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Advanced Melanoma Detection Using the ConvMixer Model on ISIC and PH2 Dermatoscopic Images

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ABSTRACT

Background: Melanoma is the most aggressive form of skin cancer and is associated with high mortality when not diagnosed at an early stage. Recent advances in dermatoscopic image analysis combined with artificial intelligence have demonstrated considerable potential for improving diagnostic accuracy. ConvMixer, a hybrid deep learning architecture that integrates convolutional neural networks with a mixer-style design, has recently emerged as a powerful model for image classification tasks. This study aimed to evaluate the effectiveness of the ConvMixer model for automated melanoma detection using dermatoscopic images.

Methods: Dermatoscopic images were collected from two publicly available datasets: The International Skin Imaging Collaboration (ISIC) and the Public Health (PH2) database. The ISIC dataset comprised 31,696 benign lesions and 7,319 malignant melanoma images, which were divided into training (80%), validation (10%), and test (10%) sets. The PH2 dataset, consisting of 40 melanoma and 160 melanocytic nevi images, was used exclusively for external testing. Image preprocessing, normalization, and data augmentation were performed prior to model training. Model performance was assessed using sensitivity, specificity, accuracy, F1 score, and the area under the receiver operating characteristic curve (AUC).

Results: The ConvMixer model demonstrated strong discriminative ability between malignant and benign skin lesions across both datasets. On the ISIC dataset, the model achieved a sensitivity of 0.9126, specificity of 0.6683, and accuracy of 0.7142. On the PH2 dataset, higher specificity (0.95) and accuracy (0.905) were observed, along with a sensitivity of 0.725. High AUC values further confirmed robust classification performance and generalizability across datasets with differing characteristics.

Conclusion: The ConvMixer model shows strong potential as an effective AI-assisted tool for melanoma detection from dermatoscopic images. Its consistent performance on both large-scale and controlled datasets supports its applicability in diverse clinical settings, highlighting its value for early melanoma screening and decision support in dermatology.

Keywords: Melanoma, Skin neoplasms, Deep learning, Image processing, Computer-assisted, Pattern recognition, Automated

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Highlights

- ConvMixer achieved high performance in melanoma detection on both ISIC and PH2 datasets.
- Sensitivity reached 0.91 on the ISIC dataset, indicating strong capability in identifying melanoma cases.
- Testing on the PH2 dataset showed high specificity (0.95) and overall accuracy (0.91).
- Robust AUC values confirmed reliable discrimination between malignant and benign skin lesions.

Plain Language Summary

Skin cancer is one of the most common cancers worldwide, and melanoma is its deadliest form. Because melanoma can spread rapidly, detecting it as early as possible is crucial. When identified in its early stages, treatment is often highly successful. However, diagnosing melanoma requires expert knowledge and careful examination, and access to experienced dermatologists may be limited in some settings. For this reason, computer-based tools that assist doctors in identifying suspicious skin lesions are becoming increasingly important. In this study, we investigated whether a modern artificial intelligence (AI) system called ConvMixer could accurately recognize melanoma in skin images. The AI model was trained using thousands of dermatoscopic images—special magnified photographs of skin lesions—from a large international database known as ISIC. To evaluate how well the system performs under different conditions, we also tested it on a smaller but well-controlled dataset called PH2. The AI learned to distinguish between dangerous melanoma and harmless skin moles by analyzing visual patterns such as shape, color, and texture. The results showed that the system could detect melanoma with good overall accuracy. It performed particularly well in identifying melanoma cases within the large and diverse ISIC dataset, while also showing strong ability to correctly rule out harmless lesions in the smaller PH2 dataset. These findings suggest that the AI system works reliably across different types of image data. This research is important because AI tools like ConvMixer could support doctors in making faster and more accurate decisions, especially in areas where access to dermatology specialists is limited. While AI cannot replace medical professionals, it can act as a valuable assistant, helping improve early melanoma detection and ultimately saving lives through earlier treatment.

