Integrating Patient Data Into Skin Cancer Classification Using Convolutional Neural Networks: Systematic Review

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Outline

- Introduction
- Methods
- Results
- Conclusion
- References

1.

Introduction

Introduction

- Integration between Image features and patient metadata
- Classifying Skin Cancer
- A review of 11 papers discussing the case above
- The included studies
  - analyzed the amount and type of patient data used for integration
  - the encoding and fusing techniques
  - the reported results

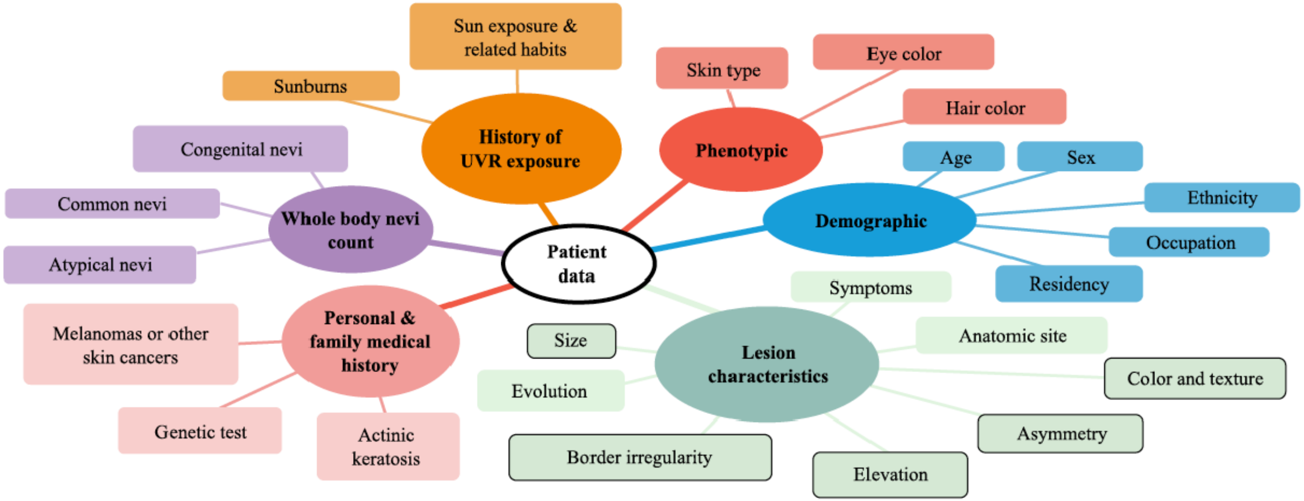
2.

Methods

Type and Amount of Patient Data

- Various types of patient data have been shown to assist dermatologists.
- **Key question**: Which and how many different types of patient data have been tested for CNN-based classification?

Figure 1. An overview of patient data considered by dermatologists while diagnosing skin lesions. The framed characteristics in the figure illustrate the fraction of patient data that can potentially be recognized by convolutional neural networks from a single image input. UVR: ultraviolet radiation.



Encoding and Fusing Techniques

- *Key questions:*
  - What are the encoding and fusing techniques applied in the studies?

Reported Study Results

- *Key questions:*
  - What is the classification task? Is it a binary or multiclass problem?
  - Which skin lesions should be distinguished?

Applied Performance Metrics

- The included publications reported **different statistical metrics** as the study end points
  - If the classes in the test set are approximately equally distributed, then **accuracy** is frequently used
  - **Sensitivity and specificity** are further common study end points, especially if there is an imbalance between the samples of both classes
  - The **area under the curve (AUC)** was used as an integral performance measure for the algorithms.

3.

Results

Classification Tasks

- 5 studies → binary classifications
- 6 studies → 5 to 8 different skin diseases or lesions

Table 1. Summary table.

