angola	4.67	48.07	58.83
Anguilla	2.00	15.27	58.51
Antarctica	34.83	84.80	83.57
Antigua and Barbuda	7.67	31.67	70.64
Argentina	30.67	84.17	71.39
Armenia	42.33	66.23	80.07
Aruba	17.67	55.67	78.96
Australia	44.50	87.90	69.58
Austria	18.83	42.13	80.69
Azerbaijan	20.00	46.83	66.45
Bahamas	24.83	69.47	78.13
Bahrain	21.00	63.00	73.94
Bangladesh	42.50	59.30	87.48
Barbados	17.67	39.50	72.07
Belarus	13.33	45.60	72.98
Belgium	21.00	44.93	72.21
Belize	11.67	59.13	68.49
Benin	7.50	51.47	78.75
Bermuda	20.67	62.63	67.61
Bhutan	59.17	66.03	90.70
Bolivia	26.33	76.13	78.26
Bonaire, Sint Eu...	3.50	36.47	69.24
Bosnia ...	23.33	44.43	73.23
Botswana	22.83	82.13	80.00
Brazil	47.67	83.37	74.70
Brunei Darussalam	8.67	21.73	48.78
Bulgaria	25.33	46.47	77.12
Burkina Faso	7.50	60.83	74.72
Cabo Verde	10.17	67.23	55.22
Cambodia	62.83	81.02	92.15
Cameroon	4.67	67.20	70.02
Canada	41.50	69.43	81.16
Cayman Islands	6.67	28.07	68.78
Central African Rep..	0.83	16.67	50.21
Chile	20.83	65.90	67.78
China	58.83	78.73	81.48
Colombia	23.83	75.73	69.25
DRC	6.83	40.70	56.60
Cook Islands	3.83	22.23	68.28

Table 4: Country wise accuracies through various experimental settings : Part 1/5

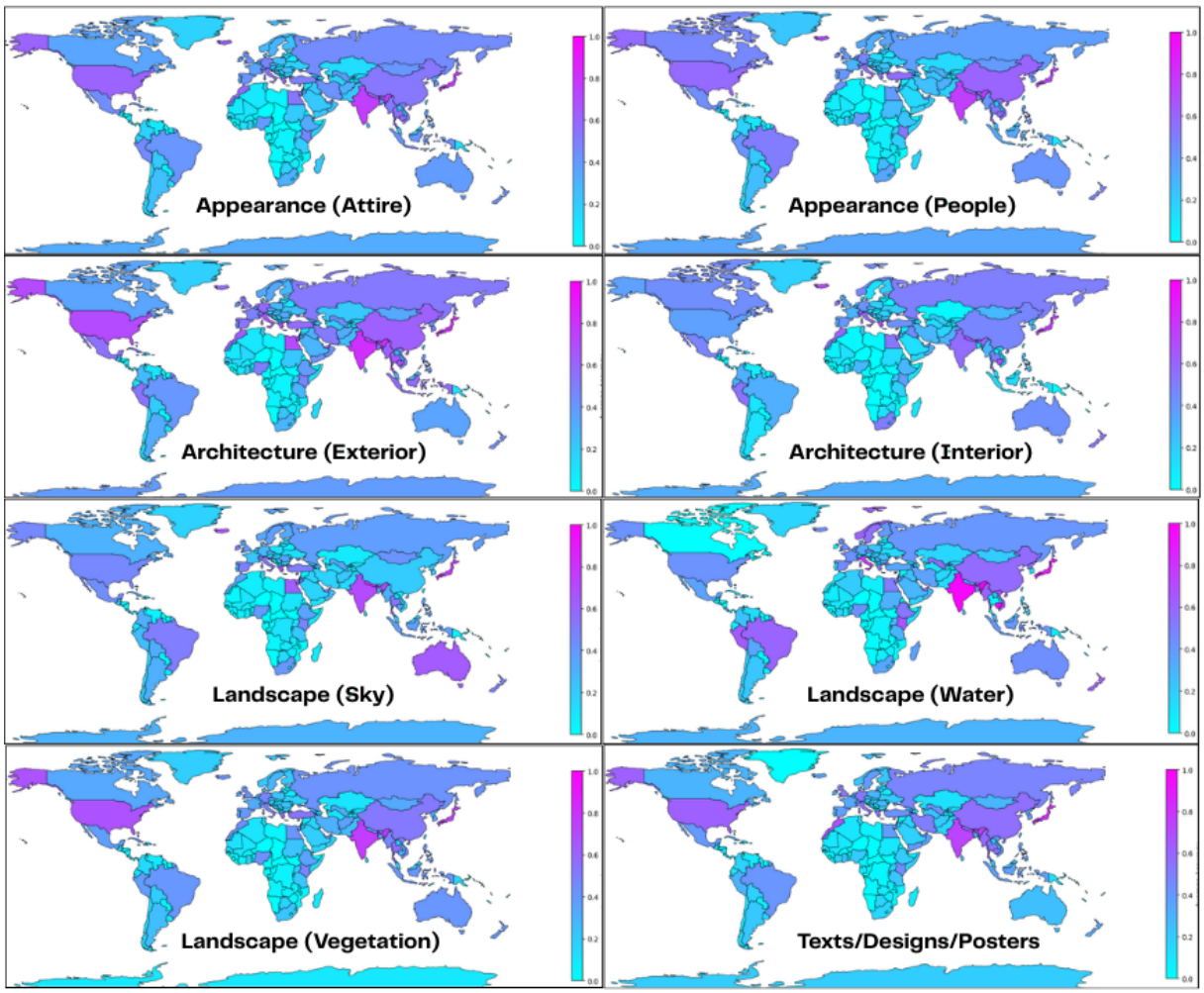

Figure 15: Image Feature categories VS Country wise Accuracy

Figure 16: Region wise effect of perturbations

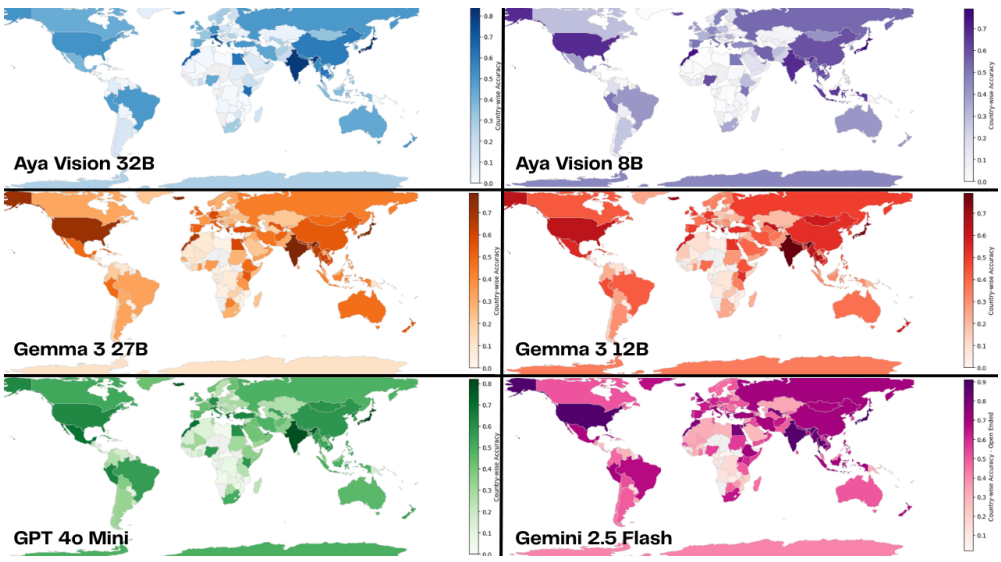

Figure 17: Accuracy over each country's images through open-ended Experiments

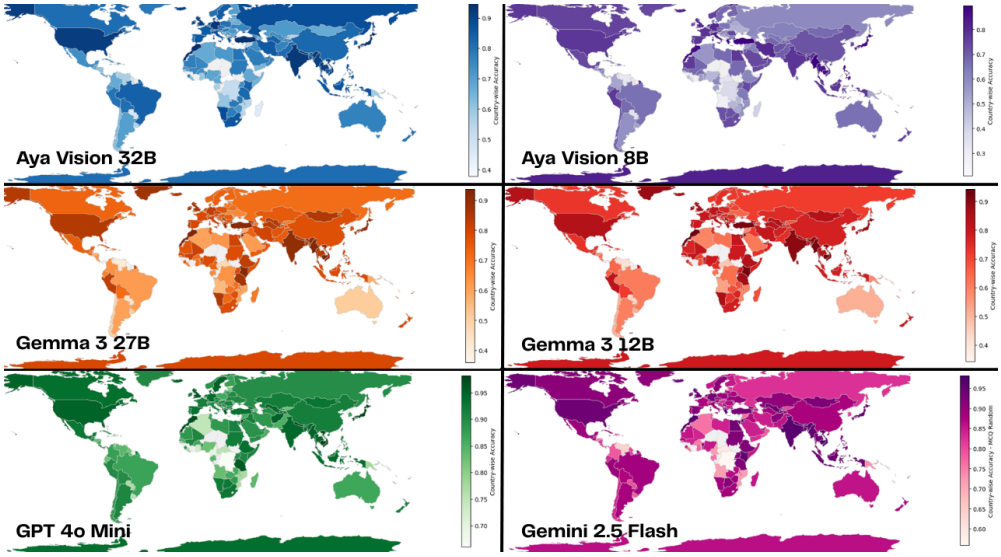

Figure 18: Accuracy over each country's images through MCQ Experiments with random distractors

