

SKIN LESION ANALYSIS TOWARD MELANOMA DETECTION: A CHALLENGE AT THE 2017 INTERNATIONAL SYMPOSIUM ON BIOMEDICAL IMAGING (ISBI), HOSTED BY THE INTERNATIONAL SKIN IMAGING COLLABORATION (ISIC)

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ABSTRACT

This article describes the design, implementation, and results of the latest installment of the dermoscopic image analysis benchmark challenge. The goal is to support research and development of algorithms for automated diagnosis of melanoma, the most lethal skin cancer. The challenge was divided into 3 tasks: lesion segmentation, feature detection, and disease classification. Participation involved 593 registrations, 81 pre-submissions, 46 finalized submissions (including a 4-page manuscript), and approximately 50 attendees, making this the largest standardized and comparative study in this field to date. While the official challenge duration and ranking of participants has concluded, the dataset snapshots remain available for further research and development.

Index Terms— Dermatology, dermoscopy, melanoma, skin cancer, challenge, deep learning, dataset

1. INTRODUCTION

The most prevalent form of cancer in the United States is skin cancer, with 5 million cases occurring annually [1, 2, 3]. Melanoma, the most dangerous type, leads to over 9,000 deaths a year [2, 3]. Among all cancers, skin cancer is also the most readily available to inspection, as it occurs on the surface of the body. Even though most melanomas are first discovered by patients [4], the diagnostic accuracy of unaided expert visual inspection is only about 60%, suggesting that some curable instances of melanoma are missed [5].

Dermoscopy is a recent technique of visual inspection that both magnifies the skin and eliminates surface reflection. Research has shown that with proper training, diagnostic accuracy with dermoscopy is 75%-84% [5, 6, 7]. In an attempt to better scale dermoscopic expertise, procedural algorithms, such as “chaos and clues,” “3-point checklist,” “ABCD rule,” “Menzies method,” “7-point checklist,” and “CASH” (color, architecture, symmetry, and homogeneity), were developed [6, 8]. Regardless, some clinicians forgo these methods in favor of heuristics from experience, as well as the “ugly duckling” sign (outlier on patient) [9].

As recent reports have shown a growing shortage of dermatologists per capita [10], scaling of human expertise continues to be a challenge. This finding has spawned an interest in building techniques for automated assessment of dermoscopic images [11, 12, 13, 14]. However, most of these studies have used isolated silos of data for analysis that are not available to the broader research community. While an earlier effort to create a public archive of images was made [14, 15], the dataset was far too small (200 images) to fully represent scope of the task.

The International Skin Imaging Collaboration (ISIC) has begun to aggregate a large-scale publicly accessible dataset of dermoscopy images. Currently, the dataset houses more than 20,000 images from leading clinical centers internationally, acquired from a variety of devices used at each center. The images are screened for both privacy and quality. The associated clinical metadata has also been vetted by recognized melanoma experts. Broad and international participation ensures that the dataset contains a clinically representative distribution.

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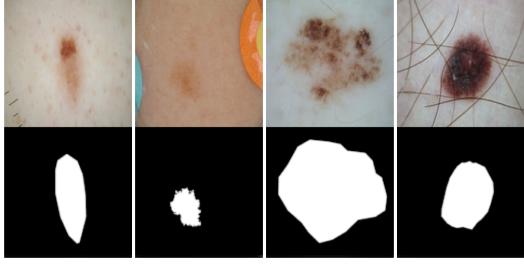


Fig. 1. Images from “Part 1: Lesion Segmentation.” *Top:* Original images. *Bottom:* Segmentation masks.

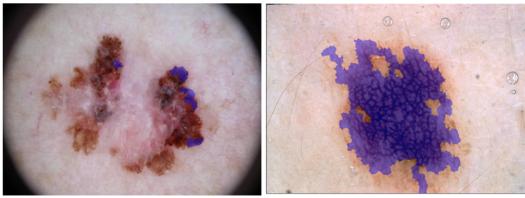


Fig. 2. Images from “Part 2: Dermoscopic Feature Classification”. Ground truth labels highlighted in purple. *Left:* Streaks. *Right:* Pigment Network.

The ISIC dataset was the foundation for the first public benchmark challenge on dermoscopic image analysis in 2016 [16, 17]. The goal of the challenge was to provide a dataset snapshot to support development of automated melanoma diagnosis algorithms across 3 parts of lesion analysis: lesion segmentation, lesion dermoscopic feature detection, and lesion classification.