Study	Patient data types	Result (without/with)	Classification task	CNN[a] architecture	Data set	Samples, n
Bonechi et al [42]	4 types: age, sex, location, and presence of melanocytic cells	Accuracy: 0.8344/0.8834	Binary: benign or malignant (MEL[b], BCC[c], SCC[d])	ResNet50	ISIC[e]	5405
Chin et al [43]	5 types: age; sex; size; how long it existed; changes in size, color, or shape including bleeding and itching	Accuracy: 0.84/0.92	Binary: low risk or high risk for MEL	DenseNet121	Own	5289
Gonzalez-Diaz [44]	2 types: age and sex	Accuracy: 0.848/0.859	Binary: MEL yes or no	ResNet50	2017 ISBI[f] challenge+interactive atlas of dermoscopy [45]+ISIC	6302
Gessert et al [46]	3 types: age, sex, and location	Sensitivity: 0.725/0.742; specificity: data not available	8 classes: MEL, NV[g], BCC, AK[h], BKL[i], DF[j], VASC[k], SCC	EfficientNets	ISIC (HAM10000 [47], BCN_2000 [48], MSK [49])+7-point data set [50]	27,665
Kawahara et al [50]	3 types: sex, location, and elevation	Sensitivity: 0.527/0.604; specificity: 0.902/0.910	5 classes: MEL, BCC, NV, MISC[l], SK[m]	Inception V3	7-point data set	808

Table 1. Summary table.

Study	Patient data types	Result (without/with)	Classification task	CNN[a] architecture	Data set	Samples, n
Kharazmi et al [51]	5 types: age, sex, location, size, and elevation	Accuracy: 0.847/0.911	Binary: BCC yes or no	Convolutional filters of learned kernel weights from a sparse autoencoder	Own	1199
Li et al [52]	3 types: age, sex, and location	Sensitivity: 0.8544/0.8764; specificity: data not available	7 classes: NV, MEL, BKL, BCC, AKIEC[n], VASC, DF	SENet154	ISIC 2018 data set	10,015
Pacheco and Krohling [53]	8 types: age, location, lesion itches, bleeds or has bled, pain, recently increased, changed its pattern, and elevation	Accuracy: 0.671/0.788	6 Classes: BCC, SCC, AK, SK, MEL, NV	ResNet50	Own	1612
Ruiz-Castilla et al [54]	3 types: age, sex, and size	Accuracy: 0.61/0.85	Binary: MEL yes or no	Shallow network with 2 convolutional layers	ISIC	300
Sriwong et al [55]	3 types: age, sex, and location	Accuracy: 0.7929/0.8039	7 classes: AKIEC, BCC, BKL, DF, MEL, NV, VASC	AlexNet	HAM10000	16,720
Yap et al [56]	3 types: age, sex, and location	Mean average precision: 0.726/0.729; Accuracy: 0.721/0.720	5 classes: BCC, SCC, MEL, BKL, NV	ResNet50	ILSVRC[o] 2015 [57]+own	2917 (only testing)

- MEL: melanoma.
- BCC: basal cell carcinoma.
- SCC: squamous cell carcinoma.
- ISIC: International Skin Imaging Collaboration.
- ISBI: International Symposium on Biomedical Imaging
- NV: melanocytic nevus.
- AK: actinic keratosis.
- BKL: benign keratosis-like lesion.
- DF: dermatofibroma.
- VASC: vascular lesion.
- MISC: summary of dermatofibroma, lentigo, melanosis, miscellaneous, and vascular lesion.
- SK: seborrheic keratosis.
- AKIEC: actinic keratosis and intraepithelial carcinoma.
- ILSVRC: ImageNet Large Scale Visual Recognition Challenge.