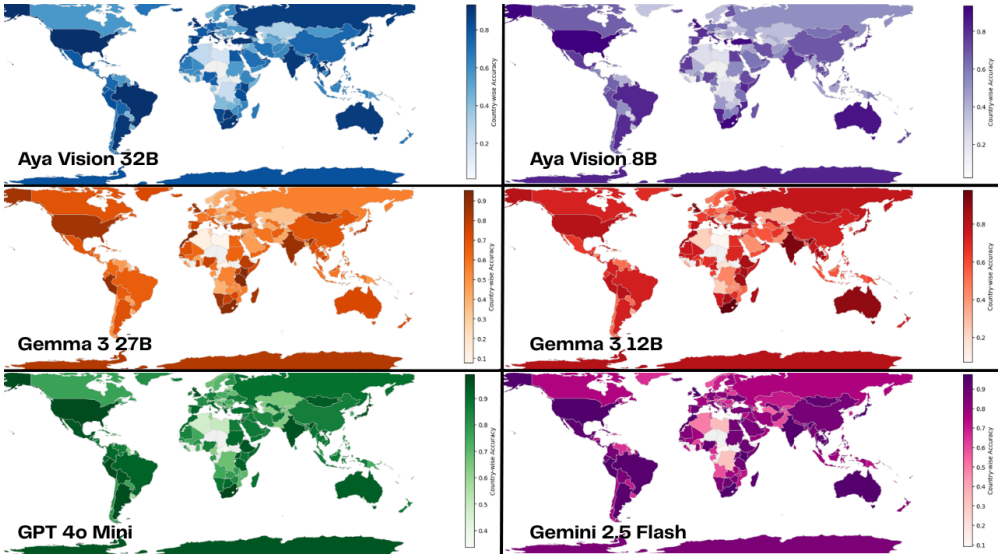

Figure 19: Accuracy over each country's images through MCQ Experiments with similar distractors