The second instance of this challenge was hosted in 2017, featuring an expanded dataset and additional classification categories. In the following sections, the provided datasets, tasks, evaluation metrics, participation rate, and the results of this challenge are described.

2. DATASET DESCRIPTIONS & TASKS

Similar to the prior year challenge [16], the 2017 challenge consisted of 3 tasks: lesion segmentation, dermoscopic feature detection, and disease classification. For each, data consisted of images and corresponding ground truth annotations, split into training ($n=2000$), validation ($n=150$), and holdout test datasets ($n=600$). Participants were allowed to download training datasets only. Predictions could be submitted on validation and test datasets. The validation submissions provided instantaneous feedback in the form of performance evaluations, as well as ranking in comparison to other participants. Test submissions only provided feedback after the deadline. The training, validation, and test datasets continue to be available for download at: <http://challenge2017.isic-archive.com/>

Part 1: Lesion Segmentation Task: Participants were asked to submit automated predictions of lesion segmen-

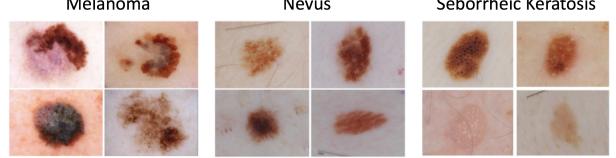


Fig. 3. Example images from “Part 3: Disease Classification.”

tions from dermoscopic images in the form of binary masks. Lesion segmentation training data included the original image, paired with the expert manual tracing of the lesion boundaries also in the form of a binary mask, where pixel values of 255 were considered inside the area of the lesion, and pixel values of 0 were outside (Fig. 1).

Part 2: Dermoscopic Feature Classification Task: Participants were asked to automatically detect four clinically defined dermoscopic features, “network,” “negative network,” “streaks,” and “milia-like cysts,” [18, 19]. Pattern detection involved both localization and classification (Fig. 2). To reduce the variability and dimensionality of spatial feature annotations, the lesion images were subdivided into superpixels using the SLIC algorithm [20]. Lesion dermoscopic feature data included the original lesion image and a corresponding set of superpixel masks, paired with superpixel-wise expert annotations for the presence or absence of the dermoscopic features. Validation and test sets included images and superpixels without annotation.

Part 3: Disease Classification Task: Participants were asked to classify images as belonging to one of 3 categories (Fig. 3), including “melanoma” ($n=374$ training), “seborrheic keratosis” ($n=254$ training), and “benign nevi” ($n=1372$ training), with classification scores normalized between 0.0 to 1.0 for each category. Lesion classification data included the original image, paired with both the gold standard diagnosis, as well as approximate age (5 year intervals), and gender (when available).

3. EVALUATION METRICS

Details of evaluation metrics have been previously described [16, 17]. For classification decisions, any confidence above 0.5 was considered positive for a category. For segmentation tasks, pixel values above 128 were considered positive, and pixel values below were considered negative.

For evaluation of classification decisions, the area under curve (AUC) measurement from the receiver operating characteristic (ROC) curve was computed by taking the integral of true positive rate with respect to the false positive rate [16].

Additionally, for classification of melanoma, specificity was measured on the operating curve where sensitivity was equal to 82%, 89%, and 95%, corresponding to dermatologist classification and management performance levels, and theoretically desired sensitivity levels, respectively [17].

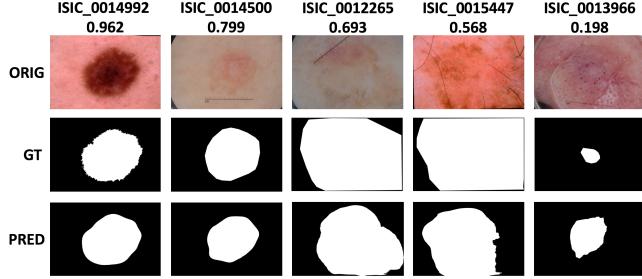


Fig. 4. Part 1 example segmentations from top ranked participant submission. *Top Row:* Original images. *Middle Row:* Ground truth segmentations. *Bottom Row:* Participant predictions. ISIC identifiers and Jaccard Index values are listed at each column head.