Introduction

Melanoma, a deadly skin cancer, is on the rise globally. Early detection significantly increases survival rates, nearly guaranteeing a 100% survival rate if identified in its initial stages. Soldiers, often exposed to higher levels of sunlight, exhibit increased incidence rates of skin cancer [1]. Globally, there were approximately 19.3 million new cancer cases (18.1 million excluding non-melanoma skin cancers) and nearly 10 million cancer-related deaths (9.9 million excluding non-melanoma skin cancers) reported in 2020 [2].

Malignant melanoma, the most aggressive form of skin cancer, is notably lethal. In Iran, skin cancer is the most prevalent form of cancer, and its incidence is on the rise. Currently, cancer is a primary health issue both in Iran and globally, and it also stands as a priority in research agendas, focusing on the impact of common diseases on the quality of life. Increased exposure to sunlight during military service without adequate protection is a leading cause of higher rates of both melanoma and non-melanoma skin cancers among soldiers compared to the general population [3].

Early diagnosis and appropriate treatment are crucial in cancer care, significantly impacting patient survival and recovery rates. Image processing, as a decision-making tool, aids physicians in early cancer detection. These high-speed, non-invasive image processing mechanisms accelerate the identification of cancer cells, ultimately improving cancer patients' survival chances. Melanoma, a deadly cancer type, has seen an increasing incidence worldwide. Soldiers are particularly susceptible to skin cancer due to higher exposure to sunlight during their service [1].

Malignant melanoma accounts for about 1% of all malignant skin tumors. The stage of melanoma progression, like other cancers, predicts treatment success. Patients with early-stage melanomas (thin tumors) have a 97% five-year survival rate after surgical removal. In contrast, patients with advanced melanoma that has metastasized to regional lymph nodes or other organs have a less than 10% five-year survival rate. Patients with any other systemic metastases have the worst prognosis, with a one-year survival rate of 41% [4]. Therefore, the approaches used so far for melanoma treatment depend on the cancer stage and include surgery, radiotherapy, and immunotherapy [5]. Skin melanoma predominantly occurs in individuals with fair skin phenotypes, particularly in geographic areas with intense sun exposure. In the United States, over 98% of cases are reported in Caucasian individuals [6].

In the past decade, there has been significant progress in artificial intelligence (AI) research and publications. Studies have shown that convolutional neural network (CNN) algorithms can classify skin lesions from dermatoscopic images with superior or at least equivalent performance compared to physicians. Although AI algorithms have shown very promising results for skin cancer diagnosis in reader studies, their generalizability and applicability in everyday clinical practice remain unclear [7].

Recent advancements in AI in dermatology have shown potential for enhancing the accuracy of skin cancer diagnosis. These capabilities could strengthen current diagnostic processes and improve skin cancer management approaches. A clearer understanding of this technology may alleviate physicians' concerns about AI and promote its use in clinical settings. Ultimately, the development and validation of AI technologies, regulatory approval, and widespread acceptance by dermatologists and other physicians may enhance patient care. Skin cancer diagnosis using technology holds the potential to improve the quality of life, reduce healthcare costs by minimizing unnecessary procedures, and provide greater access to high-quality skin assessments. Dermatologists play a crucial role in the development and application of AI capabilities in skin cancer management [8].

The primary advantage of CNNs over their predecessors lies in their ability to autonomously identify relevant features without human supervision [9]. The architecture of CNNs is inspired by the neuronal structures in the brains of humans and animals. Specifically, a complex sequence of cells in the visual cortex of cats is emulated by CNNs. This sequence is replicated in CNNs, capturing the intricate processing of visual stimuli that occur naturally in the brain, thereby enhancing the networks' ability to recognize and analyze complex patterns in data [10].

Background and literature review

Various studies have been conducted to diagnose melanoma and categorize images of skin lesions. In research by Jain et al. in 2015, a method was proposed for melanoma skin cancer detection using image processing tools. The system input is a skin lesion image, followed by the application of advanced image processing techniques for analyzing the presence of skin cancer. The tools dissect the lesion image to examine various melanoma parameters, like asymmetry, border, color, diameter, etc. by analyzing texture, size, and shape for image segmentation and feature characterization. The extracted feature parameters are then used to classify the image as either normal skin or a melanoma lesion [11].