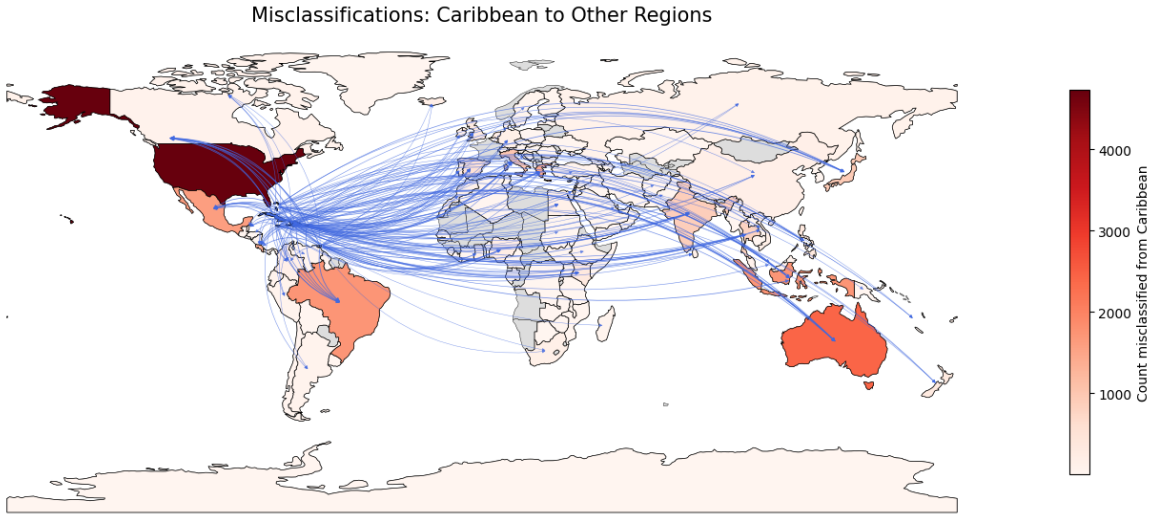

Figure 20: Mis-classification map : Caribbean

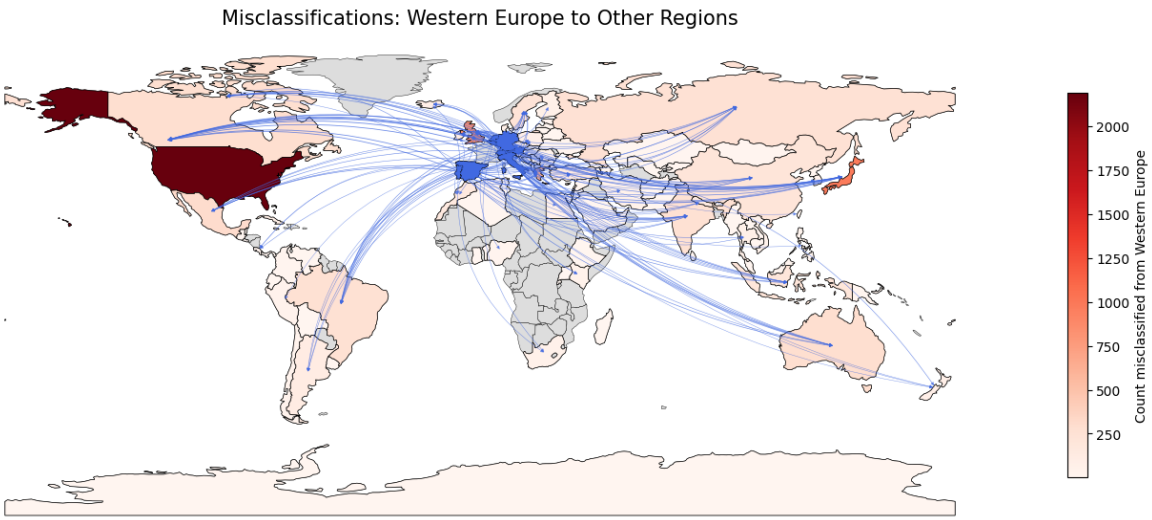

Figure 21: Mis-classification map : Western Europe

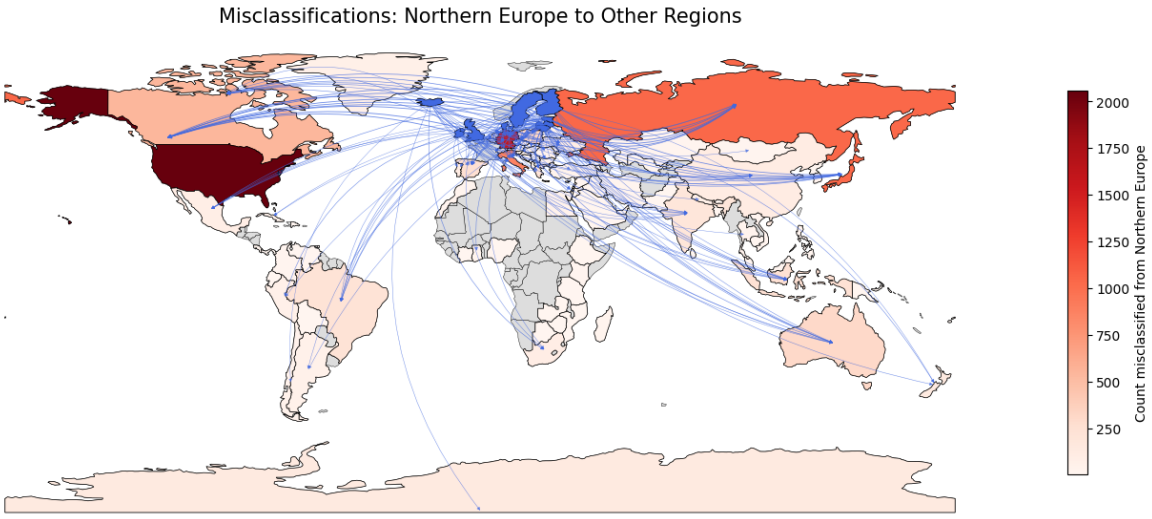

Figure 22: Mis-classification map : North Europe

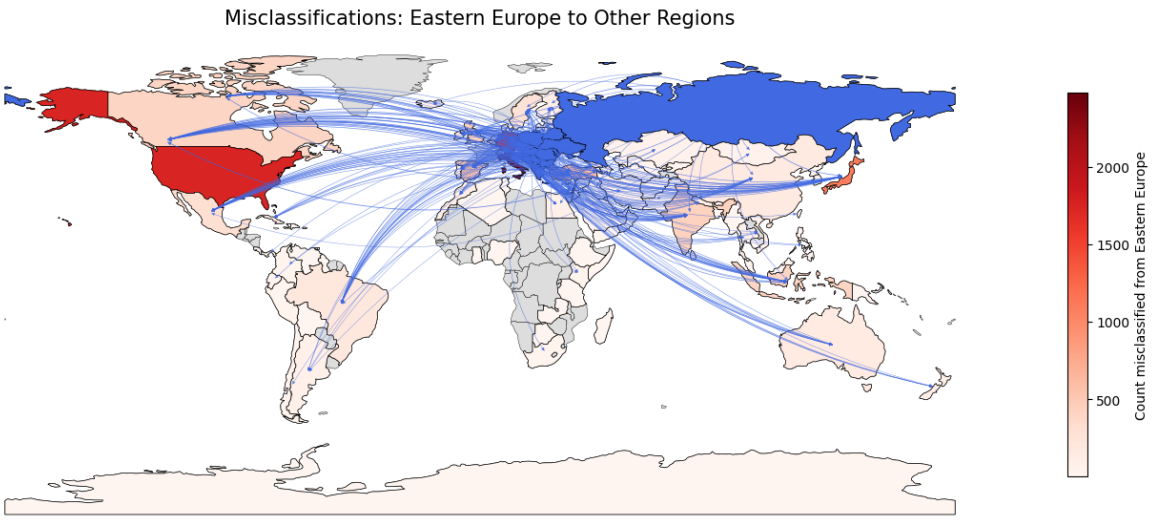

Figure 23: Mis-classification map : Eastern Europe

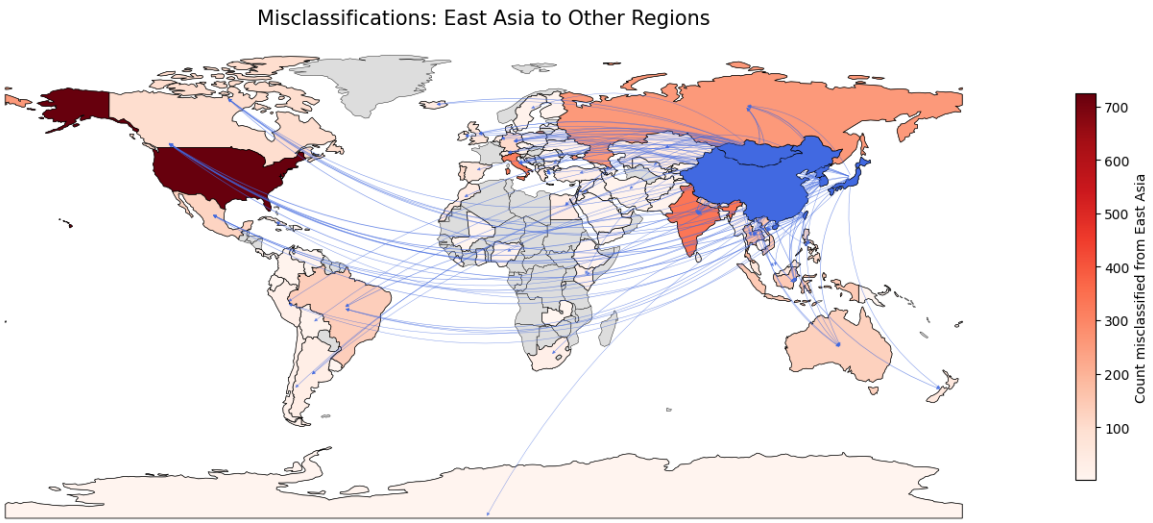

Figure 24: Mis-classification map : East Asia

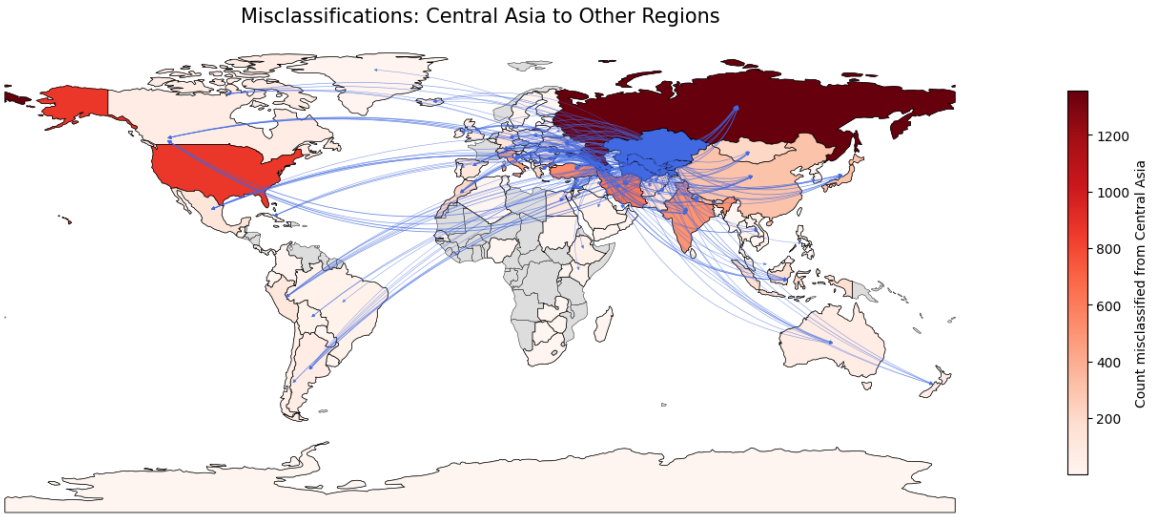

Figure 25: Mis-classification map : Central Asia

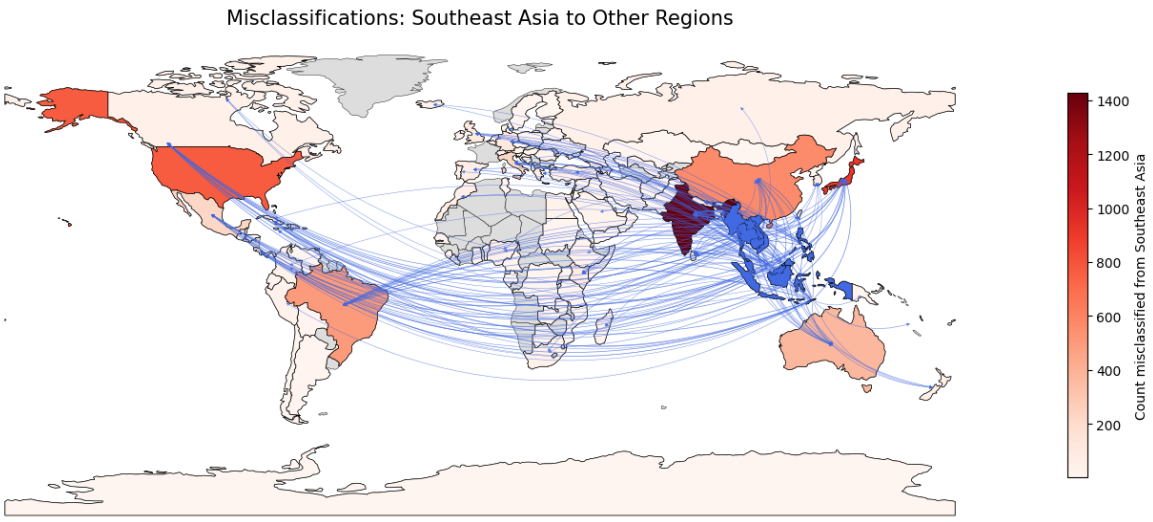

Figure 26: Mis-classification map : South East Asia