Types and Amount of Patient Data

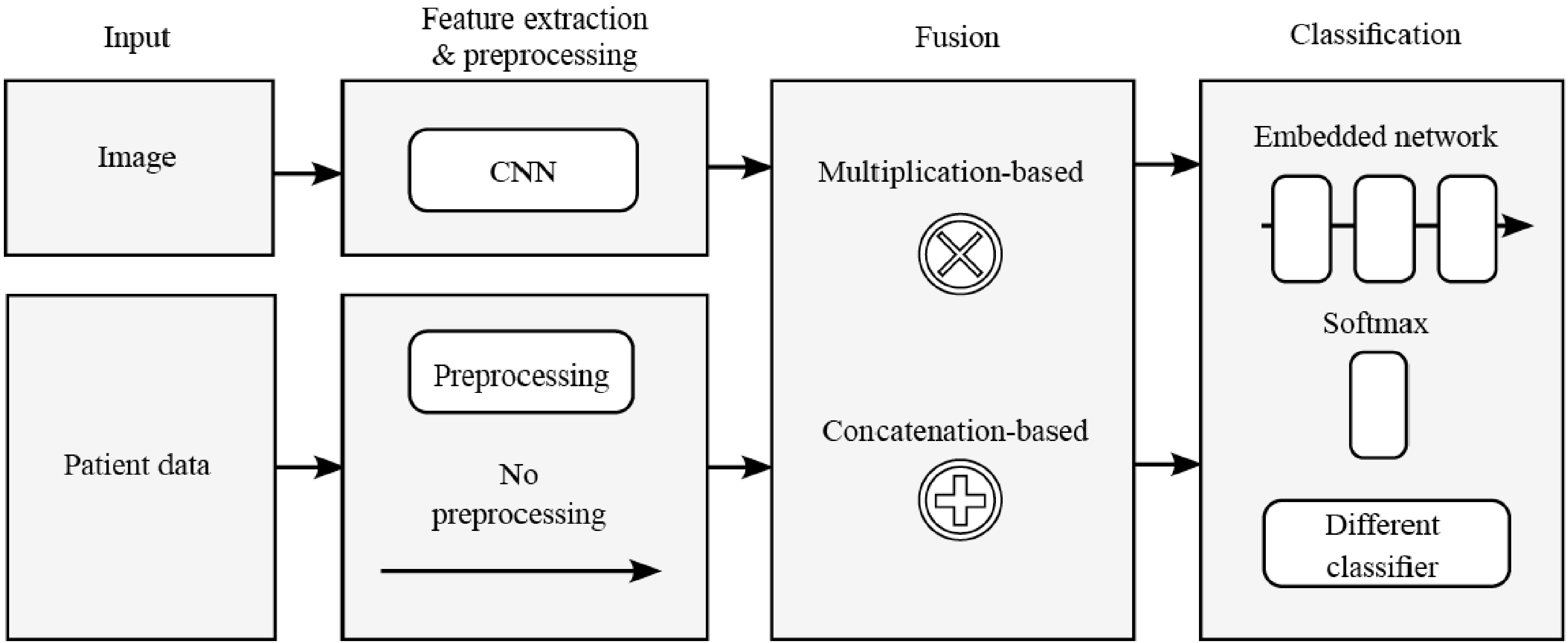
- Most of the studies included three types of patient data (7/11, 64%).
- The most commonly included types of data were patient’s age and sex (studies: 10/11, 91%).
- The third most commonly considered feature was lesion location (studies: 8/11, 73%).
- Elevation and lesion size were considered in 27% (3/11) of studies.

Encoding

- The means of choice to encode the patient data was **one-hot encoding** in most cases
- For continues data, one-hot encoding is only possible after discretization→ divided the age ranging from 0 to 95 in the sections of 5 years (Bonechi et al [42])
- Li et al [52] normalized the age in the range between 0 and 1
- Deal with missing values:
  - Gessert et al [46] → a negative fixed value for missing data
  - Li et al [52] → average values for continuous data and the most frequent values for discrete patient data.

Fusing Techniques

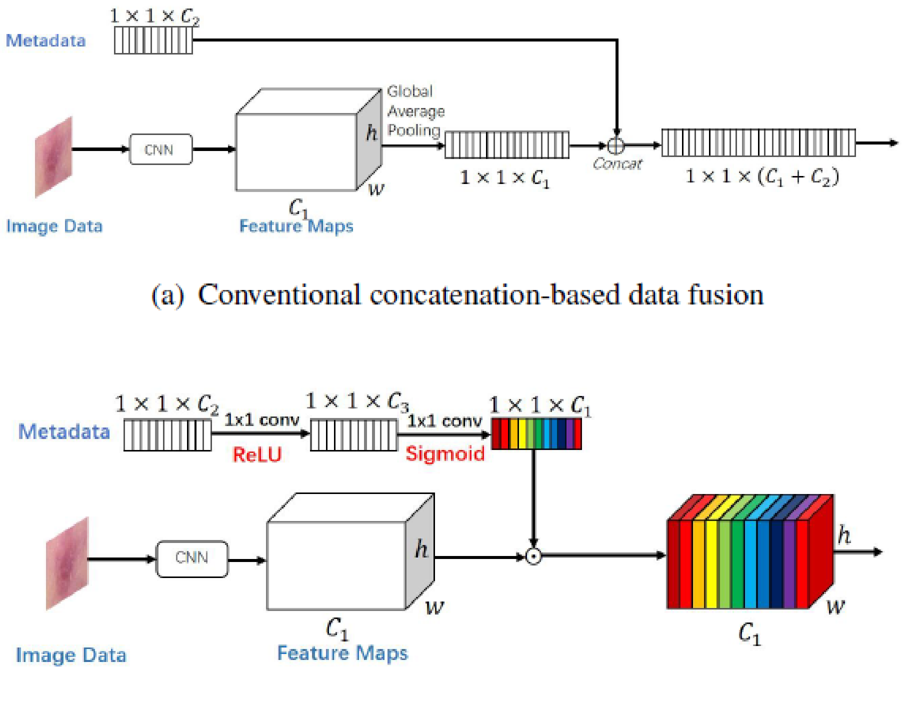
Figure 2. Overview of the different fusing techniques in the main function blocks of the combined classifier. CNN: convolutional neural network.