In 2016, Pennisi et al. introduced a melanoma image segmentation method based on Delaunay triangulation. They applied this method to skin lesion images, achieving a final diagnostic accuracy of 93.5% [1]. In the same year, Kanimozhi et al. proposed an approach using artificial neural networks for skin cancer detection. This method utilized asymmetry, border, color, and diameter features for enhanced analysis of cancer images. The results indicated an impressive 97% accuracy rate in neural network training [12].

In 2018, Heller et al. proposed a method for melanoma detection based on morphological features. This approach set up a computer-aided diagnostic system for skin cancer detection [13]. Another study by Tan et al. in 2019 suggested an intelligent decision-making system for skin cancer diagnosis. Recognizing the significance of an effective pattern of lesions as a key step in ensuring successful classification, various features, such as asymmetry and irregularity around the lesion were considered for categorization. Subsequently, two enhanced particle swarm optimization (PSO) models were proposed for optimizing these features [14].

In 2019, Alickovic developed a model for breast cancer detection and classification of cancerous masses using a neural network. The empirical results of this research assessed the method's accuracy at 99% [15]. Singh, in 2020, proposed the use of a newly devised generative adversarial network (GAN) for breast tumor classification by identifying the region of interest (ROI) in a mammogram. The proposed method showed an accuracy of 80%, outperforming previous techniques. Various feature extraction methods are commonly employed for better classification of abnormalities in mammograms [16]. In a study by Chanda and Sarkar in 2020, a feature extraction technique utilizing multiple statistical parameters, including entropy, mean, regression, correlation, and standard deviation, was presented to detect the presence of masses in images [17].

In 2020, Zhang et al. introduced a novel image processing method for early detection of skin cancer. This approach utilized an optimized CNN, which was enhanced using a whale optimization algorithm. To evaluate the proposed method, it was compared with several existing techniques. The simulation results indicated that the proposed approach outperformed the compared methods, showcasing its effectiveness in early skin cancer detection [18].

In the research conducted by Erfani in 2018, a deep learning-based method for classifying skin cancer images was introduced. This method employed a CNN to learn the features of the images. The study also tested the proposed approach using the Public Health (PH2) database [19], which contains 200 images categorized into normal, atypical, and melanoma classes. The results obtained from this evaluation confirmed the effectiveness of the proposed method in accurately classifying skin cancer images [20].

Abhishek et al. highlighted the need for AI research in dermatology to access clinical data and photographic imagery of various skin types. They emphasized that data should be produced through international collaboration in skin imaging to facilitate accurate research [21]. Martorell et al. believed that advancements in AI technologies should be pioneering, safe, and based on the generosity of the dermatology community. They stressed the necessity of publicly accessible databases with extensive images and clinical information to enhance the reliability of these systems [22].

Mahmood et al. stated that AI in dermatology will continue evolving by focusing on improving the diagnostic accuracy of machine learning models, determining the use of predictive models through prospective trials, and developing smartphone applications to optimize virtual healthcare [23]. Gumolin et al. emphasized the need for more clinical trials providing evidence of clinical effectiveness while successfully overcoming identified barriers. With these research objectives in mind, a suitable role for AI in dermatology may be realized [24].

Materials and Methods

This section elucidates the methodology employed in leveraging the ConvMixer model for melanoma detection. The study utilized two primary datasets: The International Skin Imaging Collaboration (ISIC) and the PH2 databases, which are comprehensive collections of dermatoscopic images. These datasets were chosen for their diversity and relevance in skin lesion classification research.

In this study, the ISIC database served as a primary source for dermatoscopic images. We employed a targeted approach to gather images, categorizing them into benign (including melanocytic nevi) and malignant (including melanoma) classes. The benign category comprised a vast collection of 31,696 images, while the malignant category included 7,319 images. These images underwent rigorous preprocessing to ensure data quality and consistency for model training.

The dataset division was strategically executed, allocating 80% of the images to the training set and evenly splitting the remaining 20% into validation and test sets, accounting for 10% each. This split was designed to optimize the model's learning while providing a robust framework for its validation and performance evaluation.

