Clinical Skin Lesion Diagnosis using Representations Inspired by Dermatologist Criteria

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Motivation

- Few CAD systems can diagnose the lesions
- Three primary difficulties:

  (1)various illumination conditions

  (2)non-uniform focal lengths and unconsistent size of viewing frame

  (3)more categories of diseases in clinical images

Main Contribution

- Verify the measurability of the medical criteria
- Propose comprehensive medical representations for skin lesions
- Create a clinically oriented diagnosis system
- Test on SD-198 datasets

Related work

- **Diagnosing Skin Diseases by Dermatologists**
  - subjective
  - Observation
    - visual information: shape, color(Journal of American Academy of Dermatology,2006)
    - ABCD criteria(European Journal of Dermatology,1994)
    - 7-point rule(Archives of Dermatology,1998.)

Related work

- **CAD(computer aided diagnosis) for Skin Lesions**
  - machine learning,computer vision
    - A comparison of machine learning methods for the diagnosis of pigmented skin lesions. (Journal of Biomedical Informatics, 2001)
    - Feature selection for optimized skin tumor recognition using genetic algorithms.(Artificial Intelligence in Medicine,1999)
    - Digital imaging in dermatology.(Computerized Medical Imaging and Graphics,1992)

  - only in dermoscopic images

Related work

- **Criteria of Skin Disease**
  - ABCD criteria(European Journal of Dermatology,1994):
    - Asymmetry
    - Border
    - Color
    - Diameter
- Main idea:Dermatological criteria to visual representations
- **Structure, color ,shape**

Representation

- **Structure Representation**
  - Multi-Space Texture of Lesion (MST-L)

$$MST(x) = [G_i(x)]_{i=1}^{K},$$

  - Texture Symmetry of Lesion (TS-L)

$$TS_i(x) = [G_i(L(x)_1), G_i(L(x)_2), S_i(x)].$$

$$S_i(x) = \{|g_{ij}^1 - g_{ij}^2|\}_{j=1}^{d},$$

- **Color Representation**
    - Color Name of Lesion (CN-L)

$$[p(C_l|c)]_{l=1}^{M} \propto \sum^{N} p(C_l|c_i)\, g^{\sigma}\left(|c_i - c|_{Lab}\right),$$

$$CN(x) = \underset{C_l}{\operatorname{argmax}}\, [p(C_l|c)]_{l=1}^{M}.$$

- Continuous Color Values of Lesion (CCV-L)

$$CCV(c) \propto p(C, c) \times \theta(c),$$

$$\theta(c) = \sum_{|c|} n(c)u(c),$$

- **Shape Representation**
  - Peripheral Symmetry of Lesion (PS-L)

$$PS(x) = F(A(L(x)^1), A(L(x)^2)),$$

  - Adaptive Compactness of Lesion (AC-L)

$$\mathrm{Com} = \frac{4\pi A}{P^2},$$

$$A_L = \sum_{z \in L(x)} p(C|c, z),$$

Experiments

Experiments

	Components	#	Features	Dimension	KNN		SVM		RF	
					ACC	SE	ACC	SE	ACC	SE
Baseline	Texture	1	SIFT	21000	20.35	19.17	25.55	24.75	21.42	21.25
		2	HOG	12400	19.14	17.85	17.62	14.45	10.54	10.66
		3	LBP	23200	15.13	14.80	18.89	14.69	14.61	13.24
		4	BRIEF	19200	16.74	15.62	12.21	8.39	15.67	15.03
		5	SURF	38400	17.47	16.50	31.17	25.35	27.34	26.52
		6	Wavelet	256	15.94	15.52	14.82	12.73	13.37	14.02
		7	ORB	19200	20.53	21.44	23.21	22.94	18.86	17.46
	Color	8	CH	256	12.33	12.58	4.19	4.41	18.77	16.81
		9	CN	21000	20.02	20.10	20.23	21.62	27.64	28.73
		10	ColorSIFT	21000	21.29	19.62	22.51	21.43	28.49	27.24
	Border	11	GIST	512	21.93	21.52	16.49	17.19	15.01	12.33
		12	Gabor	4000	13.67	13.00	10.15	8.62	13.73	12.43
		13	Prewitt	900	12.55	13.14	11.91	10.76	11.27	10.87
		14	Sobel	10000	12.27	12.03	10.42	10.18	13.46	12.46
		15	Canny	10000	15.22	17.16	13.91	14.51	16.46	15.20
	Integration	16	1&10&11	2500	47.36	47.23	46.84	47.24	48.06	46.73
Ours	Structure	17	MST-L	21000	44.99	45.62	48.06	46.38	43.23	42.73
		18	TS-L	21000	47.30	47.80	48.94	47.21	43.92	43.07
	Color	19	CN-L	21000	42.50	43.24	38.91	39.78	44.59	46.21
		20	CCV-L	21000	42.80	43.97	40.13	39.22	45.32	45.70
	Shape	21	PS-L	10000	30.04	30.47	38.58	38.29	38.94	36.87
		22	AC-L	10000	31.50	29.75	39.73	38.92	37.61	35.42
	Integration	23	18&20&22	3000	**57.62**	**56.41**	**56.47**	**53.15**	**57.81**	**56.65**

Experiments

Method		ACC	SE
Deep features [33]	CaffeNet	42.31	41.57
	CaffeNet + ft	46.69	45.18
	VGGNet	37.91	37.25
	VGGNet + ft	50.27	48.25
	GoogleNet	35.33	35.21
	GoogleNet + ft	46.48	45.86
	ResNet	48.78	47.62
	ResNet + ft	53.35	51.24
Doctors	General D	49.00	47.50
	Junior D	52.00	53.40
	Expert	83.29	85.00
Ours		**56.47**	**53.15**

Conclusion

- Verify that the criteria can be measured by computers
- The proposed representations outperform both the low-level features and the deep features.

My own thinking

- Deep learning algorithms have a large space to improve
- It’s important to understand all the medical criteria and transfer them to visual expressions
- It’s always a good new to create a new dataset!!