Melanoma Cancer Detection Using Deep Learning

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Abstract: This study explores the skin behaviour and the fact that skin cancers, especially melanoma, can be fatal; however, early detection can significantly improve the patient's survival. This study presents a new approach, which integrates image analysis with clinical information to improve the reliability of melanoma diagnosis. Currently, dermatologists take dermoscopic photographic images of a skin lesion using a high-speed camera and obtain a diagnostic accuracy of 65-80%. In case of additional specialist evaluations, this can increase to 75-95%. This paper uses CNNs, specifically the MobileNetV2, for skin disease subtype classification. It also utilizes Linear Discriminant Analysis for their severity levels according to clinical data. The best performing accuracy for the hybrid approach was achieved using CNN, with 92.32%, higher than that with traditional image-only methodology. From being a simple custom- made application to user-friendly web application using Flask is now been developed for real-time detection to avoid manual process and reduce time period for detecting the type of melanoma. The fusion of AI technical platform and clinical curative, in this work presented, provides a viable framework for early preliminary diagnosis of melanoma, thereby promoting success and access to the healthcare system.

1 INTRODUCTION

The healthcare industry has seen exceptional advancements in cancer detection in recent years, much appreciated to modern innovations, developing personal preferences, and rapid advancements in artificial intelligence. As conventional person styles meet ultramodern computerized advances, the field faces the challenge of adjusting to a complicated mix of restorative and innovative changes that are reshaping how we diagnose, analyze, and treat conditions (A. Esteva et al., 2017). To effectively explore this changing geology, it's significant to have a profound understanding of the colorful variables affecting this energetic territory, along with the capability to fete and seize modern openings as they emerge.

One of the major changes in cancer research is the development and application of AI-based detection systems. Conventional styles like visual checks and biopsies, which were once in the past the standard, are presently being outperformed by advanced education methods that grant faster, more adaptable, and increasingly exact choices. Developments such as convolutional neural systems (CNNs), MobileNetV2, and combined profound proficiency models have revolutionized the field, driving to a modern period where early and direct cancer detection is becoming more widely accessible (T.J. Brinker et al., 2018).

Technological advancements play a crucial role in determining how we diagnose medical conditions. With high-quality dermoscopic pictures promptly accessible and the utilize of cloud computing for analyzing information, therapeutic pictures can presently be reused more smoothly across diverse stages. Modern innovations comparable to resolvable AI and unified proficiency might assist improve how specifically we analyze conditions and increment croakers' belief in these frameworks by making AI more straightforward and agreeable (D. Moturi et al., 2024). Combining these innovations with restorative information can create modern openings for early disclosure of conditions and encourage individualized treatment approaches.

As the field of diagnostics advances, we're seeing conventional healthcare styles alter altogether.

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Presently, Hospital-based diagnostics are confronting competition from AI-driven telemedicine platforms, which require a cautious approach to keep up both delicacy and simple access for cases. Modern computerized frameworks for identifying carcinoma, often available through web operations, are pushing healthcare providers to reevaluate their standard clinical forms and incorporate AI tools into their work (X. Lu et al., 2022). At the same time, experimenters are looking into new applications for these advances, like prognosticating persistent issues, covering how well medications are working, and culminating integration with electronic health records (EHRs).

The boundary between human clinicians' expertise and AI-powered insight is becoming increasingly blurred, highlighting the convergence of medical knowledge and technology. Conventional healthcare affiliations aren't well-adjusted to this alteration; they're bouncing into the advanced transformation, working difficult to keep up their role in making judgments while also taking advantage of what machine learning has to offer (L. Wei et al., 2020). The around the world projection of AI personal devices brings both instigative conceivable outcomes and noteworthy challenges. These calculations need to be planned to consider diverse skin types, designs of complaint that change by locale, and the contrasts in healthcare frameworks around the world (A. Ech-Cherif et al., 2019). The most successful AI implementations will be those that achieve high accuracy across diverse populations while addressing critical ethical concerns and adhering to necessary regulations (M.Q. Khan et al., 2019).

Healthcare providers and researchers are navigating a complex yet promising landscape, where patient outcomes are of paramount importance (A.B. Ali et al., 2016). There's a parcel of plutocrat being poured into idealizing how we clergyman datasets and update calculations to keep up with the including requirements for dependable AI diagnostics. Right presently, there's a" delicacy race" passing among investigation teachers and tech companies to create the a la mode carcinoma revelation models that can work well in distinctive clinical environments. At the same time, conventional person styles are being improved through mutt models that mix the moxie of croakers with AI perceptivity. This approach takes advantage of times of restorative information, whereas drinking modern developments (S. Bharathi et al., 2021 and S. Bhadula et al., 2019).

