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| **No.** | **Title** | **Author’s Name** | **Year of Publication** | **Methodology** | **Results** | **Drawbacks** |
| 1. | Radiomic and deep learning analysis of dermoscopic images for skin lesion pattern decoding | Zheng Wang, Chong Wang, Li Peng, Kaibin Lin, Yang Xue, Xiao Chen, Linlin Bao, Chao Liu, Jianglin Zhang & Yang Xie | 26 August 2024 | -Integrated deep learning and radiomics analysis of dermoscopic images, supplemented with patient metadata. -Utilized the ISIC archive (2016–2020) and two external test sets. Employed Mask R-CNN for lesion segmentation and extracted quantitative radiomic features for classification. | Achieved high diagnostic performance with AUROC scores of 99%, 95%, and 96% in distinguishing benign from malignant lesions across different datasets. Demonstrated the effectiveness of combining deep learning, radiomics, and patient metadata in skin lesion diagnosis. | **Dataset Variability:** The primary dataset is from the ISIC archive, which may not fully represent the diversity of skin lesions across different populations and imaging conditions.  **Model Generalizability:** Despite using external test sets, the model's performance in real-world clinical settings with varying image qualities and patient demographics remains to be fully validated.  **Integration Complexity:** Combining deep learning, radiomics, and patient metadata increases system complexity, which may pose challenges in implementation and require substantial computational resources. |
| 2. | Melanoma Skin Cancer Detection Using Deep Learning and Classical Machine Learning Techniques: A Hybrid Approach | Jinen Daghrir, Lotfi Tlig, Moez Bouchouicha, Mounir Sayadi | 17 March 2021 | -Designed a hybrid system combining Convolutional Neural Network (CNN) with classical machine learning classifiers.  -Extracted features describing borders, texture, and color of skin lesions.  - Used majority voting to merge predictions from CNN and classical classifiers. | -The hybrid model demonstrated improved melanoma detection performance compared to using CNN or classical classifiers individually. -Emphasized the efficacy of combining deep learning with traditional methods for enhancing diagnostic accuracy. | -Specific performance metrics (accuracy, precision, recall) were not explicitly mentioned, making quantitative comparison challenging. -The system requires validation on larger, more diverse datasets for confirming its generalizability. -Integration complexity could limit real-world applicability. |
| 3. | Melanoma Skin Cancer Detection using Deep Learning | Alastin Porathur, Darshit Rupapara, Sumit Kumar, Zohair Merchant, Pratibha Rane | 12 Dec 2023 | -The researchers employed Convolutional Neural Networks (CNNs), specifically using the Xception architecture, to detect melanoma.  -hey enhanced image data through data augmentation and preprocessing techniques. The CNN model was trained to classify skin lesions based on visual features, aiming for high accuracy, and reduced diagnostic delays. This approach was evaluated on a dataset of skin images to detect melanoma effectively. | -The model achieved an accuracy of 97 percent on a test set of skin lesion images.  -The study found that using Xception CNN architecture for melanoma detection significantly improved accuracy, sensitivity, and specificity. It also reduced false positives and false negatives, showing potential for early melanoma detection.  -However, the model requires further validation on more diverse datasets to ensure robustness and general applicability in clinical settings. | **Dependence on High-Quality Datasets**: The model requires diverse and well-labeled datasets for effective training. A limited or biased dataset may affect its performance.  **Not a Replacement for Dermatologists**: While the system aids in early detection, it is not intended to replace a professional's diagnosis.  **Need for Continuous Improvement**: The accuracy of the model can be further enhanced with more research and development to improve its reliability.  **Accessibility Issues**: Ensuring accessibility for all users, especially in low-resource settings, is an ongoing challenge. |
| 4. | Early Melanoma Detection Based on a Hybrid YOLOv5 and ResNet Technique | Manar Elshahawy, Ahmed Elnemr, Mihai Oproescu, Adriana-Gabriela Schiopu, Ahmed Elgarayhi, Mohammed M Elmogy, Mohammed Sallah | 30 August 2023 | -Combines YOLOv5 for lesion detection and ResNet for feature extraction.  -Uses publicly available melanoma datasets (like ISIC and HAM10000) for training.  -Images underwent normalization and resizing to fit the input requirements of the models. | -Two experiments were conducted, with training and testing splits of 80% and 20% respectively, achieving high performance metrics.The best results (99% precision, 98.6% recall) were achieved with specific hyperparameters (batch size 32, learning rate 0.0001).  -The model outperforms traditional methods, showing strong melanoma detection potential. Future improvements focus on integrating personalized data and testing across broader datasets for better generalization. | -The model might not generalize well to datasets with different image characteristics. Results may vary when applied to datasets from different demographics or environments.  -Training the hybrid model requires significant computational resources, making it less accessible for real-time applications or environments with limited hardware.  -The model might overfit if the training data is not sufficiently diverse, leading to reduced performance on unseen data. |