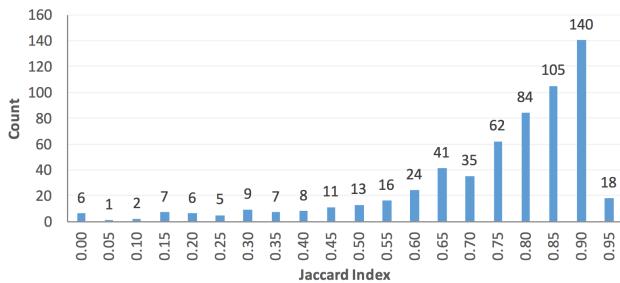


Fig. 5. Histogram of Jaccard Index values for individual images from top segmentation task participant submission.

Segmentation submissions were compared using the Dice coefficient, the Jaccard Index, and pixel-wise accuracy [16]. Participant ranking used Jaccard.

4. RESULTS

The 2017 challenge saw 593 registrations, 81 pre-submissions, and 46 finalized submissions (including a 4 page arXiv paper with each). The workshop at ISBI saw approximately 50 attendees. To date, this has been the largest standardized and comparative study in this field, accounting for the size of the dataset, the number of algorithms evaluated, and the number of participants. In the following, the results for each challenge part are investigated.

Part 1: Lesion Segmentation Task: 21 sets of prediction scores on the final test set were submitted for the segmentation task, and 39 were submitted to the validation set. The top ranked participant achieved a Jaccard Index of 0.765, an accuracy of 93.4%, and a Dice coefficient of 0.849, using a variation of a fully convolutional network ensemble (a deep learning approach) [21]. Example segmentations are shown in Fig. 4, and a histogram of individual image Jaccard Index measurements is shown in Fig. 5. Subjectively assessing the quality of the segmentations, one can observe that segmentations of Jaccard Index 0.8 or above tend to appear still visually

Method / Rank	AVG	Net-work	Neg. Net-work	Streaks	Milia-Like Cyst
[22] / 1	0.895	0.945	0.869	0.960	0.807
[23] / 2	0.833	0.835	0.762	0.896	0.838
[23] / 3	0.832	0.828	0.762	0.900	0.837

Table 1. Part 2: Dermoscopic Feature Classification AUC Measurements. AVG = Average across all categories.

“correct”, or yielding of clinical diagnostic utility, which is in agreement with prior reports that measured an inter-observer agreement of 0.786 on a subset of 100 images from the ISIC 2016 Challenge [13]. When Jaccard falls to 0.7 or below, the “correctness”, or clinical utility, of the segmentation can be debated. 156 out of 600 images (26%) fell at or below a Jaccard of 0.7. 91 images (15.2%) fell at or below Jaccard of 0.6. This suggests a failure rate of 15% to 26%, which is far higher than the pixel-wise failure rate of 6.6%.

Part 2: Dermoscopic Feature Classification Task: For the second year in a row, dermoscopic feature classification has received far less participation than other tasks. Only 3 submissions [22, 23] on the test set were received from 2 parties. Whether this is due to the technical framing of the task (how well it maps to existing frameworks), or the perceived importance of the task, is a matter of current investigation.

Regardless, performance levels of those submissions that were received (Table 1) demonstrated that localization of dermoscopic features is a tractable task for computer vision approaches. AUC measurements were above 0.75 ubiquitously, with an average close to 0.9.

Part 3: Disease Classification Task: The disease classification task received 23 final test set submissions, and 39 validation set submissions. Performance characteristics of the average (AVG) classification winner [24], seborrheic keratosis (SK) classification winner [25], and melanoma (M) classification winner [26], respectively, are shown in Table 2, as well as 3 fusion strategies also used in the previous challenge [17]: score averaging (AVGSC), linear SVM (L-SVM), and non-linear SVM (NL-SVM) using a histogram intersection kernel. Fusion strategies utilize all submissions on the final test set, and are carried out via 3-fold cross-validation. SVM input feature vectors included all disease category predictions. Both SVM methods used probabilistic SVM score normalization, producing an output confidence between 0.0 and 1.0, correlating with the probability of disease on a balanced dataset [13]. ROC curves for the 3 submissions and the best fusion strategy (Linear SVM) are shown in Fig. 6.