Fusing Techniques

- In 82% (9/11) of studies → concatenation-based fusion
- Li et al [52] → a multiplication-based fusion
  - CNN → SENet
  - the authors used patient data to control the importance of each image feature channel at the last convolutional layer
  - Thus, the network was able to focus on specific parts of the image feature based on patient data.
  - The authors determined the multiplication-based fusion to be superior to the concatenation-based approach in multiple network architectures.

(Li et al) A Multiplication -based Fusion



(a) Conventional concatenation-based data fusion

(b) Proposed multiplication-based data fusion

Fig. 1. The proposed multiplication-based data fusion can make the metadata directly control the importance of each feature channel, helping the network focus on more discriminative channels, while the conventional concatenation-based method may not.

(Li et al) A Multiplication-based Fusion

Table 1. Comparison of the proposed multiplication-based fusion approach with two baseline approaches on multiple backbone CNN architectures.

Backbones	No metadata	Concatenation-based	Ours
AlexNet	74.68 ± 0.92	76.55 ± 1.25	$\mathbf{78.26}\pm1.55$
VGG19	81.60 ± 1.67	82.35 ± 1.68	$\mathbf{84.06}\pm1.16$
ResNet50	82.50 ± 1.31	82.98 ± 1.35	$\mathbf{84.02}\pm1.50$
DenseNet161	84.59 ± 1.42	85.85 ± 0.92	$\mathbf{87.03}\pm1.40$
SENet154	85.44 ± 1.09	86.46 ± 0.69	$\mathbf{87.64}\pm0.52$
PNASNet-5	87.90 ± 1.32	87.25 ± 0.73	$\mathbf{89.09}\pm0.67$

(Sriwong et al)