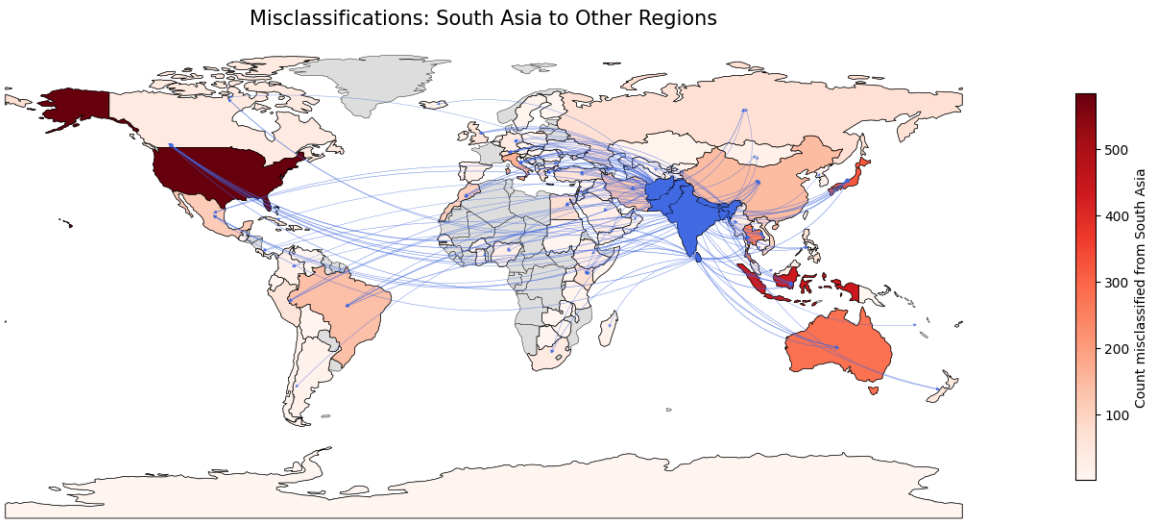

Figure 27: Mis-classification map : South Asia

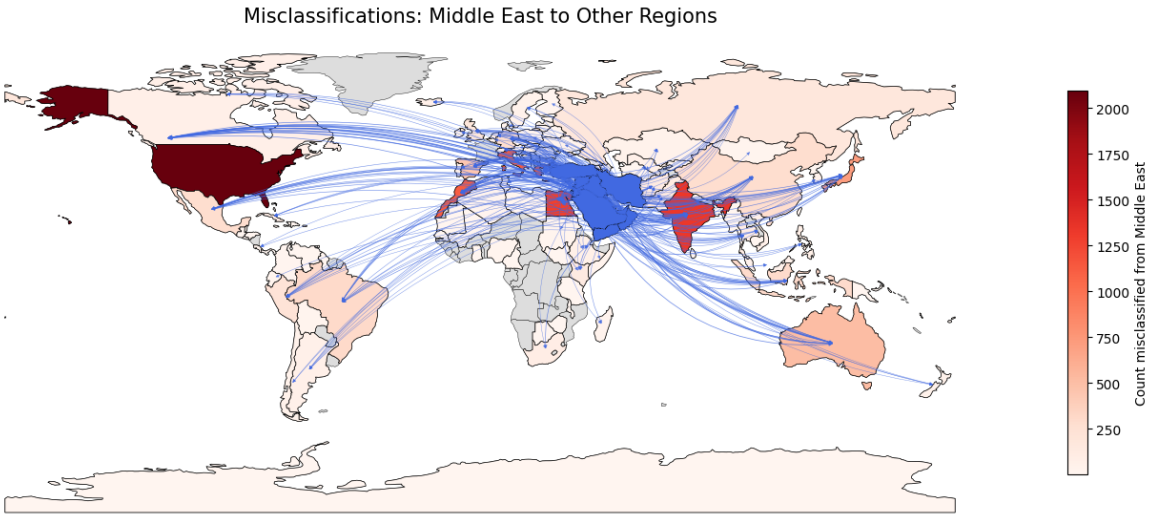

Figure 28: Mis-classification map : Middle East

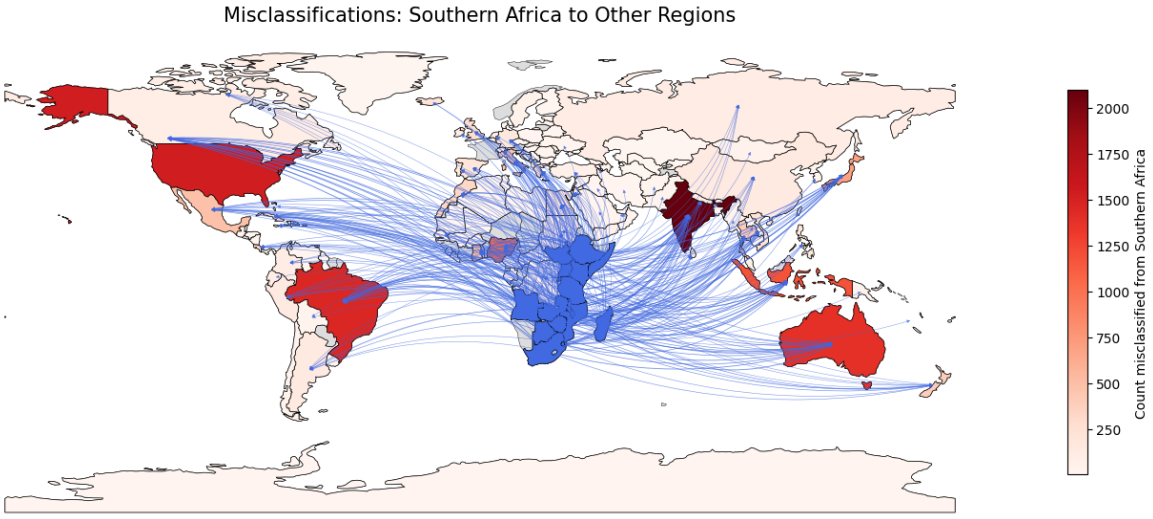

Figure 29: Mis-classification map : Southern Africa

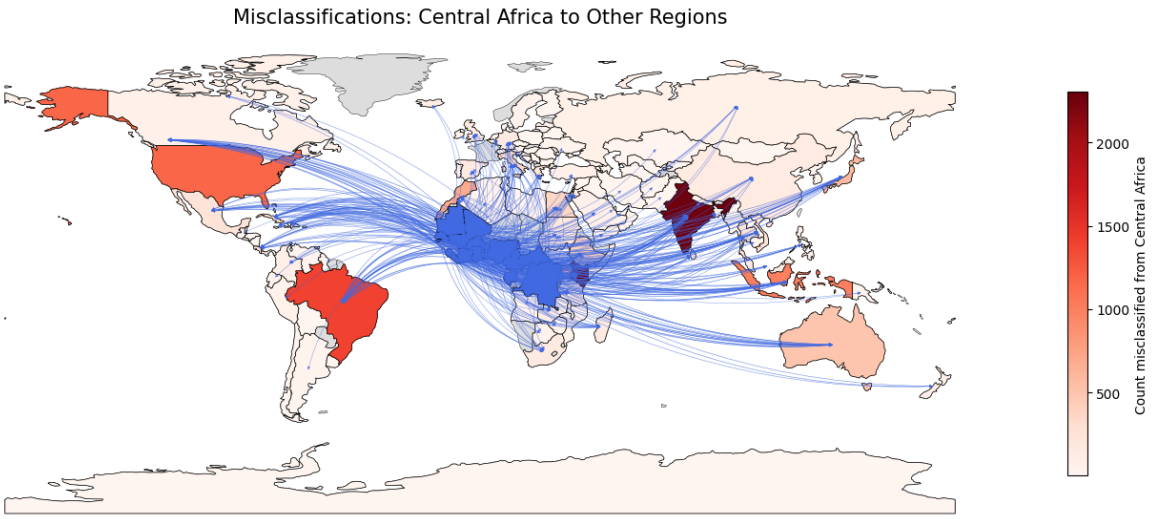

Figure 30: Mis-classification map : Central Africa

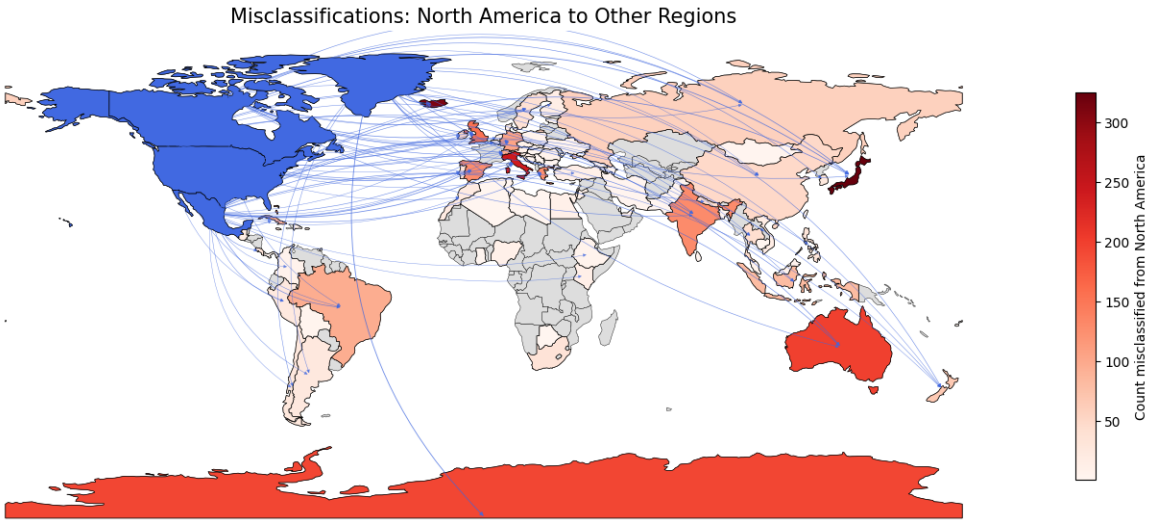

Figure 31: Mis-classification map : North America

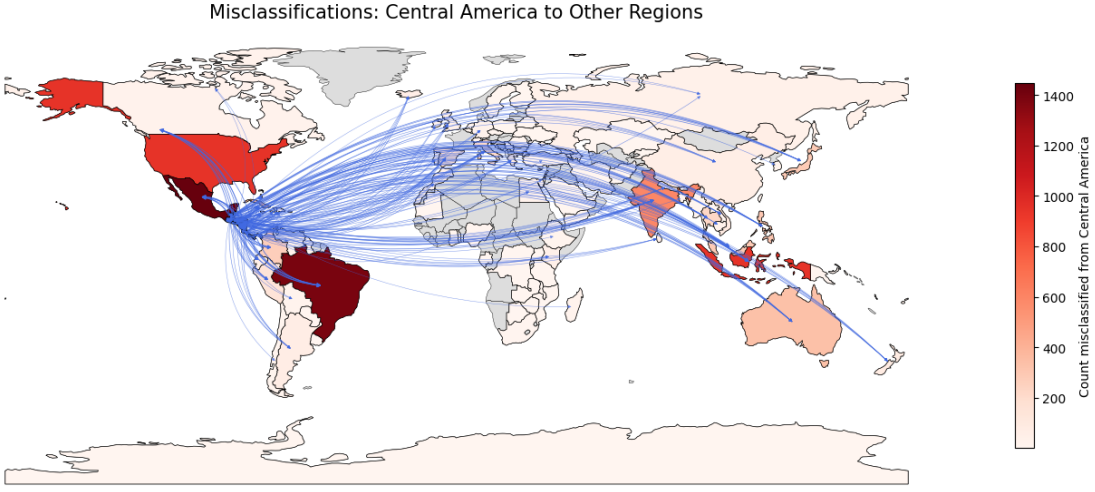

Figure 32: Mis-classification map : Central America

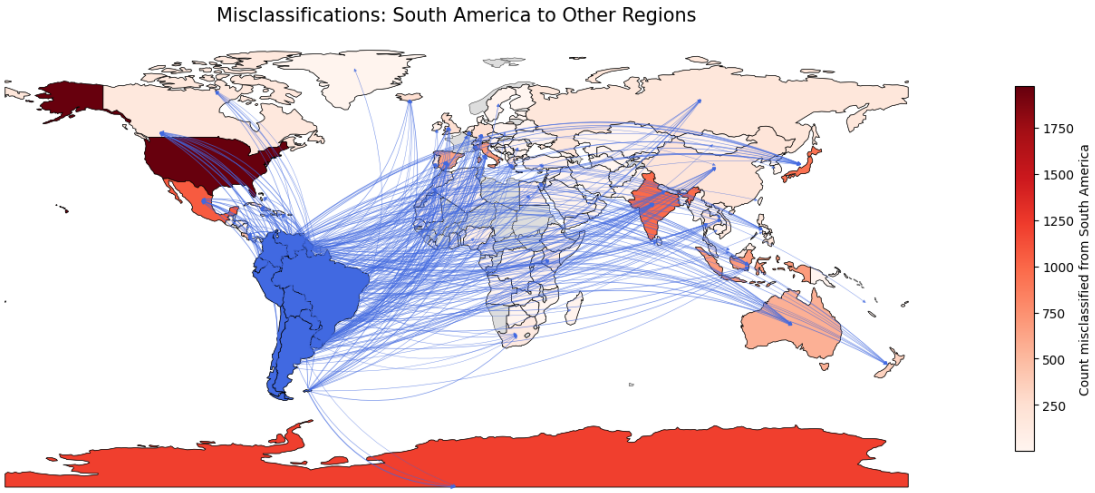