| 5. | A Melanoma Skin Cancer Detection Using Machine Learning Technique: Support Vector Machine | Praveen Banasode, Minal Patil and Nikhil Ammanagi | 2021 | -High-quality skin images were collected for analysis.  -Images were converted into BGR-Gray and BGR-HSV color spaces to facilitate computer processing and binary code interpretation.  -Relevant features from the images were identified to aid in classification. A Support Vector Machine (SVM) algorithm was utilized to classify the skin images, distinguishing between melanoma and non-melanoma cases. | -The method achieved an accuracy of 96.9%, with a sensitivity of 95.7% and specificity of 90.2%.  -Various outputs, such as pre-processed images, masked and segmented images, and transformed results, were generated to illustrate the classification process and validate the outcomes.  -To reduce computational complexity, additional parameters were optimized within the SVM model, ensuring faster processing without compromising accuracy. | -The method relies heavily on the quality of input images; low-quality or blurred images can adversely affect accuracy.  -The study's effectiveness across diverse populations and varying image conditions was not extensively evaluated, potentially limiting its broader applicability. |
| 6. | Melanoma Detection Using Deep Learning-Based Classifications | Ghadah Alwakid, Walaa Gouda, Mamoona Humayun, Najm Us Sama | 8 Dec 2022 | -The researchers applied Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN) to improve the quality of dermoscopic images. This enhancement aimed to provide clearer images for subsequent analysis.  - Regions of Interest (ROI) were segmented from the enhanced images to isolate the lesion areas, facilitating focused analysis.  -To address data disparity and imbalance, data augmentation techniques were employed, ensuring a more robust training dataset.  -The study utilized a Convolutional Neural Network (CNN) and a modified version of ResNet-50 to classify skin lesions into seven categories from the HAM10000 dataset. The dataset included an unequal sample of seven types of skin cancer. | -The study developed a deep learning model for skin cancer detection, achieving an accuracy of 0.86, precision of 0.84, recall of 0.86, and F-score of 0.86.  -Techniques to address dataset imbalance improved the robustness of the model. Utilization of ESRGAN improved image quality, aiding in better lesion segmentation and classification.  -The modified ResNet-50 architecture demonstrated strong potential for accurate skin cancer detection. | -The study faced limitations such as dataset imbalance, which could affect performance and generalizability, especially for rare skin cancer types.  -Training on dermoscopic images limits the model's applicability to non-dermoscopic clinical images.  -Additionally, the use of deep learning with a small, imbalanced dataset raises concerns about potential overfitting. |
| 7. | Enhanced skin cancer diagnosis using optimized CNN architecture and checkpoints for automated dermatological lesion classification | M Mohamed Musthafa, Mahesh T R, Vinoth Kumar V & Suresh Guluwadi | 2 August 2024 | -Acquire a comprehensive dataset of skin lesion images and Standardize image size (e.g., 224x224 pixels) and apply normalization to adjust pixel values. Address class imbalance using techniques such as oversampling or data augmentation.  -Using a Convolutional Neural Network (CNN), leverage pre-trained models like ResNet, EfficientNet, or VGG for transfer learning to utilize robust feature extraction.  -Design the CNN with multiple convolutional layers, pooling layers, and fully connected layers. Incorporate a dropout layer to prevent overfitting.  -Experiment with parameters like learning rate, number of layers, and activation functions to enhance model performance.  -Apply techniques like L2 regularization and batch normalization to reduce overfitting and improve generalization. | -The CNN model achieved 97.86% accuracy, with high F1-scores across all categories, particularly excelling in Melanoma (mel) and Basal Cell Carcinoma (bcc).  -The model demonstrated excellent AUC-ROC values, highlighting its ability to distinguish between benign and malignant lesions effectively.  -The model's MSE was 0.375, RMSE was 0.612, and MAE was 0.5, reflecting strong predictive accuracy and low error rates.  -It showed a high true positive rate with minimal confusion between skin lesion types, reinforcing its reliability. | -The model was trained on the HAM10000 dataset, which, while diverse, may not represent the full spectrum of dermatoscopic images encountered in real-world settings.  -The model did not integrate clinical factors, such as patient history, which could enhance diagnostic accuracy.  -The model requires further validation on a broader set of images to ensure its robustness in practical, clinical environments. |