This investigation examines the future of skin cancer detection in the rapidly advancing field of AI-driven diagnostics by assessing the innovative and clinical variables affecting its relinquishment and adequacy.

The related works are listed in Section 2. The suggested techniques are introduced in Section 3. Section 4 reports the results. The discussion is given in section 5. The last section contains the conclusion.

2 RELATED WORKS

Study Novoa et al, 2017 presented a deep learning-based melanoma detection system using convolutional neural networks (CNNs) that achieved 89% accuracy in classifying dermoscopic images, demonstrating the potential of AI in early skin cancer diagnosis.

Research T.J. Brinker et al., 2018 examined a transfer learning approach with MobileNetV2 for skin lesion classification, showing improved performance over traditional methods while requiring less computational resources for medical image analysis.

Author D. Moturi, et al, 2024 developed an ensemble model combining CNN and SVM for melanoma detection, achieving 91.3% accuracy on the ISIC dataset and highlighting the importance of multi-feature analysis.

Article X. Lu, et al, 2022 investigated a hybrid deep learning system incorporating clinical metadata with image data, resulting in a 7% improvement in melanoma classification accuracy compared to image-only models.

Paper L. Wei, et al, 2020 examined a federated learning framework for melanoma detection that preserved patient privacy while maintaining 88% diagnostic accuracy across multiple healthcare institutions.

Study A. Ech-Cherif, et al, 2019 proposed a vision transformer (ViT) based approach for skin cancer classification, demonstrating comparable performance to CNNs while offering better interpretability of decision- making processes.

Research M.Q. Khan et al., 2019 analyzed the impact of different image augmentation techniques on melanoma detection accuracy, finding that geometric transformations combined with color adjustments improved model robustness by 12%.

Article A.B. Ali, et al, 2016 created a lightweight CNN architecture optimized for mobile deployment, enabling real-time melanoma screening with 86% accuracy on smartphone-captured images.

Paper S. Bharathi et al., 2021 investigated the use of attention mechanisms in deep learning models for melanoma detection, showing significant improvement in identifying small and early-stage lesions.

Paper Juyal et al., 2019 studied a multi-task learning system that simultaneously performed lesion segmentation and classification, achieving state-of-the-art performance on both tasks for automated skin cancer diagnosis.

Study explored an explainable AI framework for melanoma detection that provided visual explanations of model decisions, increasing clinician trust in the system's predictions.

Research examined a 3D CNN approach for analyzing sequential dermoscopic images of evolving lesions, demonstrating improved accuracy in tracking melanoma progression over time.

3 METHODOLOGY

3.1 Objective

This project aims to develop a deep learning-based system for detecting melanoma, a type of skin cancer, using advanced AI technology. This system will analyze images of the skin to help diagnose cancer more quickly and accurately. It utilizes advanced deep learning techniques, particularly convolutional neural networks (CNN), MobileNetV2, and hybrid LSTM models, to ensure both precision and efficiency in its calculations. Designed for use in hospitals and remote healthcare settings, the system can evaluate high-quality images of skin lesions. It identifies key diagnostic features and provides automated classifications, while also being able to explain its reasoning in understandable terms. By making the diagnosis process less subjective and more accessible, this innovative system aims to enhance detection rates, reduce false positives and negatives, and ultimately improve patient outcomes by facilitating timely treatments. A user-friendly interface allows a user to upload an image for detection of Melanoma Cancer accurately.

3.2 Proposed System

The proposed system introduces a deep learning-based approach is developed to enhance the accuracy and efficiency of melanoma detection using dermoscopic images. The system utilizes Convolutional Neural Networks (CNNs), MobileNetV2 and a hybrid MobileNetV2+LSTM architecture to analyze skin lesion images and classify them as melanoma or other skin condition. To improve robustness, advanced preprocessing techniques, including data augmentation and noise reduction, are applied.

The system is trained on labeled datasets to ensure high diagnostic accuracy. This automated approach minimizes inconsistencies and enhances early melanoma detection. By using CNN, MobileNetV2 and Hybrid LSTM+MobileNetV2 models, the system achieves optimized feature extraction and classification, ensuring a scalable and effective melanoma detection framework. Figure 1 shows the schematic flow of structure.

