[1] M. A. Arshed, S. Mumtaz, M. Ibrahim, S. Ahmed, M. Tahir, and M. Shafi, “Multi-Class Skin Cancer Classification Using Vision Transformer Networks and Convolutional Neural Network-Based Pre-Trained Models,” Information, vol. 14, no. 7, Art. no. 7, Jul. 2023, doi: 10.3390/info14070415.

(2) In this article, Arshed et al. explore the use of Proposed Vision Transformer (ViT) networks and CNN-based pre-trained models for classifying multiple types of skin cancer. (3) This study used different data augmentation methods to address data imbalance in dataset classes. Pre-trained ResNet-50 architecture is used as a feature extractor and the last layer of the model is mapped with dense layers (1024, 512, 256, 128, 64, and 7) and fine-tuned. The same methods were used for all other CNN-based pre-trained models. (4) The scope of the research includes comparing the performance of ViT models with CNN-based models and comparing their effectiveness in multi-class skin cancer classification. (5) This article is valuable to my research on identifying the architectures most effective in multi-class skin cancer classification. (6) A limitation of the study is the potential overfitting due to the use of data augmentation techniques on an imbalanced dataset and this study used the HAM10000 dataset from Kaggle, which, while widely used, may have inherent limitations regarding its size and diversity, potentially impacting the model's generalizability to other datasets or real-world scenarios. (7) The author indicates that further improvements are needed for data preprocessing to reduce the overfitting. The ViT models outperform the CNN-based transfer-learned models, The ViT models are more effective in Multi-Class Skin Cancer Classification. (8) This article does not make a basis for my research but it gives much useful information about different architectures that can be used for multi-class classification.

[2] V. A. Nancy, P. Pachaiyappan, M. Arya, and B. S. Ahamed, “Comparative study and analysis on skin cancer detection using machine learning and deep learning algorithms,” Multimedia Tools and Applications, vol. 82, pp. 1–45, Aug. 2023, doi: 10.1007/s11042-023-16422-6.

(2) In this article, Nancy et al. compare the effectiveness of machine learning and deep learning algorithms in detecting skin cancer. The authors conduct a systematic literature review to identify key trends and techniques in the field, followed by an experimental evaluation using publicly available datasets such as ISIC, HAM10000, and PH2. This paper compares the performance of various ML models and feature extraction methods (HOG features, LBP, and PSO) used for skin cancer detection and Pre-trained models like Alexnet, ResNet-18, and VGG-16 models as feature extractors and used to train SVM. They also review some hybrid approaches both DL and ML models combine to detect skin cancer. (4) The scope of the research includes an experimental analysis of deep learning models and their comparison with traditional ML algorithms when detecting skin cancer. (5) This article is useful to my research on comparing existing Deep learning and machine learning approaches on several publicly available dataset and their effectiveness and also compares data augmentation and without augmentation performance comparison. (6) The variation in lesion size poses and unbalanced datasets in training neural networks for skin cancer diagnosis are the challenges in skin cancer identification. (7) The authors conclude that while DL techniques, particularly CNN-based models, show superior performance, further research is needed to validate these findings across more diverse populations. (8) This article gives a better understanding of existing Deep learning and Machine learning models and techniques for further study.

[3] A. M. Obaid, A. S. Shawkat, and N. S. Abdulhussein, “A powerful deep learning method for skin cancer detection,” J Autonom Intell, vol. 7, no. 1, Nov. 2023, doi: 10.32629/jai.v7i1.1156.

(2) In this article, Obaid et al. present a deep learning approach for detecting skin cancer using convolutional neural networks (CNNs). (3) The authors utilize the HAM10000 dataset, using over 10,000 annotated images of skin lesions, to train and evaluate their model. They employ the Keras Sequential API to build a CNN with layers such as Conv2D, MaxPool2D, and dense layers. The performance metrics used include Precision, Recall, and F1-score for the model. Different pre-trained models such as ResNet50, DenseNet121, and VGG11 are considered for comparative analysis. Normalization, rotation, and cropping are pre-processing techniques that enhance the robustness and accuracy of the models in the study. The use of the Adam optimizer and learning rate reduction techniques also improves the performance of the developed model. (4) The paper focuses on research in developing a CNN-based diagnostic for skin cancer classification and comparing the results with benchmark models. (5) It is useful for my research involving the application of deep learning in medical diagnostics, especially those related to early skin cancer diagnosis. (6) The major limitation of this work is overfitting due to class imbalance in the dataset. The authors have done data augmentation to solve this problem. (7) The authors then conclude that the proposed model provides a high accuracy rate of 97.12%, which may be helpful for clinical purposes in practical applications. (8) The paper will help in designing and evaluating CNN-based models for the detection of skin cancer in my research on Skin Cancer Detection with 3D-TBP.

[4] D. S. Syed and D. E. M. Albalawi, “Improved Skin Cancer Detection with 3D Total Body Photography: Integrating AI Algorithms for Precise Diagnosis,” Jul. 08, 2024, Research Square. doi: 10.21203/rs.3.rs-4677329/v1.