| 8. | "Early and accurate detection of melanoma skin cancer using hybrid level set approach" | Mahmoud Ragab, Hani Choudhry, Mohammed W. Al-Rabia, Sami Saeed Binyamin, Ahmed A. Aldarmahi, Romany F. Mansour | 2022 | |  | | --- | |  |  |  | | --- | | Developed a hybrid level set approach for lesion segmentation in dermoscopic images, addressing artefacts like hair, gel, bubbles, and reflections. | | Achieved 94.40% accuracy and 93% success rate in classifying melanoma lesions. | The study does not specify the computational efficiency of the proposed method, which is crucial for real-time clinical applications. Additionally, the approach may require validation on more diverse datasets to ensure generalizability. |
| 9. | Deep learning model to improve melanoma detection in people of color | Oluwatobi O. Kushimo, Ayodeji Olalekan Salau, Oladapo J. Adeleke, Doyinsola S. Olaoye | 2023 | |  | | --- | |  |  |  | | --- | | Developed a deep learning model trained on a diverse dataset of dermoscopic images representing both light and dark skin tones to detect melanoma. | | Achieved 99% accuracy for melanoma detection in light skin and 98% in dark skin, demonstrating effectiveness across skin tones. | The study does not specify the size and diversity of the dataset used, which are crucial for generalizability. Additionally, real-world clinical validation is necessary to confirm the model's applicability in diverse clinical settings. |
| 10. | Skin cancer detection using multi-scale deep learning and transfer learning | Mohammadreza Hajiarbabi | 2023 | Developed a multi-scale deep learning model with transfer learning for melanoma detection. The system preprocesses images, applies data augmentation, and utilizes a CNN initialized with ImageNet weights, fine-tuned for melanoma classification. | Achieved 94.42% accuracy, 88.5% recall, 91.75% precision, and an AUC of 0.94, outperforming existing methods. | The study does not specify the size and diversity of the dataset used, which are crucial for generalizability. Additionally, real-world clinical validation is necessary to confirm the model's applicability in diverse clinical settings. |
| 11. | Skin Melanoma Diagnosis Using Machine Learning and Deep Learning with Optimization Techniques: Survey | Zhraa B. Kadeem, Qusay O. Mosa | 2024 | Surveyed recent studies employing machine learning, deep learning, and optimization techniques for automated melanoma diagnosis. | Identified advancements in computational methods enhancing diagnostic accuracy and assisting dermatologists | Emphasized the need for further research to address challenges such as high intraclass variance of melanomas, visual resemblance between melanoma and non-melanoma lesions, and presence of artifacts in images. |
| 12. | Increasing Melanoma Diagnostic Confidence: Forcing the Convolutional Network to Learn from the Lesion | Norsang Lama, R. Joe Stanley, Anand Nambisan, Akanksha Maurya, Jason Hagerty, William V. Stoecker | 2023 | Deep learning model trained to focus on lesion features, using ISIC 2020 dataset for melanoma detection. | AUC score improved from 0.9 to 0.922, demonstrating increased diagnostic confidence. | Potential for further improvements in handling complex lesion boundaries or less common types of melanoma. |
| 13. | Developing an efficient method for melanoma detection using CNN techniques | Devika Moturi, Ravi Kishan Surapaneni & Venkata Sai Geethika Avanigadda | 2024 | Deep learning techniques (MobileNetV2, DenseNet) for melanoma detection, focusing on CNN models. | After the model evaluation, the accuracy for the MobileNetV2 was 85% and customized CNN was 95%. | Further work required for model validation across diverse datasets |
| 14. | Issues in Melanoma Detection: Semisupervised Deep Learning Algorithm Development via a Combination of Human and Artificial Intelligence | Xinyuan Zhang PhD  Ziqian Xie  PhD | 2022 | Semisupervised deep learning, combining human and artificial intelligence | achieved an accuracy of around **94.7%** in detecting melanoma from dermoscopic images. It also reported improved sensitivity (85.6%) and specificity (98.2%) when combined with human expert knowledge. | The model's real-world scalability and generalizability need further investigation. |
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