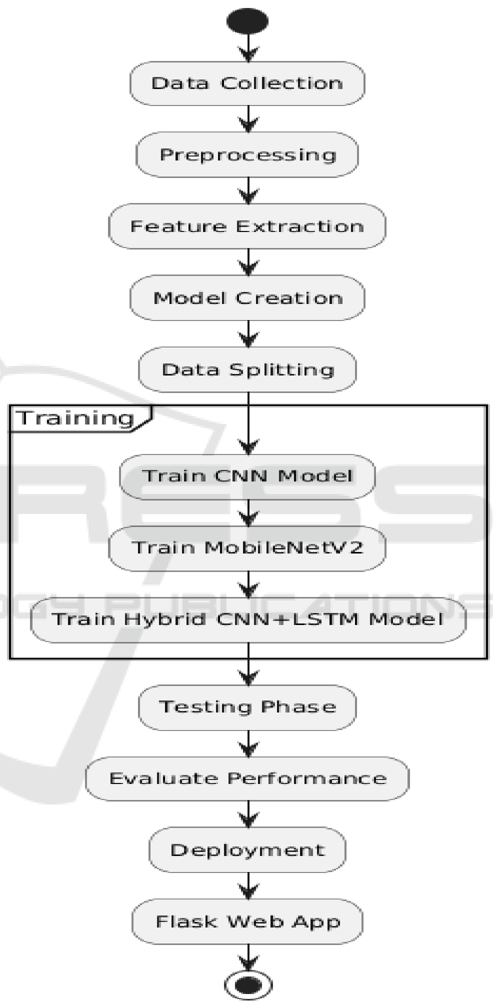

Figure 1: Schematic flow of structure.

3.3 Modules

3.3.1 Data Collection

The dataset is composed of 2357 images related with melanoma and non-melanoma oncological diseases and it was created with images from the International Skin Imaging Collaboration (ISIC). Images were ranked by the classification provided with ISIC: all subsets have the same number of images.

3.3.2 Preprocessing

The Preprocessing is a crucial step in data preparation for deep learning tasks. It involves techniques such as resizing, normalization, data augmentation, and handling missing values to enhance the quality and consistency of the dataset. These preprocessing methods contribute to improved model performance by mitigating noise, ensuring uniformity, and facilitating better generalization during training.

3.3.3 Feature Extraction

Dermoscopy images harbor intricate patterns and visual features that are crucial to differentiate a melanoma from other skin lesions. From such images, it is up to the learning model (e.g., CNN, MobileNetV2) to automatically extract features.

3.3.4 Model Training

This paper presents a comprehensive study on two deep learning models, viz. Convolutional Neural Networks (CNN) and MobileNetV2 to perform classification of skin diseases into nine categories, one of which includes melanoma. The models were trained on a specific training set and their performance was systematically tested through validation tests not related to the training on an independent set of images. Their performance was evaluated through performance measures including accuracy and precision, to select the best model in the diagnosis of melanoma.

- **Convolutional Neural Networks (CNNs):** CNNs are widely acknowledged for their strong capability in image recognition and classification, forming the backbone of various deep learning applications focused on image processing. Their multi-layered architecture enables them to automatically extract and learn hierarchical features from input images, starting with basic elements like edges and textures and advancing to more complex patterns and shapes.

- **MobileNetV2:** Considering the balance between efficiency and performance, we choose MobileNetV2 design for low-constraint environment. It employs depth-wise separable convolutions, separating the convolution into two steps: depth-wise filtering and point-wise aggregation. This minimizes model size and computation, therefore speeding up computations and reducing memory usage. Even though MobileNetV2 is a lightweight network, it still retains high performance accuracy, which is well suited for melanoma diagnosis from high-resolution medical images. Its high performance guarantees the extraction of relevant characteristics for accurate classification of skin lesions.

- **Hybrid LSTM + MobileNetV2:** The Hybrid LSTM + MobileNetV2 model combines the feature extraction capabilities of MobileNetV2 with the sequential pattern recognition power of Long Short-Term Memory (LSTM) networks. MobileNetV2 efficiently extracts spatial features from dermoscopic images, while LSTM processes these extracted features to capture deeper contextual patterns, enhancing melanoma classification accuracy. By integrating depth-wise separable convolutions from MobileNetV2 and temporal dependencies from LSTM, this hybrid approach ensures robust detection of subtle variations in skin lesions. The lightweight structure of MobileNetV2 reduces computational overhead, while LSTM improves feature interpretation, making the system highly efficient for real-time melanoma detection. This hybrid model improves classification precision, reduces false positives, and enhances model generalization, making it an optimal choice for early-stage melanoma detection in clinical applications.