(2) In this article, Syed et al. explore the effectiveness of Convolutional Neural Networks (CNN) with 3D Total Body Photography (3D-TBP) for enhancing skin cancer detection. (3) The authors used the ISIC 2024 dataset, consisting of high-resolution 3D-TBP images, to train the convolutional neural network (CNN). The research incorporates transfer learning techniques with the base model of VGG16, ResNet, Inception Networks and advanced data augmentation and model optimization methods such as batch normalization and dropout regularization methods for reduce overfitting. Hyper parameter tuning and cross-validation employed to ensure robust model performance. (4) The study focuses on improving diagnostic accuracy and generalizability across various skin types and lesion morphologies by utilizing 3D imaging data. (5) This article is useful to my research because this used the ISIC 2024 dataset and the different pre-trained models used as transfer learning and provide good benchmark for further research. (6) A key limitation noted is the need for larger and more diverse datasets to further validate the model's generalizability in clinical settings. (7) The authors conclude that their CNN model achieves a partial area under the ROC curve (pAUC) exceeding 85% at an 80% true positive rate, demonstrating its potential for practical deployment in clinical diagnostics. (8) As our research is combined with 3D-TBP this research provides a good starting point to our research and this article gives analysis on CNN pre-trained models on performing ISIC 2024 dataset.

[5] C. Xin et al., “An improved transformer network for skin cancer classification,” Computers in Biology and Medicine, vol. 149, p. 105939, Oct. 2022, doi: 10.1016/j.compbiomed.2022.105939.

(2) In this article, Xin et al. propose an improved vision transformer (VIT) network named SkinTrans for the classification of skin cancer and evaluate its performance against VITs and CNN architectures. (3) The research employs two datasets HAM10000 and a clinical dataset collected through dermoscopy to train and evaluate the SkinTrans model. Collected data set undergoes sequence of preprocessing steps data normalization, data augmentation and balanced sampling. Proposed VIT model use multi-scale and overlapping sliding windows for image serialization and the application of contrastive learning to enhance feature discrimination. (4) The scope of the study is to improve the accuracy of skin cancer classification by leveraging the advanced capabilities of vision transformers, which have shown significant success in image classification tasks. (5) This article is useful to my research on utilizing transformer networks in medical imaging, especially for improving diagnostic accuracy in skin cancer detection and gives the Grad-Cam method to evaluate the attentions in vision transformers. (6) The main limitation highlighted is the model's slower processing speed for high-resolution images and the need for validation in extensive clinical trials. (7) The model proposed in this paper has achieved 94.3% accuracy on HAM10000 and 94.1% accuracy on their dataset. (8) This article will provide valuable insights into the application of vision transformers for medical image classification and it can be utilized when developing skin cancer detection using 3D-TBP.

[6] Clinician’s Ability to Identify Non-Melanoma Skin Cancer on 3D-Total Body Photography Sectors That Were Initially Identified during in-Person Skin Examination with Dermoscopy.,” 2023; Hobelsberger et al., 2023, 2024

(2) This article examines the role of 3D total body imaging in improving the accuracy and efficiency of monitoring skin lesions over time. (3) The main objective of the study is to evaluate the benefits of integrating 3D total body imaging into routine dermatological practices for sequential lesion monitoring, particularly for individuals at high risk of melanoma. (4) The research uses a case series approach, providing practical examples of how 3D imaging aids dermatologists in identifying changes in skin lesions that may indicate malignancy. (5) The findings are particularly useful for clinicians focused on early detection of melanoma, as the study demonstrates improved lesion tracking with reduced reliance on subjective observation. (6) One limitation of this study is its small sample size, which may not provide comprehensive generalizability of the findings. Additionally, the integration of 3D imaging requires advanced infrastructure, which may not be available in all clinical settings. (7) Future research should focus on expanding sample size and evaluating the cost-effectiveness of implementing 3D imaging in broader healthcare systems. (8) This article provides insights into novel dermatological practices and emphasizes the importance of precision in lesion monitoring. While it will not be the core of my research, its methodological insights will guide the adaptation of advanced imaging techniques into my study framework.

[7] F. F. Gellrich, A. Strunk, J. Steininger, F. Meier, S. Beissert, and S. Hobelsberger, “Comparison of the efficacy of skin examination using 3D total body photography to clinical and dermoscopic examination,” *EJC Skin Cancer*, vol. 2, p. 100264, Dec. 2024, doi: 10.1016/j.ejcskn.2024.100264.

(2) In this article, Smith et al. examine the effectiveness and limitations of using three-dimensional total body photography (3D-TBP) alone for detecting non-melanoma skin cancer (NMSC). (3) The authors conducted a study involving 130 patients with 167 suspected NMSC lesions. Skin examinations were performed using dermoscopy followd by surgery, and 3D-TBP images were independently evaluated and compared with histological results. (4) The study focuses on comparing the diagnostic accuracy of 3D-TBP and traditional dermoscopy in detecting basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and invasive skin tumors. (5) This study is useful for research on skin cancer detection methods, as it highlights the limitations and potential of 3D-TBP in identifying advanced skin tumors. (6) A key limitation is the lower sensitivity of 3D-TBP compared to dermoscopy, particularly in detecting early-stage tumors. (7) The authors recommend further research to improve the effectiveness of 3D-TBP, possibly by integrating digital dermoscopy or capturing additional images of hard-to-see areas. (8) While this article will not directly form the basis of my research, it provides valuable insights into advanced imaging techniques for skin cancer detection and will supplement my study on diagnostic technologies.

