Group G Report

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1 Link to repository in github

Github-link:

- LINK(CLICK ME)

2 Metadata summary

The metadata and images used in this project originate from the PAD-UFES-20 dataset. The dataset was collected by the Dermatological and Surgical Assistance Program (PAD) at the Federal University of Espírito Santo (UFES), Brazil. It consists of clinical images captured using smartphones and corresponding patient clinical metadata collected during medical appointments between 2018 and 2019.
The metadata consists of 26 attributes, including age, gender, and other clinical variables. Only six attributes are guaranteed to be complete, namely patient_id, lesion_id, image_id, age, region, and biopsy status. The attributes can help identify a correlation between the diagnosis and the patient's environment.

We compared the distribution of diagnostic labels in our group with the distribution in the full dataset [1]. We found that the relative frequencies of the six diagnostic categories closely resemble those of the entire data set, as is shown in Figure 1.

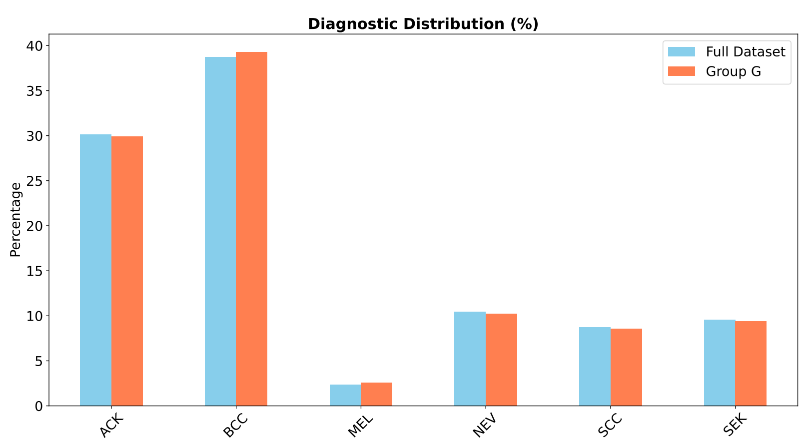

Figure 1: Comparison between the distribution of the diagnostic

[1] In this report, comparisons to the "full dataset" refer to the dataset metadata_with_groups, not the original metadata file. The metadata_with_groups dataset excludes approximately 200 images that are present in the full metadata dataset.

An analysis of our group's metadata reveals missing information across several demographic and clinical attributes. In particular, data related to gender, family cancer history, skin cancer history, and environmental components (such as pesticide use and water/sewage access) are frequently absent. This is not a surprise, as mentioned earlier only 6 attributes are guaranteed. The missing information is quite substantial, as seen in Figures 2 and 3. In Figure 2 we see almost a third of the gender entries are empty, and therefore unknown. This is not only in our dataset, but also in the entire dataset.

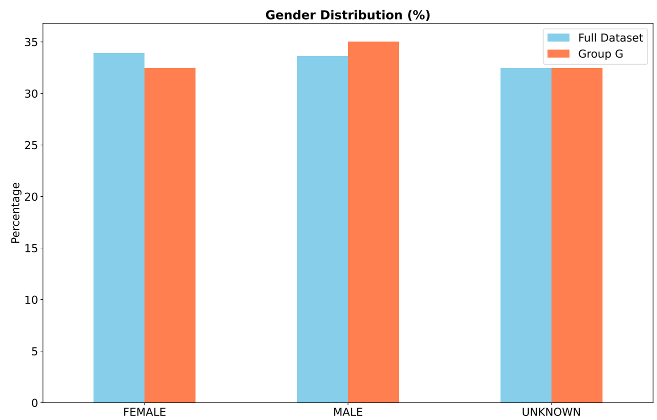

Figure 2: Gender distribution (male, female and empty entries)

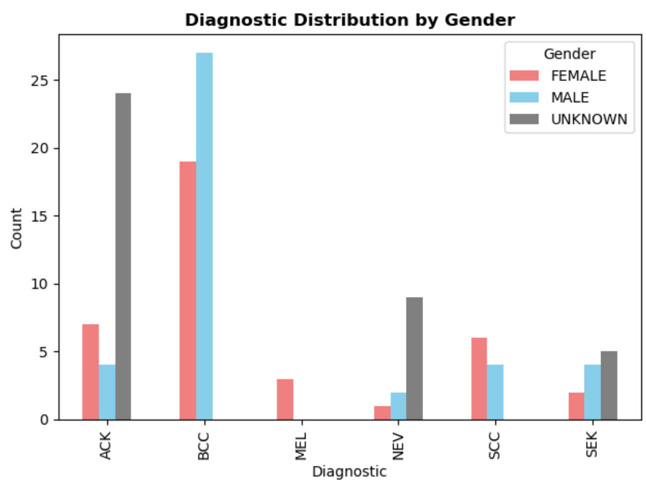

Figure 3: Diagnostic distribution by gender (male, female and empty entries).