Figure 33: Mis-classification map : South America

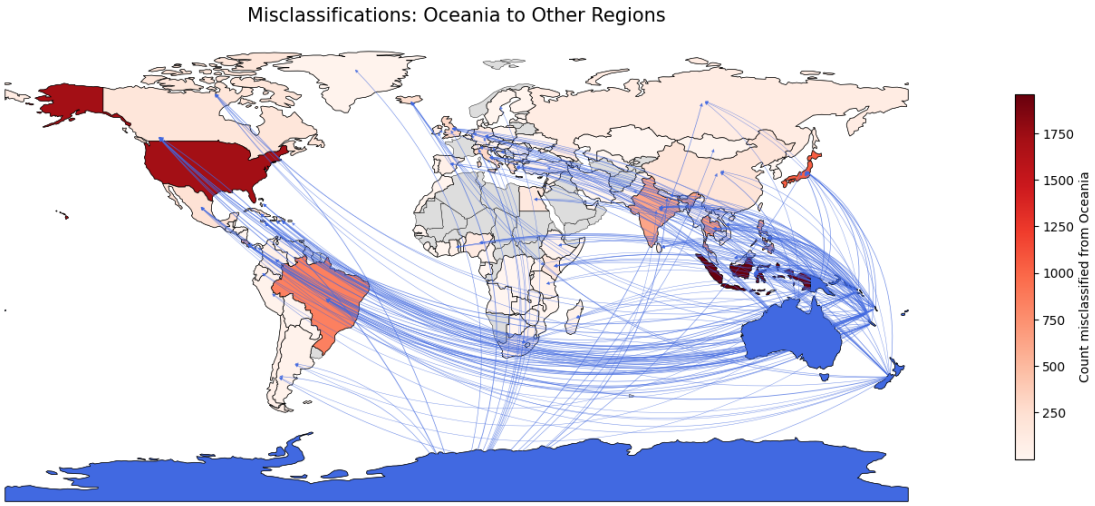

Figure 34: Mis-classification map : Oceania

Figure 35: Examples from ours (1st,4th) as well as other works : GIMMICK (2nd), CVQA (3rd) : The 1st and 4th image have the key features required for classifying the image accurately, occupying a tiny portion of the image making it relatively difficult i.e the flag patch in image 1 ,and name of mountain in image 4's signboard. While, in Image 2 and image 3 , the key features i.e the text on attire or the (car, city name signboard, multilingual texts on left) make the samples relatively easier to classify