Additionally, the PH2 dataset, known for its well-curated collection of dermatoscopic images, was utilized exclusively for testing purposes. It included 40 images classified as melanoma and 160 images as melanocytic nevi. The inclusion of this dataset aimed to provide a comprehensive assessment of the model's diagnostic capabilities and to validate its performance across diverse image collections.

The ConvMixer model, a novel deep learning architecture, was employed for its advanced capabilities in image processing and classification. Prior to model training, extensive preprocessing of the datasets was conducted, including normalization and data augmentation, to enhance the quality of inputs and improve training efficiency.

Model training involved optimally setting hyperparameters to ensure a balance between learning rate and regularization to prevent overfitting. The training process was iteratively refined, with performance metrics, such as accuracy, sensitivity, specificity, and AUC, being closely monitored.

Results

In this section, we present the results obtained from applying the ConvMixer model to the ISIC and PH2 datasets. The analysis focuses on the model's ability to distinguish between melanoma and melanocytic nevi.

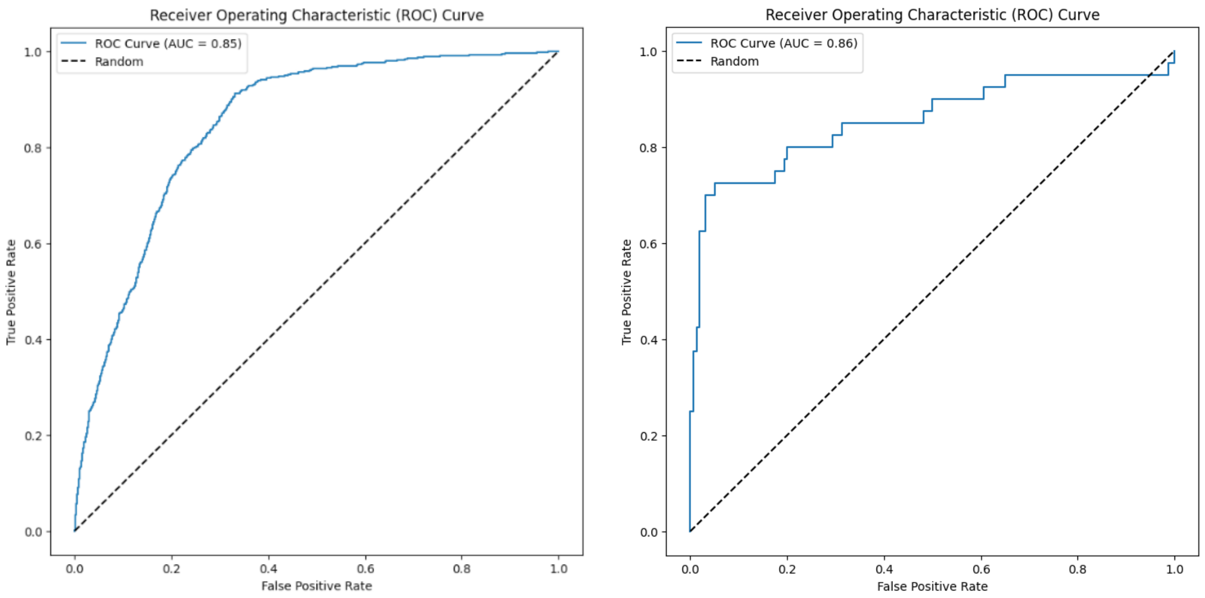

Figure 1. The left side shows the ROC curve for the ISIC dataset, and the right side shows the ROC curve for the PH2 dataset at the best threshold

Table 1 highlights the distinct performance metrics of the ConvMixer model on each dataset. The model demonstrates higher sensitivity on the ISIC dataset, suggesting better detection of true positives. Conversely, it shows higher specificity on the PH2 dataset, indicating a stronger ability to correctly identify true negatives. The accuracy and F1 score differences between the datasets reflect the model's overall performance and its capability to balance precision and recall.