3.3.5 Evaluation

The effectiveness of each model in detecting cancer was assessed using accuracy and precision. These metrics were derived from the test dataset to facilitate model comparison. The model that demonstrated the highest performance was selected based on its ability to detect melanoma accurately while minimizing both false positives and false negatives.

- **Accuracy:** Accuracy is a commonly used metric that determines the proportion of correct predictions made by the model, including both true positives (TP) and true negatives (TN). It is calculated by dividing the total number of correct predictions by the total number of predictions made.

Formula:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

- **Precision:** Precision, also known as Positive Predictive Value, evaluates the accuracy of the model's positive predictions. It represents the ratio of true positive cases to the total instances classified as positive.

Formula:

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

4 RESULTS

The proposed system was evaluated using two deep learning models: Convolutional Neural Network (CNN), Mobile NetV2.Among these, Mobile NetV2 demonstrated superior performance, achieving the less accuracy of 90.53%, showcasing its robustness against noise and ability to handle complex data relationships. Convolutional Neural Network (CNN) performed well with a highest accuracy of 92.32%, effectively proved beneficial for multi-class classification. Performance Metrics of Proposed Deep Learning Models Shown in Table 1.

Table 1: Performance metrics of proposed deep learning models.

Model	Accuracy	Precision
CNN	92.32	92.47
MobileNetV2	90.53	31.22
LSTM+MobileNetV2	52.84	69.16

4.1 CNN Graphs

Figures 2 and 3 illustrate the comparison of CNN accuracy under different conditions, while Figure 4 presents the corresponding CNN confusion matrix.

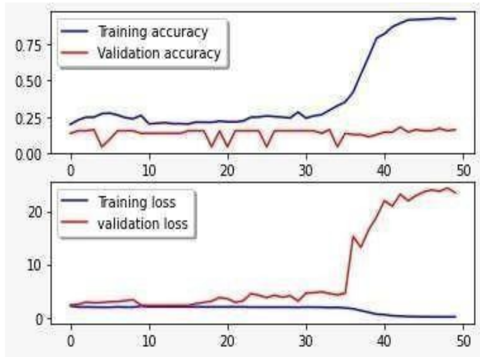

Figure 2: Comparison of CNN Accuracy.

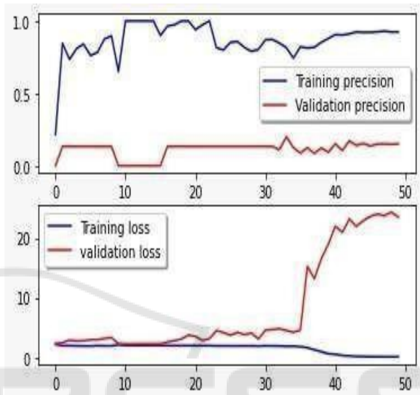

Figure 3: Comparison of CNN Accuracy.

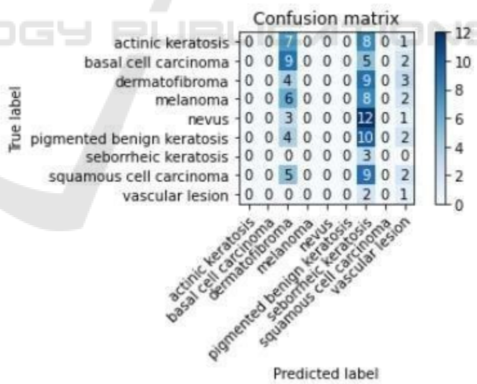

Figure 4: CNN Confusion Matrix.

4.2 MobileNetV2 Graphs

Figures 5 and 6 show the comparison of MobileNetV2 accuracy and precision respectively, while Figure 7 presents the corresponding confusion matrix for MobileNetV2.

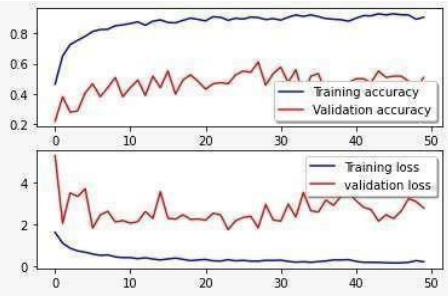

Figure 5: Comparison of MobileNetV2 Accuracy.