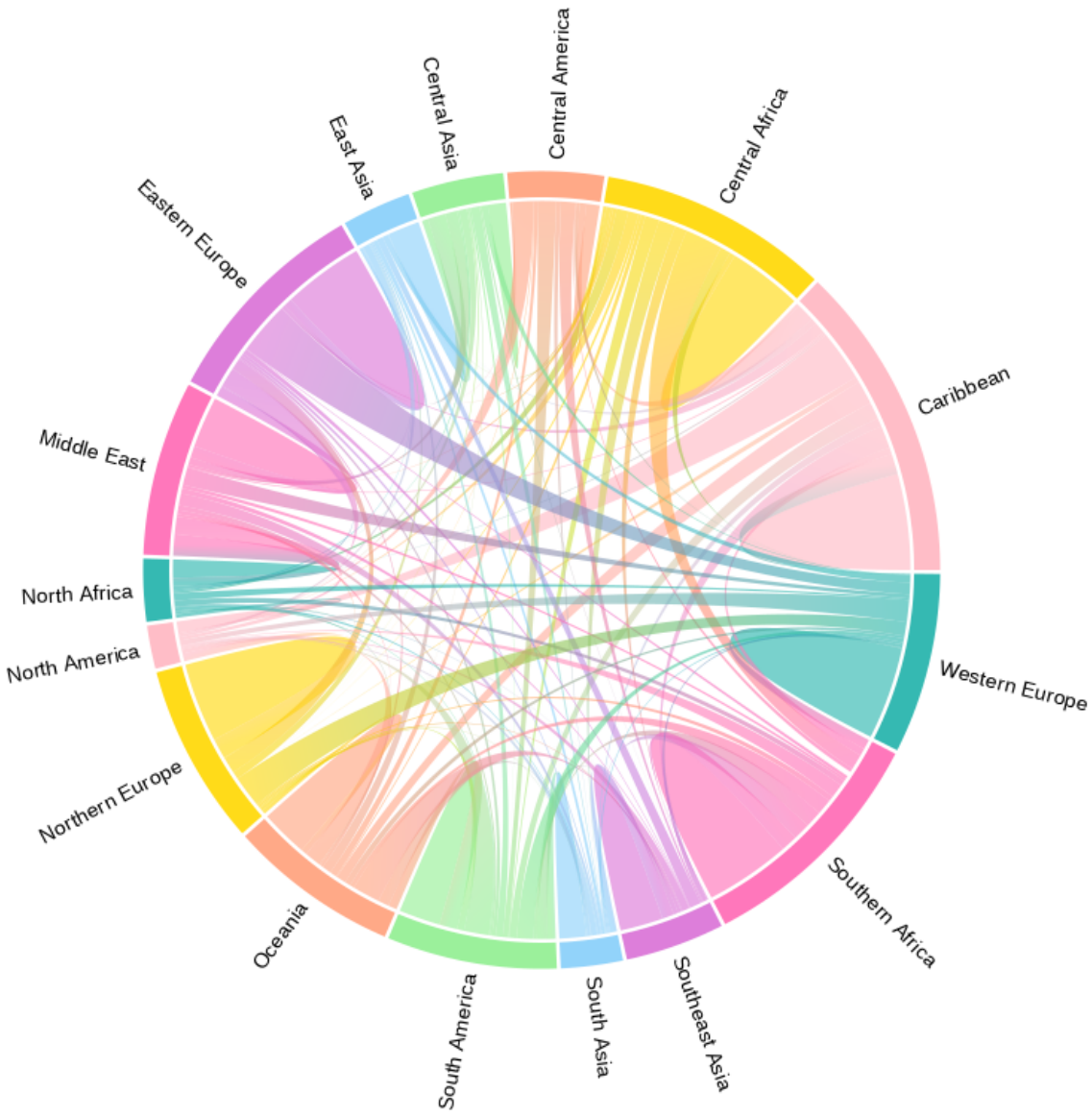

Figure 36: Chord Diagram of Mis-classifications between each region

Country name	Open-Ended	MCQs with Similar choices	MCQs with Random choices
Costa Rica	26.00	73.23	72.16
Croatia	47.83	72.83	83.92
Cuba	47.50	76.83	77.92
Curaçao	20.83	61.07	80.96
Cyprus	13.67	59.33	69.19
Czechia	40.50	66.07	83.90
Côte d'Ivoire	13.33	60.00	71.47
Denmark	32.50	66.93	78.54
Dominica	15.17	61.17	67.04
Dominican Republic	15.00	56.37	70.43
Ecuador	21.50	76.10	73.05
Egypt	60.50	77.07	83.84
El Salvador	4.83	65.93	63.40
Estonia	21.83	43.90	70.30
Eswatini	0.50	28.70	53.07
Ethiopia	41.00	80.93	80.24
Falkland Islands	8.83	92.13	90.35
Faroe Islands	30.33	71.30	90.66
Fiji	22.83	64.10	76.93
Finland	32.33	67.80	76.31
France	40.83	73.77	83.70
French Guiana	3.00	64.73	53.93
French Polynesia	24.67	81.90	83.97
Gabon	5.33	56.00	66.67
Gambia	3.33	41.40	53.16
Georgia	32.00	71.40	83.37
Germany	54.83	71.30	87.54
Ghana	26.33	70.53	67.80
Gibraltar	19.00	62.27	79.48
Greece	66.67	91.00	91.06
Greenland	27.00	65.43	84.90
Grenada	3.50	37.77	63.75
Guadeloupe	1.50	48.80	71.09
Guam	11.33	70.43	55.57
Guatemala	19.67	75.50	74.38
Guernsey	1.83	66.50	81.14
Guyana	8.83	52.33	52.66
Haiti	27.83	71.23	65.98
Vatican City State	8.67	43.77	74.31
Honduras	4.67	64.13	66.98
Hong Kong	22.67	65.23	86.70
Hungary	24.83	49.00	78.44
Iceland	69.00	82.27	89.04

Table 5: Region wise accuracies through various experimental settings : Part 2/5

Country name	Open-Ended	MCQs with Similar choices	MCQs with Random choices
India	78.33	90.03	90.10
Indonesia	48.83	67.76	84.97
Iran	50.83	70.40	83.27
Iraq	28.67	60.60	76.84
Ireland	48.33	74.57	87.63
Isle of Man	6.17	52.03	77.91
Israel	35.67	76.33	73.99
Italy	60.00	82.30	85.40
Jamaica	28.17	60.20	70.58
Japan	81.17	88.92	91.75
Jersey	3.67	50.37	71.69
Jordan	44.00	79.03	89.04
Kazakhstan	18.33	44.73	77.73
Kenya	56.00	88.57	88.15
North Korea	47.33	25.64	81.26
South Korea	47.83	67.23	79.90
Kuwait	12.83	52.30	68.70
Kyrgyzstan	20.17	37.30	69.48
Laos	26.50	38.53	80.25
Latvia	17.00	41.63	72.47
Lebanon	27.00	73.63	78.09
Liberia	9.33	50.97	65.37
Libya	6.67	22.87	73.10
Liechtenstein	6.17	34.03	72.29
Lithuania	24.00	54.43	74.40
Luxembourg	13.33	21.90	62.29
Macao	17.00	66.42	85.38
Madagascar	24.17	81.20	65.40
Malawi	8.33	54.80	66.39
Malaysia	28.33	73.28	83.65
Maldives	39.33	80.20	82.08
Mali	13.83	65.43	80.11
Malta	47.67	79.57	90.95
Martinique	4.33	53.60	72.85
Mauritania	12.00	76.77	80.28
Mauritius	38.33	92.00	79.52
Mexico	53.17	79.77	79.69
Moldova	7.67	35.23	63.57
Monaco	30.17	54.83	69.69
Mongolia	50.83	82.41	81.39
Montenegro	22.17	44.37	81.00
Morocco	67.83	85.40	93.75
Mozambique	5.17	66.57	63.78
Myanmar	61.50	76.56	92.62

Table 6: Region wise accuracies through various experimental settings : Part 3/5

Country name	Open-Ended	MCQs with Similar choices	MCQs with Random choices
Namibia	0.00	83.40	85.35
Nepal	65.00	72.53	89.72
Netherlands	46.00	74.63	86.86
New Caledonia	7.50	55.03	64.98
New Zealand	53.83	76.40	82.58
Nicaragua	6.83	69.87	69.64
Nigeria	47.33	79.13	73.78
North Macedonia	10.17	44.27	74.44
Norway	32.50	48.17	79.45
Oman	31.67	71.40	77.59
Pakistan	30.33	53.57	79.32
Palau	15.83	71.23	71.97
Palestine, State of	9.00	73.53	83.59
Panama	4.33	80.17	60.86
Papua New Guinea	13.50	61.87	63.38
Paraguay	6.17	52.23	54.29
Peru	54.83	85.73	83.61
Philippines	43.67	74.82	85.94
Poland	28.83	62.00	79.17
Portugal	43.50	58.60	84.39
Puerto Rico	16.67	68.97	72.52
Qatar	19.50	56.63	66.04
Romania	31.50	56.43	79.02
Russian Federation	52.67	73.13	77.18
Rwanda	29.50	71.73	73.72
Réunion	5.33	90.87	69.21
Saint Helena, Ascension and Tristan da Cunha	3.33	71.40	57.44
Saint Kitts and Nevis	14.17	41.23	64.61
Saint Lucia	16.83	61.40	79.33
Saint Martin (French)	4.00	45.43	69.48
Samoa	23.33	68.43	71.19
San Marino	10.17	35.00	54.01
Saudi Arabia	26.00	65.53	74.69
Senegal	21.83	78.73	78.20
Serbia	24.33	58.70	79.14
Seychelles	26.33	92.87	76.83
Sierra Leone	8.83	56.53	75.23
Singapore	51.33	74.91	80.15
Saint Martin (Dutch)	7.17	50.77	75.14
Slovakia	12.33	32.33	67.41
Slovenia	24.00	53.40	75.09
Solomon Islands	3.33	22.53	69.22
Somalia	24.67	75.30	78.46