Both datasets yielded high area under the curve (AUC) scores (Figure 1), affirming the model's strong discriminative power in distinguishing between malignant and benign skin lesions. The AUC for ROC curves provides a single measure of the model's overall performance across various thresholds. A higher AUC indicates better discriminative ability. For the ISIC dataset, the ROC curves at different thresholds (normal and best) showed the model's adaptability in discriminating between positive and negative classes under varied conditions. The ROC curves for the PH2 dataset reaffirmed the model's robustness in classification, particularly at the best threshold.

When comparing the two datasets, the higher sensitivity for ISIC can be attributed to its larger and more diverse nature, necessitating a model that can effectively identify a broader range of melanoma presentations. The PH2 dataset, being smaller and more controlled, allowed for higher specificity and overall accuracy, indicating the model's strong performance in a more consistent dataset environment.

This analysis underscores the ConvMixer model's capabilities in melanoma diagnosis, highlighting its potential in varied clinical settings. The different performance metrics on each dataset also emphasize the importance of considering dataset characteristics when assessing AI model performance in medical imaging.

Table 1. Applying the ConvMixer model to the ISIC and PH2 datasets

Metric	ISIC Dataset (Best Threshold)	PH2 Dataset (Best Threshold)
Sensitivity	0.9126	0.725
Specificity	0.6683	0.95
Accuracy	0.7142	0.905
F1 Score	0.5451	0.7532

Discussion

The high accuracy and AUC scores achieved by the ConvMixer model on both the ISIC and PH2 datasets highlight its effectiveness in melanoma detection. Its capability to adapt to a local dataset demonstrates its potential in diverse clinical settings. Despite its high performance, the model shows room for improvement in sensitivity. The selection of an optimal threshold to balance sensitivity and specificity remains a crucial challenge, especially for clinical applications.

The findings align with existing research, indicating the significant potential of deep learning models in dermatology [17]. However, the results also underscore the need for comprehensive datasets that better represent the diversity of skin lesions encountered in clinical practice. The promising results suggest the model's suitability for integration into clinical workflows. However, they also emphasize the need for human oversight, particularly in cases where model reliability is lower. As AI models, like ConvMixer become more integrated into healthcare, issues such as algorithmic bias, model interpretability, and ethical considerations must be addressed to ensure fair and transparent usage.

The discussion highlights the strengths and potential areas for improvement of the ConvMixer model, stressing the importance of considering dataset characteristics when evaluating model performance. It also points to the necessity of ongoing research and adaptation in real-world clinical settings.

Limitations and challenges

This section delves into the limitations and challenges encountered during the research. While the ISIC and PH2 datasets are comprehensive, they might not fully represent the global population diversity. This could limit the model's applicability in varied demographic settings. The integration of AI in healthcare necessitates addressing technical and ethical issues to ensure responsible and equitable use. The rapidly evolving nature of AI and medical imaging necessitates continual learning and model updating to maintain accuracy and relevance. Ensuring patient data privacy and consent in AI model development is paramount. Mitigating biases, especially in skin lesion classification across diverse skin types, is crucial for equitable healthcare delivery. It is also essential to balance AI assistance with physician expertise to avoid over-reliance on technology, while maintaining ethical transparency in AI algorithms and decision-making processes.

Addressing these challenges is crucial for the successful integration of AI models, like ConvMixer, in clinical practice, ensuring they remain effective and equitable tools in medical diagnostics.

Future directions and recommendations

Looking ahead, the following directions and recommendations are proposed to enhance the ConvMixer model's application in melanoma detection. Incorporating patient history and demographic data could significantly improve diagnostic accuracy. Testing the model on more diverse datasets, representing various skin types and conditions, is crucial for global applicability. Pilot studies in clinical settings can validate the model's practical utility and identify areas for refinement. Developing methods to interpret deep learning decisions can enhance trust and usability in clinical environments. Ongoing collaboration with medical experts can ensure the model aligns with clinical needs and ethical standards. These steps aim to bridge the gap between AI research and clinical application, ultimately contributing to improved patient outcomes in dermatology.

