Skin Lesion Classification with domain specific artefact debiasing and augmentation

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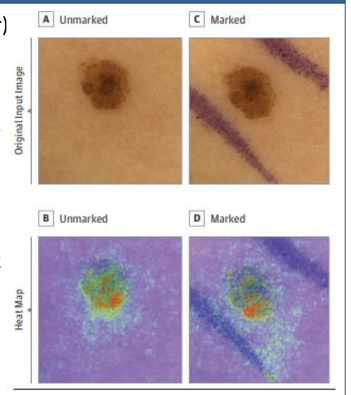
Motivation

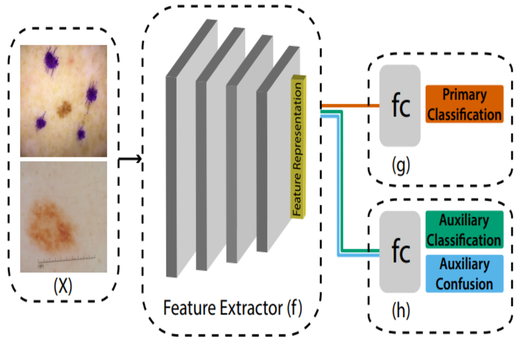
- Early diagnosis of **Melanoma**(a form of skin cancer) promises high chances of a cure.
- Accessible and accurate diagnostic tools can democratize dermatology and save lives worldwide.
- Automating this process is highly difficult since the **datasets are extremely imbalanced -** Common skin cancers contain hundreds of images, but rare forms contain very few.
- Difficult to generalize from visual features.
- Additionally, dermatologists use markings to mark location of lesions, or rulers. **Prediction irregularities due to biases** induced by these artefacts makes the problem harder.
- Data augmentation expands the training dataset and increases robustness.



Dataset

- Dermoscopic skin lesion datasets with diagnosis labels and metadata from **International Skin Imaging Collaboration (ISIC) challenge** is used.
- 2017 + 2020 ISIC challenge data (35,574 images) used - higher representation of artefacts in these datasets than other competition years.
- Pre-processed (center cropped and resized) images (256×256) used for training and testing. 33%,(3326 images) of the 2018 challenge data used as the validation set for hyperparameter tuning.

Artefact Debiasing

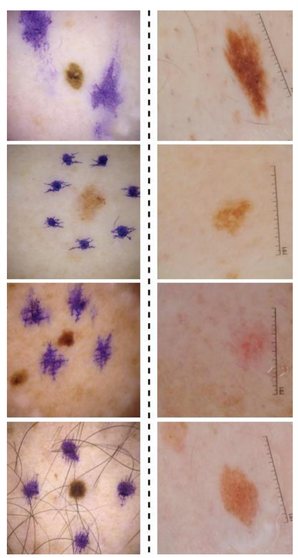


*'Turning a Blind Eye' architecture. Feature extractor, f, is implemented as **ResNeXt***

- **Unlearning** techniques: **remove bias** by minimizing the mutual information between the feature embedding and the unwanted bias.
- **Auxiliary classifier** minimizes an auxiliary classification loss, L_s *and* auxiliary confusion loss, L_{conf}

$$\mathcal{L}_{\text{conf,m}}(x_m, y_m, \theta_m; \theta_{\text{repr}}) = -\sum_{n_m} \frac{1}{n_m} \log p_{n_m},$$

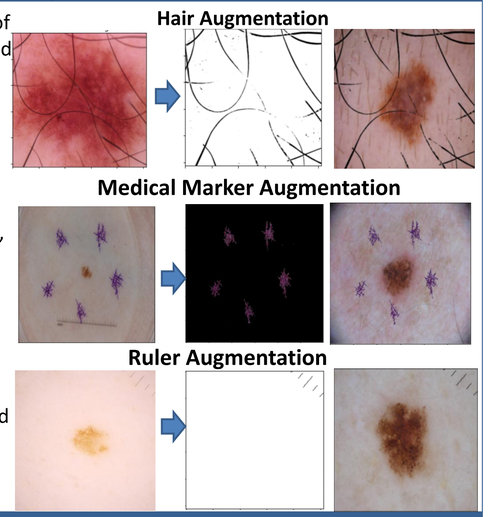
$$\mathcal{L}(x_p, y_p, x_s, y_s, \theta_p, \theta_s, \theta_{\text{repr}}) = \mathcal{L}_p(x_p, y_p; \theta_{\text{repr}}, \theta_p) + \mathcal{L}_s + \alpha \mathcal{L}_{\text{conf}},$$