Table 7: Region wise accuracies through various experimental settings : Part 4/5

Country name	Open-Ended	MCQs with Similar choices	MCQs with Random choices
South Africa	38.50	94.43	82.91
South Georgia and the South Sandwich Is..	7.17	80.70	77.99
South Sudan	25.83	65.83	82.31
Spain	51.00	83.13	84.71
Sri Lanka	37.00	61.40	82.72
Sudan	25.33	70.63	81.25
Svalbard & Jan Mayen	0.00	74.13	89.45
Sweden	35.50	54.63	81.22
Switzerland	42.17	62.53	76.40
Syria	13.00	51.63	64.82
Taiwan	23.00	51.01	80.16
Tajikistan	10.83	44.43	81.04
Tanzania	24.83	84.37	84.89
Thailand	64.17	84.49	89.08
Timor-Leste	7.83	41.77	69.67
Togo	2.33	31.67	65.98
Tonga	1.33	19.60	44.73
Trinidad and Tobago	8.00	56.23	53.62
Tunisia	20.33	40.00	75.53
Turkmenistan	22.67	48.73	82.83
Türkiye	56.33	86.10	92.24
Uganda	26.83	79.90	80.27
Ukraine	22.83	67.63	72.82
United Arab Emirates	53.00	85.30	85.30
United Kingdom	50.17	92.17	89.05
United States	67.17	91.03	87.76
Uruguay	14.17	46.33	61.10
Uzbekistan	47.17	68.63	83.07
Vanuatu	5.50	18.00	57.04
Venezuela	11.17	57.63	53.41
Viet Nam	55.50	78.74	89.77
Virgin Islands, UK	6.83	38.00	79.60
Virgin Islands, U.S.	9.67	46.73	81.72
Kosovo	6.50	28.70	65.53
Yemen	27.17	69.80	76.46
Zambia	9.50	54.80	73.29
Zimbabwe	11.67	71.03	76.05
Åland Islands	0.17	29.00	62.02
Overall	**25.14**	**61.92**	**75.06**

Table 8: Region wise accuracies through various experimental settings : Part 5/5

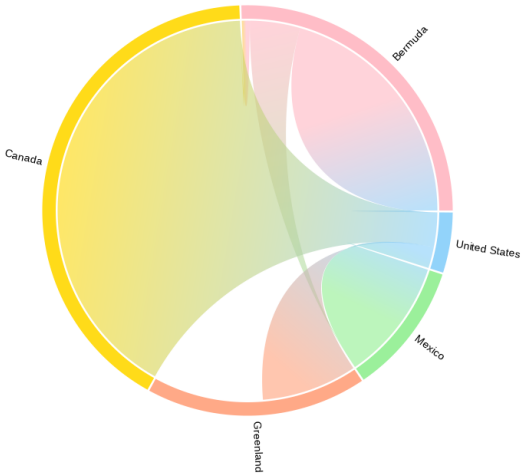

Figure 37: Chord Diagram of Mis-classifications among each region's countries : North America

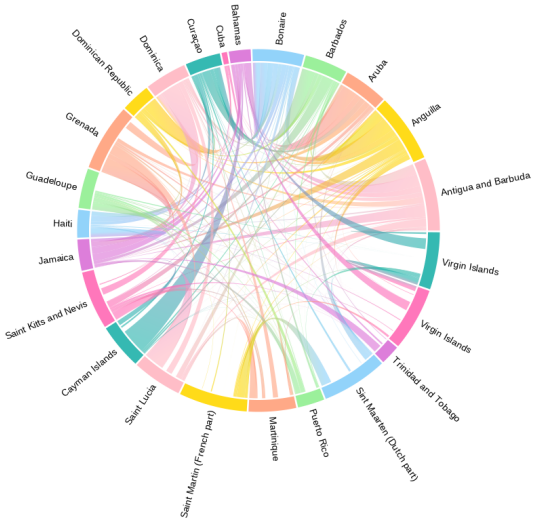

Figure 39: Chord Diagram of Mis-classifications among each region's countries : Caribbean

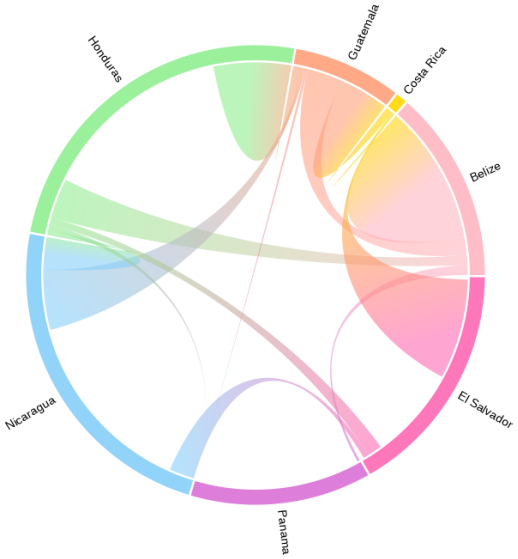

Figure 38: Chord Diagram of Mis-classifications among each region's countries : Central America

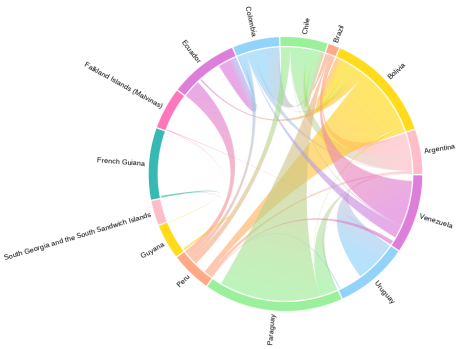

Figure 40: Chord Diagram of Mis-classifications among each region's countries : South America

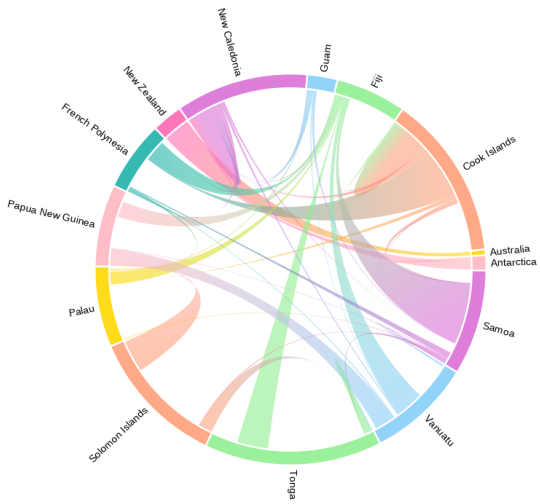

Figure 41: Chord Diagram of Mis-classifications among each region's countries : Oceania

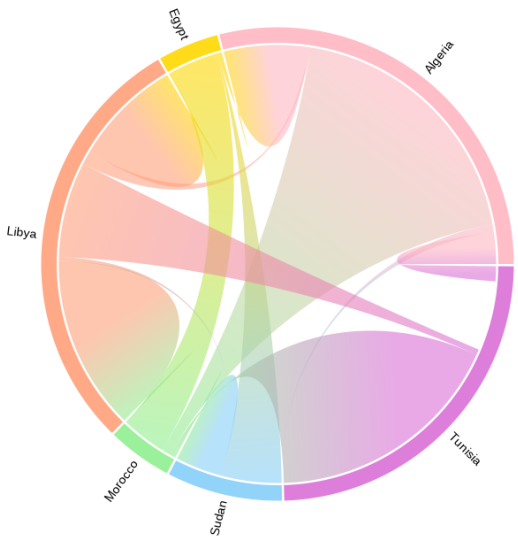

Figure 42: Chord Diagram of Mis-classifications among each region's countries : North Africa

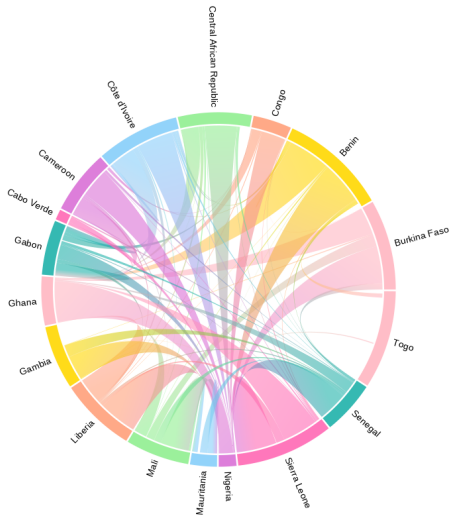

Figure 43: Chord Diagram of Mis-classifications among each region's countries : Central Africa

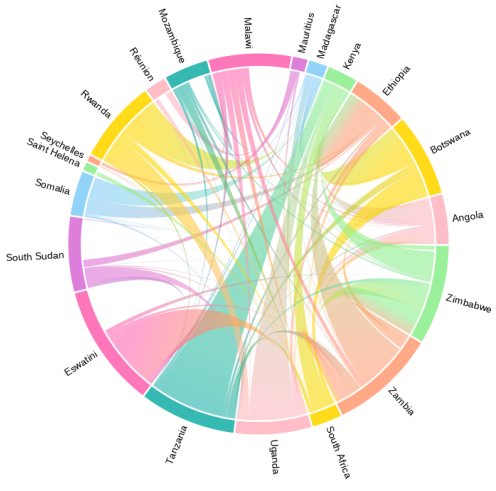

Figure 44: Chord Diagram of Mis-classifications among each region's countries : Southern Africa