Conclusion

The model demonstrated high accuracy and specificity, particularly on the PH2 dataset. Its adaptability to various datasets underscores its potential in real-world clinical scenarios. The research highlights the criticality of using diverse and extensive datasets. This ensures the robustness and generalizability of AI models in medical diagnostics. Future research could focus on integrating multifaceted data like patient history and demographic information to enhance diagnostic accuracy. Deploying the model in real-world clinical settings could provide further validation.

The conclusions drawn underscore the ConvMixer model's capability in melanoma detection and its potential impact on healthcare. They also emphasize the importance of ongoing research, particularly in terms of dataset diversity and real-world applications. Future explorations could include integrating diverse datasets and patient histories for enhanced diagnosis.

Ethical Considerations

Compliance with ethical guidelines

There were no ethical considerations to be considered in this research.

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Authors' contributions

Conceptualization: Vihan Moodi and Mohsen Rajaeinejad; Methodology: Vihan Moodi, Ali Faridfar, and Mohsen Chamanara; Software and visualization: Vihan Moodi and Alireza Mahboubian; Validation: Ali Faridfar and Allahyar Taheri; Data curation and formal analysis: Vihan Moodi and Ali Faridfar; Investigation: Vihan Moodi, Allahyar Taheri, and Mohsen Chamanara; Resources: Mohsen Rajaeinejad and Allahyar Taheri; Writing the original draft: Vihan Moodi; Review and Editing: All authors; Supervision and project administration: Mohsen Rajaeinejad.

Conflict of interest

The authors declared no conflict of interest.

References

[1] Pennisi A, Bloisi DD, Nardi D, Giampetruzzi AR, Mondino C, Facchiano A. Skin lesion image segmentation using Delaunay Triangulation for melanoma detection. Computerized Medical Imaging and Graphics. 2016; 52:89-103. [DOI:10.1016/j.compmedimag.2016.05.002] [PMID]

[2] Sung H, Ferlay J, Siegel RL, Laversanne M, Soerjomataram I, Jemal A, et al. Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA: A Cancer Journal for Clinicians. 2021; 71(3):209-49. [DOI:10.3322/caac.21660] [PMID]

[3] Riemenschneider K, Liu J, Powers JG. Skin cancer in the military: A systematic review of melanoma and nonmelanoma skin cancer incidence, prevention, and screening among active duty and veteran personnel. Journal of the American Academy of Dermatology. 2018; 78(6):1185-92. [DOI:10.1016/j.jaad.2017.11.062] [PMID]

[4] Balch CM, Buzaid AC, Soong SJ, Atkins MB, Cascinelli N, Coit DG, et al. Final version of the American Joint Committee on Cancer staging system for cutaneous melanoma. Journal of Clinical Oncology. 2001; 19(16):3635-48. [DOI:10.1200/JCO.2001.19.16.3635]

[5] Heo JR, Kim NH, Cho J, Choi KC. Current treatments for advanced melanoma and introduction of a promising novel gene therapy for melanoma. Oncology Reports. 2016; 36(4):1779-86. [DOI:10.3892/or.2016.5032] [PMID]

[6] Chang AE, Karnell LH, Menck HR. The National Cancer Data Base report on cutaneous and noncutaneous melanoma. Cancer. 1998; 83(8):1664-78. [DOI:10.1002/(SICI)1097-0142(19981015)83:83.0.CO;2-G]

[7] Konstantinos L, Stamatis G, Dias J, Stratigos A. Artificial intelligence in dermatology: Challenges and perspectives. Dermatology and Therapy. 2022; 12(12):2637-51. [DOI:10.1007/s13555-022-00833-8] [PMID]

[8] Beltrami EJ, Brown AC, Salmon PJM, Leffell DJ, Ko JM, Grant-Kels JM. Artificial intelligence in the detection of skin cancer. Journal of the American Academy of Dermatology. 2022; 87(6):1336-42. [DOI:10.1016/j.jaad.2022.08.028] [PMID]