Artefacts seen in ISIC 2020 data

Data Augmentation

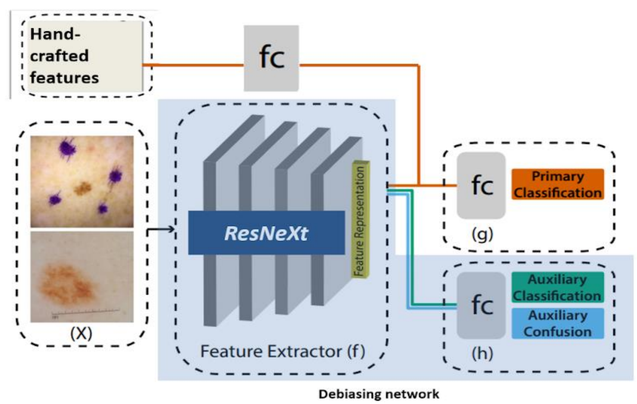
- Data augmentation by generating of synthetic images with custom designed artifacts on sampled images.
- Introduces randomness, **alleviates the problem of imbalanced data**.
- Adds new data points to the input space and preserves semantic and temporal information.
- Techniques used: blackHat filtering, morphological sampling, random artifact stamping, hair incorporation or random removal etc.
- These introduce robustness, challenges the model and **prevents overfitting.**
- Artifacts mimic real world noise and teach the model **to generalize across images.**



Hand-crafted features

- Dermatologists use the **"Asymmetry, Border, Color, and Diameter"(ABCD)** metric to classify whether a lesion is benign or malignant.
- To incorporate this intuition based on the certified classification metrics, the model is fed carefully engineered hand-crafted features that **capture the configuration, texture, and appearance of the lesion.**
- Amongst others, **Hu, Zernike Moments, Haralick features** capture different aspects of the lesion's configuration. **Local Binary Patterns (LBP)** provide a perception of depth which often absent in most computational models.
- **Color Histograms** assists in differentiating the lesions based on their appearance.

Proposed Model



Debiasing network

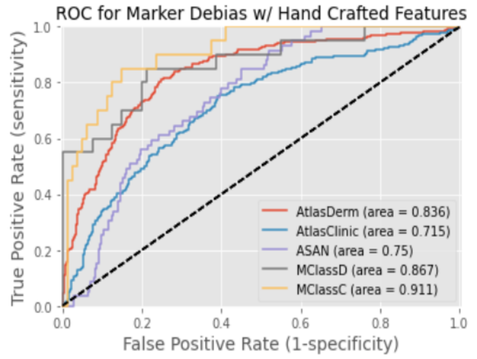
- The proposed model is built on the **ResNext-101** architecture.
- A **2-stage processing pipeline** sequentially performs **local and global feature extraction** which helps capture size, color and shape variations of lesions.
- The **first stage** thus, down samples input data to **filter irrelevant noisy artifacts** and retain only principal components affecting final decisions.
- In the **second stage**, **2 FC layers** produce **primary and auxiliary classification heads**.

Proposed Model

- To address the imbalance in data, we **concatenate hand crafted features with the extracted CNN features**. This combined output is further processed algebraically to produce the final prediction score.
- The concatenation has the effect of positively reinforcing pre-prediction decisions to confidently produce output scores.
- For training, an SGD optimizer with learning rate 0.0003 and momentum 0.9 is used.

Results

Experiment	Architecture	Atlas		ASAN	MClass	
		Dermoscopic	Clinical	Clinical	Dermoscopic	Clinical
Dermatologist	–	–	–	–	0.671	0.769
Baseline	ResNeXt-101	0.818	0.592	0.723	**0.891**	0.736
Baseline + Domain Aug	ResNeXt-101	0.832	0.693	**0.804**	0.788	0.838
Marker Debias	ResNeXt-101 + TABE	**0.836**	0.659	0.751	0.875	0.842
Ruler Debias	ResNeXt-101 + TABE	0.793	0.453	0.588	0.776	0.722
Baseline + HE	ResNeXt-101	0.83	0.581	0.724	0.886	0.774
Marker Debias + HE	ResNeXt-101 + TABE + DNN	**0.836**	**0.715**	0.75	0.867	**0.911**
Ruler Debias + HE	ResNeXt-101 + TABE + DNN	0.818	0.614	0.741	0.826	0.817



Using our proposed augmentation technique, the model performance increases up to 14.4%.

Additionally, when we incorporate hand crafted features, the model performance increases by up to 23% on the clinical data.

Significant Contributions

- A 2-stage pipeline where images are subjected to spatial operations that determine the relevant from irrelevant features and remove unwanted noise in the form of artifacts.
- Incorporate hand crafted features to capture variations in appearance, texture and shape, to mimic the traditional weighted metric used in the determination of malignant lesions.
- A novel method of data augmentation using custom designed masks for each artifact to generate synthetic data and introduce domain generalization.

Conclusions

- Given the highly imbalanced composition of the dataset, we synthesized auxiliary artifacts in addition to medical markers to successfully teach the deep unlearning model to ignore irrelevant features.
- We also integrated custom hand-crafted features into the model to increase prediction confidence which is in line with the medical community which attempts to identify the salient features of the images for the presence of a melanoma.
- Future work consists of improving sensitization of the deep unlearning model to multiple artifacts parallelly and to extend our work to predict the subtype of melanoma as well.