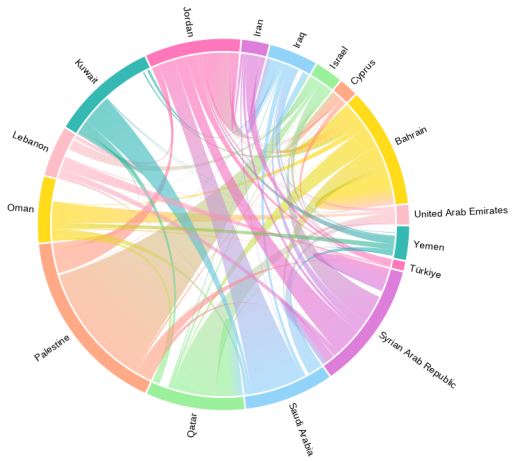

Figure 45: Chord Diagram of Mis-classifications among each region's countries : Middle East

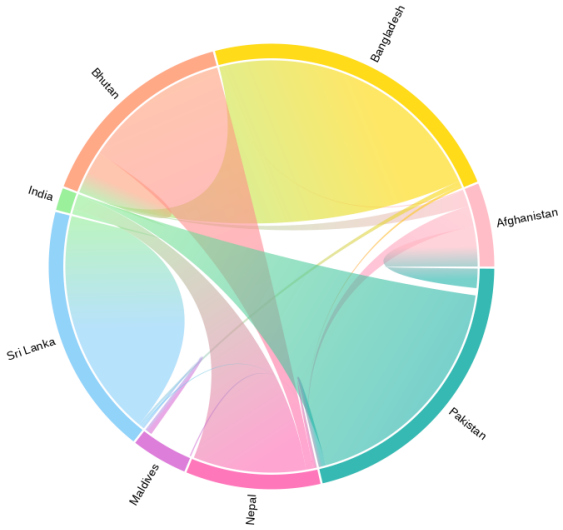

Figure 47: Chord Diagram of Mis-classifications among each region's countries : South Asia

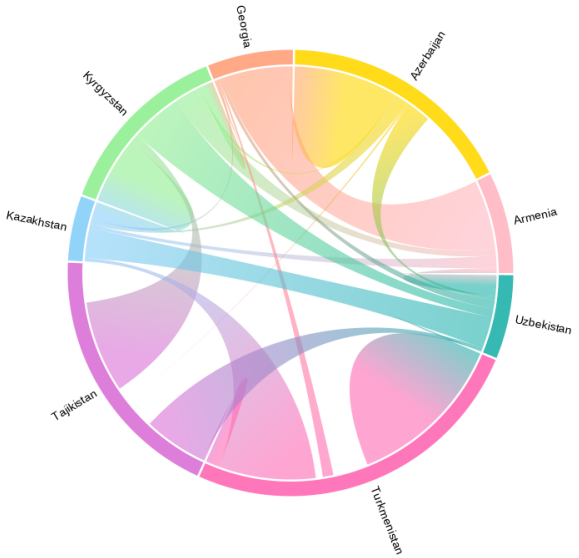

Figure 46: Chord Diagram of Mis-classifications among each region's countries : Central Asia

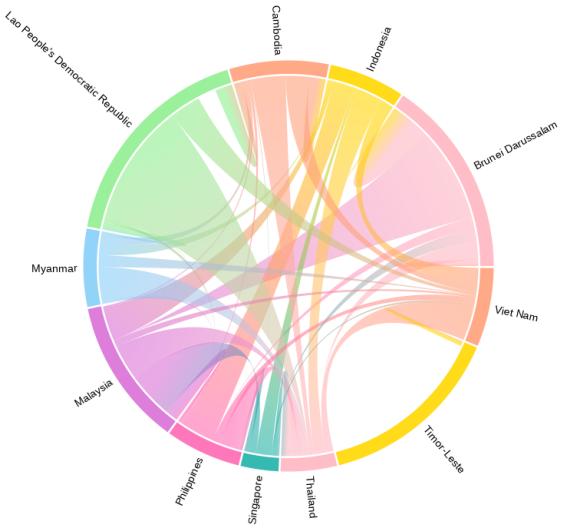

Figure 48: Chord Diagram of Mis-classifications among each region's countries : South East Asia

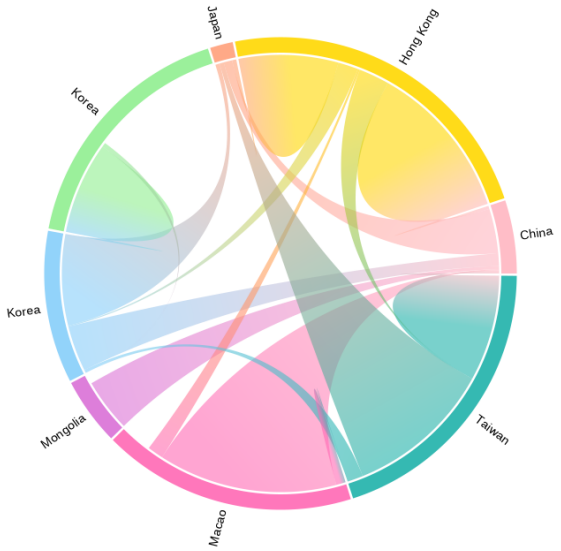

Figure 49: Chord Diagram of Mis-classifications among each region's countries : East Asia

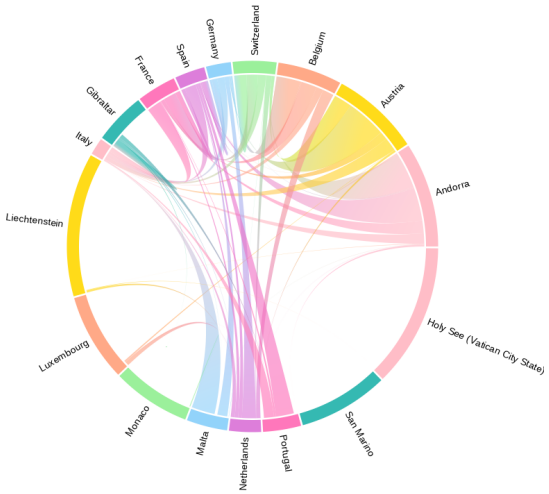

Figure 51: Chord Diagram of Mis-classifications among each region's countries : Western Europe

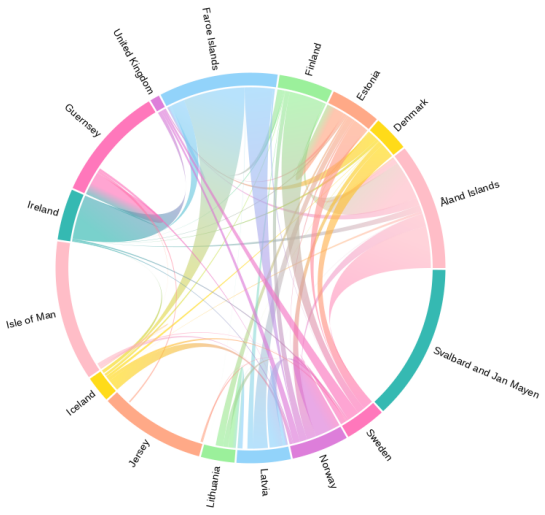

Figure 50: Chord Diagram of Mis-classifications among each region's countries : Northern Europe

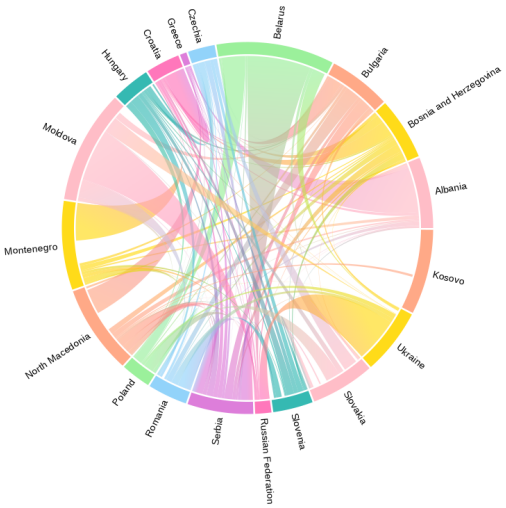

Figure 52: Chord Diagram of Mis-classifications among each region's countries : Eastern Europe