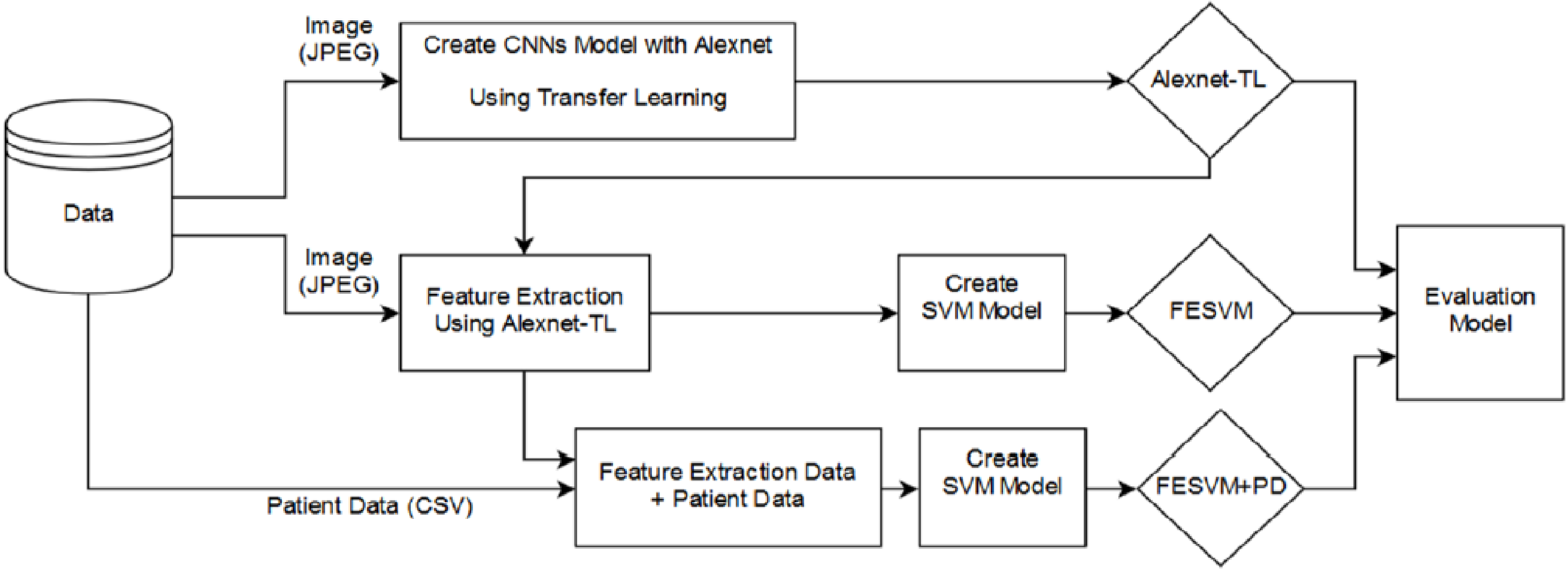


Fig. 2. The research framework proposed for the dermatological classification.

Table 2. Influence of included patient data on the classification performance of the single skin diseases or lesions[a].

Study, patient data, and metric	Skin disease										
	MEL[b]	NV[c]	BCC[d]	SCC[e]	AK[f]	AKIEC[g]	BKL[h]	DF[i]	VASC[j]	MISC[k]	SK[l]
Gessert et al [46]: age, sex, location											
AUC[m]	+[n]	(+/−)[o]	−[p]	−	+	X[q]	+	+	−	X	X
Sensitivity	−	−	−	−	−	X	−	−	−	X	X
Specificity	+	+	+	+	+	X	+	+	+	X	X
Sriwong et al [55]: age, sex, location											
Sensitivity	+	−	+	X	X	−	+	+	−	X	X
Specificity	−	+	−	X	X	+	+	+/−	+	X	X
Li et al [52]: age, sex, location											
Sensitivity	−	−	+	X	X	−	+	+	+	X	X
Kawahara et al [50]: sex, location, elevation											
Sensitivity	+	+	+	X	X	X	X	X	X	+	+
Specificity	+	+	+/−	X	X	X	X	X	X	+	+
Pacheco and Krohling [53]: age, location, itches, bleeds, pain, increased, changed, elevation											
Sensitivity	+	+	+	+	+	X	X	X	X	X	+
Specificity	+	+	+	−	+	X	X	X	X	X	+

Reported Study Results

- Table 2 shows that the improvements may go along with the degradation of classification performance for other lesion types or
- That the improvement of sensitivity for one class may be paralleled by a decrease in specificity

Reported Study Results

- In total, 36% (4/11) of studies analyzed the influence of the used patient data on the classification performance
- Li et al → The combination of patient data parameters of "age" and "location" provided the best result overall, whereas the parameter "sex" decreased performance upon integration.
- Sriwong et al→ The authors stated that the information of "sex" and "location" is more powerful when used in combination
- Pacheco and Krohling → the patient data parameters such as "bleeding" and "pain" were suitable to differentiate between pigmented (NV, melanoma, and SK) and nonpigmented lesions (AK, BCC, and SCC)

4.

Conclusions

Conclusion

- All 11 studies published so far indicate that the integration of patient data into CNN-based skin lesion classifiers **may improve** classification accuracy.
- The studies mainly used patient data that were routinely recorded (age, sex, and lesion location).
- The main differences in the presented approaches occur in the fusing techniques.

References

- Li W, Zhuang J, Wang R, Zhang J, Zheng W. Fusing metadata and dermoscopy images for skin disease diagnosis. In: Proceedings of the IEEE 17th International Symposium on Biomedical Imaging (ISBI). 2020 Presented at: IEEE 17th International Symposium on Biomedical Imaging (ISBI); April 3-7, 2020; Iowa City, IA, USA. [doi:10.1109/isbi45749.2020.9098645]
- Sriwong K, Bunrit S, Kerdprasop K, Kerdprasop N. Dermatological classification using deep learning of skin image and patient background knowledge. Int J Mach Learn Comput 2019 Dec;9(6):862-867 [FREE Full text] [doi: 10.18178/ijmlc.2019.9.6.884]