While our upcoming project will primarily focus on image-based analysis, incomplete clinical metadata could also pose a limitation. Missing information on attributes such as gender, cancer history, and environmental exposure could limit the ability to link visual patterns to patient attributes.

Our groups metadata is overall, fairly representative of the entire dataset. Therefore, many of the trends and correlations observed in our data are also present in the full dataset.

3 Images

During the annotation process, hair presence and pen marks were systematically assessed. In addition to these planned annotations, we observed other recurring image-quality issues, including imprecise segmentation masks and blurry images. The following provides more detail on these aspects.

Hair:
During the annotation process, each image was assessed and assigned a hair score on a scale from 0 to 3. In many images, hair was present only around the lesion. The group unanimously assigned a score of 0 to 40 out of the 117 images. An example of such an image is shown below.

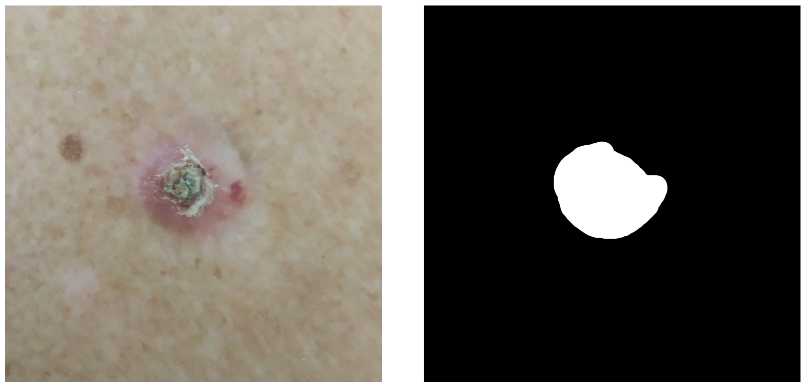

Figure 4: Image without hair interference and its segmentation mask (PAT_906_1722_328).

In contrast, some images contained hair that partially or fully overlapped the lesion. In these cases, the hair could obscure lesion boundaries and potentially interfere with further analysis. Here is an example of an image we all marked a score of 3.

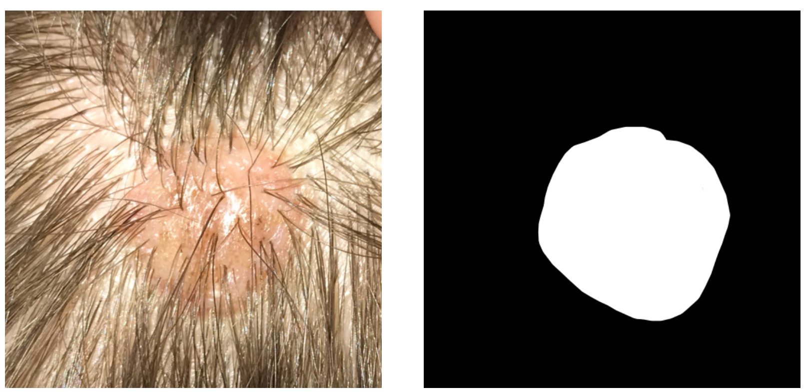

Figure 5: Image all group members marked 3 (PAT_1735_3242_27).

In cases where hair overlapped the lesion, it could obscure important visual features and reduce overall image clarity. Removing the hair covering the lesion would require substantial effort and could introduce additional uncertainty, making such images less suitable for reliable analysis.

Penmarks:
Pen marks were assessed during the annotation process. Each image was assigned a score of 0 if no pen marks were present and a score of 1 if pen marks were visible. Penmarks are known for interfere with lesion interpretation. In particular, a study[2] suggest that artefacts such as ink markings can increase false-positive predictions in deep learning models. Since we aim to train our own image-based model, the presence of such artefacts is a relevant concern.