[9] Gu J, Wang Z, Kuen J, Ma L, Shahroudy A, Shuai B, et al. Recent advances in convolutional neural networks. Pattern Recognition. 2018; 77:354-77. [DOI:10.1016/j.patcog.2017.10.013]

[10] Hubel DH, Wiesel TN. Receptive fields, binocular interaction and functional architecture in the cat's visual cortex. The Journal of Physiology. 1962; 160(1):106-54. [DOI:10.1113/jphysiol.1962.sp006837] [PMID]

[11] Jain S, jagtap V, Pise N. Computer aided melanoma skin cancer detection using image processing. Procedia Computer Science. 2015; 48:735-40. [DOI:10.1016/j.procs.2015.04.209]

[12] Kanimozhi T, Murthi A, Scholar PG. Computer aided melanoma skin cancer detection usingartificial neural network classifier. Singaporean Journal of Scientific Research. 2016; 8(2):35-42. [Link]

[13] Heller N, Bussmann E, Aneri Sh, Dean J, Papanikolopoulos N. Twin Cities: University of Minnesota Digital Conservancy; 2018. [Link]

[14] Tan TY, Zhang L, Lim CP. Intelligent skin cancer diagnosis using improved particle swarm optimization and deep learning models. Applied Soft Computing. 2019; 84:105725. [DOI:10.1016/j.asoc.2019.105725]

[15] Alickovic E, Subasi A. Normalized neural networks for breast cancer classification. Paper presented at: Cmbebih 2019. IFMBE Proceedings. 18 May 2019; Banja Luka, Bosnia and Herzegovina. [DOI:10.1007/978-3-030-17971-7_77]

[16] Singh VK, Rashwan HA, Romani S, Akram F, Pandey N, Sarker MMK, et al. Breast tumor segmentation and shape classification in mammograms using generative adversarial and convolutional neural network. Expert Systems with Applications. 2020; 139:112855. [DOI:10.1016/j.eswa.2019.112855]

[17] Basu TK, Goswami SK, Sanyal N. Advances in control, signal processing and energy systems: Select proceedings of CSPES 2018. New York: Springer; 2019. [Link]

[18] Zhang N, Cai YX, Wang YY, Tian YT, Wang XL, Badami B. Skin cancer diagnosis based on optimized convolutional neural network. Artificial Intelligence in Medicine. 2020; 102:101756. [DOI:10.1016/j.artmed.2019.101756] [PMID]

[19] Mendonca T, Ferreira PM, Marques JS, Marcal AR, Rozeira J. PH² - A dermoscopic image database for research and benchmarking. Annual International Conference of the IEEE Engineering in Medicine and Biology Society. 2013; 2013:5437-40. [DOI:10.1109/EMBC.2013.6610779] [PMID]

[20] Erfani SH. [Deep learning-based method for automatic skin cancer classification (Persian)]. Paper presented at 12th International Conference of Iranian Operations Research Society (ICORS 2019). Babolsar: Iran. [Link]

[21] De A, Sarda A, Gupta S, Das S. Use of artificial intelligence in dermatology. Indian Journal of Dermatology. 2020; 65(5):352-7. [DOI:10.4103/ijd.IJD_433_20] [PMID]

[22] Martorell A, Martin-Gorgojo A, Ríos-Viñuela E, Rueda-Carnero JM, Alfageme F, Taberner R. [Artificial intelligence in dermatology: A threat or an opportunity? (Spanish)]. Actas Dermo-sifiliograficas. 2022; 113(1):30-46. [DOI:10.1016/j.ad.2021.07.014] [PMID]

[23] Mahmood F, Bendayan S, Ghazawi FM, Litvinov IV. Editorial: The emerging role of artificial intelligence in dermatology. Frontiers in Medicine. 2021; 8:751649. [DOI:10.3389/fmed.2021.751649] [PMID]

[24] Gomolin A, Netchiporouk E, Gniadecki R, Litvinov IV. Artificial intelligence applications in dermatology: Where do we stand? Frontiers in Medicine. 2020; 7:100. [DOI:10.3389/fmed.2020.00100] [PMID]

[25] Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature. 2017; 542(7639):115-8. [DOI:10.1038/nature21056]