The 5 major trends observed involve the following: 1) All top submissions implemented various ensembles of deep learning networks. All used additional data sources to train, either from ISIC [24, 26], in-house annotations [25], or external sources [26]. 2) Classification of seborrheic keratosis appears to be an easier task in this dataset, compared to

Method	AVG-AUC	M-AUC	SK-AUC	M-SP82	M-SP89	M-SP95	M-SENS	M-SPEC	SK-SENS	SK-SPEC
[24] Top AVG	0.911	0.868	0.953	0.729	0.588	0.366	0.735	0.851	0.978	0.773
[25] Top SK	0.910	0.856	0.965	0.727	0.555	0.404	0.103	0.998	0.178	0.998
[26] Top M	0.908	0.874	0.943	0.747	0.590	0.395	0.547	0.950	0.356	0.990
AVGSC	0.913	0.872	0.954	0.778	0.605	0.435	0.214	0.988	0.600	0.975
L-SVM	0.926	0.892	0.960	0.834	0.692	0.571	0.718	0.901	0.878	0.931
NL-SVM	0.904	0.853	0.955	0.801	0.449	0.168	0.675	0.909	0.889	0.928

Table 2. Part 3: Disease classification evaluation metrics for top 3 participants, followed by average score, linear SVM, and non-linear SVM 3-fold cross-validation fusion methods. Key: M = Melanoma. SK = Seborrheic Keratosis. AVG = Average between two classes. AUC = Area Under Curve. SP82/89/95 = Specificity measured at 82/89/95% sensitivity. L-SVM = Linear SVM. NL-SVM = Non-Linear SVM. AVGSC = Average Score.

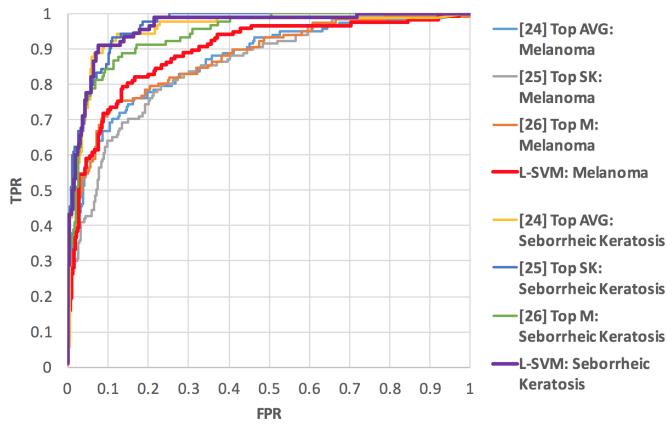


Fig. 6. ROC curves for top 3 submissions to “Part 3: Disease Classification”, as well as linear SVM fusion.

melanoma classification. This may reflect aspects of the disease, or bias in the dataset. The best performance came from the team that added additional weakly labelled pattern annotations to their training data [25]. 3) The top average performer was not the best in any single classification category. 4) The most complex fusion approach (NL-SVM) led to a decrease in performance, whereas simpler methods led to overall improvements in performance, consistent with previous findings [17]. This challenge is the second benchmark to demonstrate that a collaborative among all participants outperforms any single method alone. 5) Not all thresholds balanced sensitivity and specificity. Probabilistic score normalization in fusions is effective at balancing sensitivity and specificity [13, 17].

5. CONCLUSION

The International Skin Imaging Collaboration (ISIC) archive was used to host the second public challenge on Skin Lesion Analysis Toward Melanoma Detection at the International Symposium on Biomedical Imaging (ISBI) 2017. The challenge was divided into 3 tasks: lesion segmentation, feature

detection (4 classes), and disease classification (3 classes). 2000 images were available for training, 150 for validation, and 600 for testing. The challenge involved 593 registrations, 81 pre-submissions, and 46 finalized submissions, making it the largest standardized and comparative study in this field to date.

Analysis of segmentation results suggest that the average Jaccard Index may not accurately reflect the number of images where automated segmentation falls outside inter-observer variability. Future challenges may adjust the evaluation metric based on this observation by either using multiple segmentations per image to determine a failure threshold, or by choosing a fixed threshold based on measurements.

Poor participation was noted in dermoscopic feature detection; however submitted systems achieved reasonable performance. Future challenges may adjust the technical format of the task to more closely align with existing image detection benchmarks to better facilitate ease of participation.

Analysis of the classification task demonstrates that ensembles of deep learning approaches and additional data led to the highest performance. In addition, collaborative fusions of all participant systems outperformed any single system alone.

Limitations of this study included dataset bias (not all diseases, ages, devices, or ethnicities were represented equally across categories), and incomplete dermoscopic feature annotations. Future challenges will address limitations.

6. REFERENCES

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