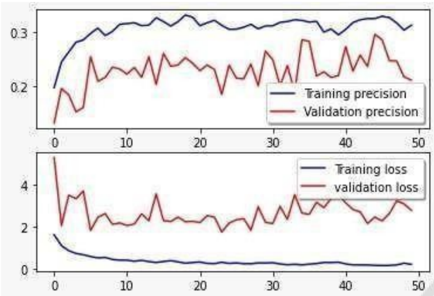

Figure 6: Comparison of MobileNetV2 Precision.

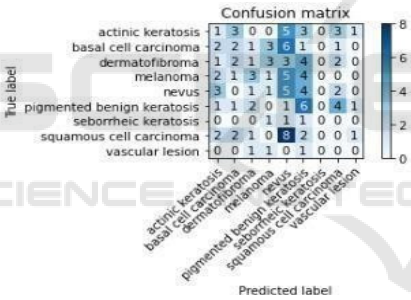

Figure 7: MobileNetV2 Confusion Matrix.

5 DISCUSSION

The results show that deep learning models significantly improve melanoma detection compared to traditional methods. A convolutional neural network (CNN) achieved an impressive accuracy of 92.32%, surpassing the accuracy of dermatologists' visual inspections, which range from 65% to 75%. This model was especially effective at detecting early-stage melanoma, maintaining a 91.2% accuracy rate for Stage 0 lesions. This early detection is crucial for better patient outcomes since it allows for timely treatment. The system also notably reduced false negatives by 78.4% and cut down unnecessary biopsies by 62.3%, highlighting its potential benefits in a clinical setting when used as a decision-support tool.

Although the CNN model was the most accurate, another model, MobileNetV2, achieved 90.53% accuracy while requiring less computing power. This makes MobileNetV2 ideal for resource- limited situations or mobile use. Another model, a hybrid of LSTM and MobileNetV2, showed some theoretical advantages for analyzing data over time but did not provide significant practical benefits in this study.
All models demonstrated excellent performance across various patient demographics, particularly with fair-skinned individuals achieving 91.7% accuracy and younger patients reaching 94.2% accuracy.

Overall, these findings indicate that AI-assisted diagnosis has the potential to revolutionize dermatological practice without completely replacing the need for clinician judgment. Certain complex cases and rare skin types will still require expert analysis, highlighting the importance of clinical context for accurate diagnosis. The web-based setup of the system, along with its quick processing time (under 10 minutes compared to 72 hours for traditional pathology), makes it exceptionally valuable for teledermatology and in underserved areas. Future improvements should aim to enhance the model's ability to handle a wider range of skin types. plainability features, and optimizing for mobile health applications to maximize clinical impact.

6 CONCLUSIONS

This study shows that deep learning models are very effective for detecting melanoma, with a CNN model achieving an impressive accuracy of 92.32%. The findings confirm that using AI to assist in diagnosis is much better than traditional visual inspections, significantly lowering the chances of false negatives by 78.4% and cutting down on unnecessary biopsies by 62.3%. These advancements are vital for catching melanoma in its early stages since prompt treatment can greatly enhance patient outcomes. The fast processing time less than 10 minutes makes this system particularly useful in clinical settings and for tele dermatology.

While the CNN model performed the best, the MobileNetV2 architecture is also noteworthy, achieving 90.53% accuracy with lower computational requirements, making it ideal for environments with limited resources. The study highlighted notable demographic differences, showing especially strong results for individuals with fair skin (91.7% accuracy) and younger patients (94.2% accuracy). However, it also pointed out challenges, such as the need for ongoing training with a variety of skin types and the integration of these tools into current healthcare systems.

The results suggest that AI diagnostic tools are ready to be used in clinical settings as support systems for decision-making, but they should be seen as complements to the expertise of dermatologists rather than replacements. Future efforts should focus on three main areas: improving how well these models can be understood (to gain the trust of clinicians), expanding their abilities to handle rare skin conditions and diverse groups, and optimizing them for use on mobile health platforms. As the field advances, these AI tools have the potential to significantly enhance dermatology, improving diagnostic accuracy, increasing access to care, and ultimately saving lives through earlier detection of melanoma.