(8) Performance of Commercial Dermatoscopic Systems That Incorporate Artificial Intelligence for the Identification of Melanoma in General Practice: A Systematic Review, *Cancers*, Apr. 2024, doi: 10.3390/cancers16071443.

(2) This systematic review evaluates the role of artificial intelligence (AI), particularly convolutional neural networks (CNNs), in the early detection of melanoma and their application in real-world clinical settings. (3) The main objective of this review is to analyze the performance metrics of AI-based diagnostic tools, including mobile applications and bedside CNN systems, for melanoma detection and to highlight their limitations and potential for clinical integration. (4) The review systematically analyzes 16 studies involving 1160 melanoma cases and 33,010 benign lesions, comparing AI-based systems' performance to that of clinicians in terms of sensitivity, specificity, and accuracy. (5) Results show that while AI demonstrates dermatologist-level performance on controlled datasets, its real-world diagnostic accuracy varies widely. Combining AI with clinician expertise enhances sensitivity and specificity, improving diagnostic outcomes. (6) Limitations include variability in study designs, underrepresentation of diverse skin types, and the reliance on curated datasets that do not fully reflect real-world conditions. There is also limited transparency in CNN architectures used by market-approved systems. (7) The review emphasizes integrating AI with clinician expertise to improve melanoma detection. Future AI systems should incorporate contextual medical information and cater to diverse patient demographics to enhance diagnostic accuracy. (8) This study provides valuable insights into the potential of AI as a complementary tool in clinical melanoma detection. Its findings inform my research by underlining the importance of combining AI with professional medical evaluations to optimize patient outcomes.

[9] A. S. Jahn *et al.*, “Over-Detection of Melanoma-Suspect Lesions by a CE-Certified Smartphone App: Performance in Comparison to Dermatologists, 2D and 3D Convolutional Neural Networks in a Prospective Data Set of 1204 Pigmented Skin Lesions Involving Patients’ Perception,” *Cancers*, vol. 14, no. 15, p. 3829, Aug. 2022, doi: 10.3390/cancers14153829.

(2) This article evaluates the diagnostic accuracy of the SkinVision® app, a CE-certified mobile health tool for melanoma risk assessment, and compares its performance with dermatologists and AI-based tools. (3) The primary aim of this study is to investigate the reliability of SkinVision® in identifying melanoma and its reception by patients and healthcare professionals. (4) The research analyzes a dataset of 1204 pigmented skin lesions and involves evaluations by dermatologists, 2D and 3D AI tools, and the SkinVision® app. The study includes ROC analysis and statistical tests to assess diagnostic performance. (5) The study highlights that SkinVision® detects a significantly higher number of high-risk lesions than dermatologists or AI tools, which may lead to unnecessary excisions and patient anxiety. (6) The limitations include low sensitivity (41%) and specificity (83%) of the app compared to dermatologists, raising concerns about over-detection and misdiagnosis. Additionally, low trust among users and experts was reported. (7) The research emphasizes the need for stringent regulations and further studies to validate the use of mobile health tools like SkinVision®. It suggests integrating AI-based tools with professional dermatological evaluations for better outcomes. (8) While this study provides critical insights into the diagnostic challenges of melanoma detection using mobile apps, it also underscores the importance of professional expertise in improving diagnostic accuracy. These findings are relevant for guiding my research on AI-assisted diagnostic tools.

(10) B. İsmail Mendi *et al.*, “Artificial Intelligence in the Non-Invasive Detection of Melanoma,” *Life*, vol. 14, no. 12, Art. no. 12, Dec. 2024, doi: 10.3390/life14121602.

(2) This paper explores the growing role of Artificial Intelligence (AI) in the non-invasive detection of melanoma, emphasizing the use of deep learning models to improve diagnostic accuracy. (3) The primary goal of this research is to evaluate AI-based diagnostic tools as accessible and accurate alternatives to traditional methods like biopsies for detecting melanoma. (4) The research examines various AI applications, including convolutional neural networks (CNNs), for analyzing dermoscopic and clinical images. It highlights the integration of datasets like ISIC, HAM10000, and PH2 to train and test AI models. (5) Results indicate that AI-based systems achieve dermatologist-level accuracy or better, with advancements in algorithms enabling faster, non-invasive melanoma detection. Multimodal approaches integrating images and metadata further improve performance. (6) The study notes challenges such as the lack of diverse datasets, underrepresentation of darker skin types, and generalizability issues due to controlled dataset environments differing from real-world clinical conditions. (7) The authors advocate for developing diverse, standardized datasets and integrating AI with dermatological expertise to enhance diagnostic reliability and reduce overdiagnosis risks. (8) This article provides valuable insights into the potential of AI in revolutionizing dermatological practice. Its focus on the challenges and opportunities of implementing AI tools informs the development of comprehensive diagnostic systems in my research.