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Skin Cancer Detection using EfficientNet

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Abstract - Skin cancer, particularly melanoma, is one of the most prevalent and life-threatening cancers, where early detection significantly improves survival rates. One of the most common and deadly malignancies is skin cancer, especially melanoma, whose survival rates are greatly increased by early identification. Conventional diagnostic techniques depend on the knowledge of dermatologists, which makes them arbitrary, laborious, and frequently unreliable. Convolutional Neural Networks (CNNs) are used in this study's automated skin cancer detection system to categorize skin lesions as benign or malignant in order to overcome these difficulties. The ResNet50 architecture, which uses convolutional, activation (ReLU), and pooling layers for effective feature extraction, is used to construct the model. Preprocessing methods such picture scaling, normalization, and augmentation are used to improve model generalization after training on the ISIC Archive dataset. The model's dependability in identifying malignant lesions with few false positives is demonstrated by performance evaluation, which shows a hightest accuracy of 94% with precision and recall rates of 92% and 90%, respectively. This study demonstrates how CNN-based methods can decrease reliance on dermatologists while increasing the speed and accuracy of skin cancer diagnosis. The suggested paradigm can help with early diagnosis and medical decision- making, which makes it useful in clinical settings. To improve diagnostic performance, future studies should concentrate on correcting class imbalance, diversifying datasets, and implementing ensemble learning techniques. Deploying AI-driven solutions in healthcare can also be facilitated by increasing model resilience for practical applications. This study advances the creation of an effective, scalable, and user-friendly skin cancer screening tool by incorporating deep learning techniques.

Keywords: Skin Cancer, Deep Learning, Convolutional Neural Networks, Image Classification, Medical Imaging, Early Diagnosis, AI in Healthcare.

Index Terms: Artificial Intelligence, CNNs, Dermatology, Medical Image Processing, Skin Lesion Classification, Transfer Learning, Explainable AI.

INTRODUCTION

One of the most prevalent forms of cancer in the world is melanoma, which is the most deadly because of its aggressiveness and quick spread if left untreated. The World Health Organization (WHO) reports that millions of new cases of skin cancer are recorded each year, resulting in substantial healthcare costs and fatalities. Since prompt care can stop cancer from progressing to advanced stages, early and precise detection is essential to increasing survival rates. Traditionally, dermatologists have used visual examination, dermoscopic imaging, and histological analysis to diagnose skin cancer.These methods, however, are less dependable in large-scale screenings due to their time commitment, specialist knowledge, and interobserver variability. Subjectivity in diagnosis frequently leads to incorrect classification, which can have a major effect on patient outcomes by causing needless biopsies or postponed therapy.

Skin cancer can now be quickly and accurately detected thanks to automated medical picture analysis made possible by recent developments in deep learning and artificial intelligence (AI). Medical imaging applications might benefit greatly from the remarkable performance of Convolutional Neural Networks (CNNs), a subtype of deep learning, in image classification tasks. CNNs are highly accurate in differentiating between benign and malignant skin lesions by learning complex patterns from dermoscopic pictures. CNNs automatically learn hierarchical features from raw images, improving generalization and resilience in contrast to typical machine learning techniques that need for handcrafted feature extraction.

This work suggests an automated method for detecting skin cancer that uses CNNs to categorize skin lesions as either benign or malignant. The ISIC Archive, a publicly accessible dataset of annotated dermoscopic pictures frequently utilized in skin cancer research, is used to train the model. ResNet50, a cutting-edge CNN architecture that makes use of residual connections to increase training efficiency and avoid the vanishing gradient issue, serves as the foundation for the deep learning model. Preprocessing methods like data augmentation, image scaling, and normalization are used to improve the model's capacity for generalization.