The group unanimously agreed on 98 out of the 117 images. Specifically, 79 images were unanimously assessed as having no visible pen marks, while 19 images were unanimously identified as containing pen markings.

In two images, all group members were uncertain whether the visible markings were pen artefacts or natural skin features. Below are the two images for which there was unanimous uncertainty about the presence of pen marks.

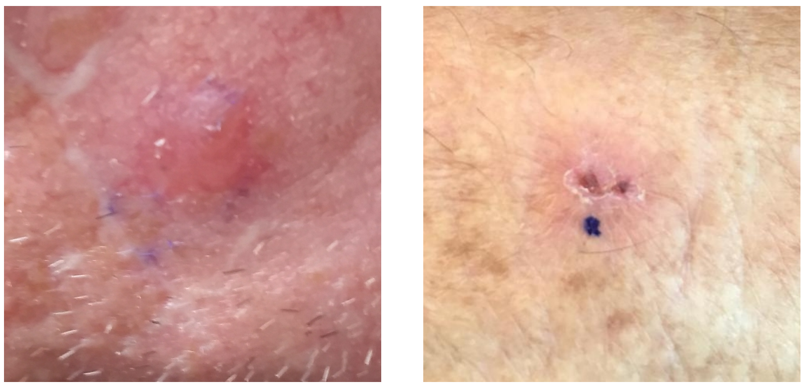

Figure 6: Images with uncertain markings (PAT_217_333_61)(PAT_872_1709_526).

[2]The study can be found via the following link: https://jamanetwork.com/journals/jamadermatology/fullarticle/2740808

Blurry images:
During the annotation of the lesion, we also noticed that some of the images were blurry. There could be several reasons for this. One reason could be that, when the image is taken, the camera might be focused on the wrong thing. This is seen in Figure 7. Here, the focus is in the bottom right corner, and moving towards the top left corner, the image gets more and more blurry. In this image it is not a problem, since the shape and color of the lesion is still clearly visible. Furthermore if the image is just unfocused, the image can still be enhanced. It is only in more extreme examples where it is a problem.

Figure 7: (PAT_201_306_781)

Other reasons for the blurriness in the images, can be caused by the camera not being held still, when the image is taken or if the quality of the camera is not good, as can be seen in Figure 8. This might be more problematic since the border of the lesion is more difficult to analyze. Here the color is very visible, but the border of the lesion is difficult to analyze, and especially in the shaky image to the left, the image can be difficult to enhance.

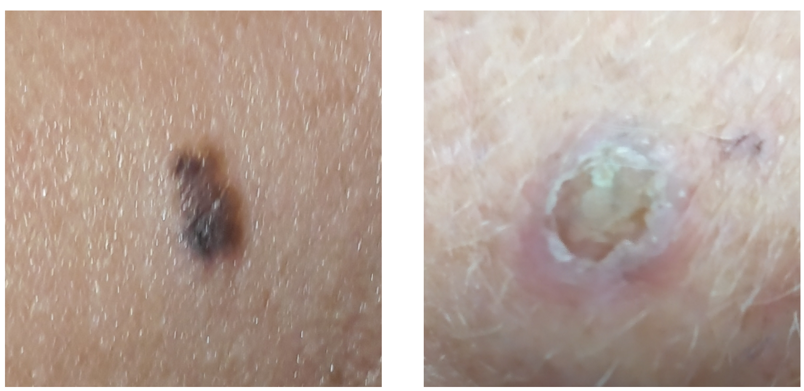

Figure 8: (PAT_194_298_367)(PAT_780_1473_791)

Unprecise masks:
In addition to hair-related challenges, mask precision was systematically evaluated during the annotation process. In total, 26 images were flagged by at least one group member as having imprecise or questionable segmentation masks. The observed inaccuracies varied in nature. In some cases, the mask appeared to follow hair structures rather than the true lesion boundary. In other instances, the mask aligned with pen marks or other visible artefacts on the skin, such as shadows, instead of the lesion itself. Below is an example where the segmentation mask might follow a pen mark rather than the actual lesion boundary.

Figure 9: Figure showing mask following penmarks (PAT_388_1590_169).

One particular image was unanimously considered unusable due to severe mask inaccuracy. In this case, the segmentation did not accurately represent the lesion. Additionally, hair coverage obscured a substantial portion of the lesion, reducing the reliability of both the image and its corresponding mask.

Figure 10: Example of mask unanimously assessed as unusable (PAT_999_20_540).