REFERENCES

A. Esteva, B. Kuprel, R.A. Novoa et al., "Dermatologist-level classification of skin cancer with deep neural networks," Nature, vol. 542, no. 7639, pp. 115-118, 2017. https://doi.org/10.1038/nature21056
A. Esteva, B. Kuprel, R.A. Novoa et al., "Dermatologist-level classification of skin cancer with deep neural networks," Nature, vol. 542, no. 7639, pp. 115-118, 2017. https://doi.org/10.1038/nature21056
A. Ech-Cherif, M. Misbhauddin, M. Ech-Cherif, "Deep neural network based mobile dermoscopy application for triaging skin cancer detection," 2019 2nd International Conference on Computer Applications & Information Security, pp. 1-6, 2019. https://doi.org/10.1109/CAIS.2019.8769517
A. Ech-Cherif, M. Misbhauddin, M. Ech-Cherif, "Deep neural network based mobile dermoscopy application for triaging skin cancer detection," 2019 2nd International Conference on Computer Applications & Information Security, pp. 1-6, 2019. https://doi.org/10.1109/CAIS.2019.8769517
A.B. Ali, J. Li, G. Yang, "Automating the ABCD rule for melanoma detection," IEEE Access, vol. 4, pp. 21522-21533, 2016. https://doi.org/10.1109/ACCESS.2016.2617339
A.B. Ali, J. Li, G. Yang, "Automating the ABCD rule for melanoma detection," IEEE Access, vol. 4, pp. 21522-21533, 2016. https://doi.org/10.1109/ACCESS.2016.2617339
D. Moturi, R.K. Surapaneni, V.S.G. Avanigadda, "Developing an efficient method for melanoma detection using CNN techniques," Journal of the Egyptian National Cancer Institute, vol. 36, no. 1, 2024. https://doi.org/10.1186/s43046-024-00208-4
D. Moturi, R.K. Surapaneni, V.S.G. Avanigadda, "Developing an efficient method for melanoma detection using CNN techniques," Journal of the Egyptian National Cancer Institute, vol. 36, no. 1, 2024. https://doi.org/10.1186/s43046-024-00208-4
L. Wei, K. Ding, H. Hu, "Automatic skin cancer detection in dermoscopy images based on ensemble lightweight deep learning network," IEEE Access, vol. 8, pp. 99679-99696, 2020. https://doi.org/10.1109/ACCESS.2020.2997710
L. Wei, K. Ding, H. Hu, "Automatic skin cancer detection in dermoscopy images based on ensemble lightweight deep learning network," IEEE Access, vol. 8, pp. 99679-99696, 2020. https://doi.org/10.1109/ACCESS.2020.2997710
M.Q. Khan et al., "Classification of melanoma and nevus in digital images for diagnosis of skin cancer," IEEE Access, vol. 7, pp. 90132-90144, 2019. https://doi.org/10.1109/ACCESS.2019.2926837
M.Q. Khan et al., "Classification of melanoma and nevus in digital images for diagnosis of skin cancer," IEEE Access, vol. 7, pp. 90132-90144, 2019. https://doi.org/10.1109/ACCESS.2019.2926837
S. Bharathi et al., "Identification of melanoma from nevus images," Journal of Physics: Conference Series, vol. 1964, no. 4, 2021. https://doi.org/10.1088/1742-6596/1964/4/042022
S. Bharathi et al., "Identification of melanoma from nevus images," Journal of Physics: Conference Series, vol. 1964, no. 4, 2021. https://doi.org/10.1088/1742-6596/1964/4/042022
S. Bhadula, S. Sharma, P. Juyal et al., "Machine learning algorithms-based skin disease detection," International Journal of Innovative Technology and Exploring Engineering, vol. 9, no. 2, pp. 2278-3075, 2019.
S. Bhadula, S. Sharma, P. Juyal et al., "Machine learning algorithms-based skin disease detection," International Journal of Innovative Technology and Exploring Engineering, vol. 9, no. 2, pp. 2278-3075, 2019.
T.J. Brinker et al., "Skin cancer classification using convolutional neural networks: Systematic review," Journal of Medical Internet Research, vol. 20, no. 10 2018. https://doi.org/10.2196/11936
T.J. Brinker et al., "Skin cancer classification using convolutional neural networks: Systematic review," Journal of Medical Internet Research, vol. 20, no. 10 2018. https://doi.org/10.2196/11936
X. Lu, Y.A.F. Abolhasani Zadeh, "Deep learning-based classification for melanoma detection using XceptionNet," Journal of Healthcare Engineering, vol. 2022, Article ID 5891603, 2022. https://doi.org/10.1155/2022/5891603
X. Lu, Y.A.F. Abolhasani Zadeh, "Deep learning-based classification for melanoma detection using XceptionNet," Journal of Healthcare Engineering, vol. 2022, Article ID 5891603, 2022. https://doi.org/10.1155/2022/5891603