The model's performance is assessed using common classification measures like accuracy, precision, recall, and F1-score. The findings show that there are few false positives and that the model successfully detects malignant lesions. The goal of this project is to create a dependable and effective AI-based tool that can help dermatologists diagnose skin cancer, lessen their burden, and enable early detection—particularly in areas with low resources or remote locations. This research improves automated illness diagnosis and increases the speed and accuracy of skin cancer detection by utilizing deep learning. The study illustrates how CNN-based models

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can improve the accuracy of diagnoses, lessen the need for human judgment, and enable widespread screenings for skin cancer. The suggested approach offers a scalable alternative for dermatological evaluations and may find practical clinical use. In order to further improve classification performance, future research will concentrate on resolving dataset imbalances, enhancing model robustness, and investigating ensemble learning techniques.

RELATED WORKS

In recent years, there has been a lot of interest in the use of deep learning, namely Convolutional Neural Networks (CNNs), for the identification of skin cancer. In order to achieve dermatologist-level classification performance, Esteva et al. [1] created a deep learning system that was trained on a sizable dataset of skin lesion photos. Their research showed that neural networks could distinguish between benign and malignant lesions with high accuracy, indicating that AI-assisted diagnostics holds promise as a therapeutic tool. By combining several CNN architectures to increase classification accuracy and decrease false positives, Codella et al. [2] significantly enhanced melanoma detection through the use of deep learning ensembles. Furthermore, the ISIC Archive [3], which offers high- quality annotated dermoscopic pictures that facilitate the training and assessment of deep learning models, has been helpful in dermatological AI research.

Various CNN designs have been investigated in a number of studies to enhance the diagnosis of skin cancer. The U-Net architecture for biomedical image segmentation was first presented by Ronneberger et al. [4] and has since been extensively used for skin lesion segmentation prior to classification. This method improves CNN-based diagnostic accuracy and feature extraction. In their study of several CNN-based models, Rajendran & Rajendran
[5] emphasized the advantages of deep networks over conventional machine learning approaches, stressing that the former automatically extract pertinent characteristics without the need for manual methods. In a comparative research between CNNs and 58 dermatologists, Haenssle et al. [6] showed how AI may help dermatologists by showing that deep learning models were on par with or even better than human experts in melanoma diagnosis.

Comparative studies have also looked at how effective different CNN architectures are. Xie & Li [7] evaluated EfficientNet, VGG, and Inception networks for skin cancer classification and found that EfficientNet offered better feature extraction capabilities because of its compound scaling strategy. Tschandl et al. [8] showed that dermatologists who used CNN predictions in their study of human–computer collaboration in skin cancer diagnosis were more accurate than those who only used conventional diagnostic techniques. Wang & Yang [9] conducted a thorough examination of machine learning approaches for skin cancer detection and discovered that deep learning models often performed better than traditional approaches. [10] highlighted the necessity for strong AI-driven solutions while talking about issues including clinical integration, model interpretability, and dataset bias. Our study expands on these results by evaluating the clinical feasibility of an EfficientNet- based CNN model trained on the ISIC Archive. Each convolutional operation is followed by ReLU activation to increase non- linearity and improved pattern recognition.

Pooling Layers: To minimize computation and assist avoid overfitting, max-pooling is employed to shrink the spatial size of the feature maps.The ultimate classification decision is made by fully connected layers, which combine the characteristics that convolutional layers have learned.

LIMITATIONS

Notwithstanding the encouraging outcomes of CNN- based skin cancer diagnosis, a number of drawbacks need to be taken into account prior to clinical implementation. The reliance on high-quality, well-annotated datasets is one significant drawback. The ISIC Archive offers a sizable number of dermoscopic pictures; however,

because malignant cases are frequently underrepresented in comparison to benign lesions, dataset imbalance is still an issue. When the model performs well on common classes but struggles with rare malignant instances, this imbalance may result in skewed predictions and an increase in false negatives.

The model's generalizability across various demographic groups and imaging settings is another drawback. Images captured from different devices, in varied lighting situations, or from patients with variable skin tones may not be well-represented by deep learning models trained on particular datasets. CNNs may perform worse when used on unseen data from various sources, according to studies like those by Bonettini et al. [10], which calls for domain adaptation strategies. Furthermore, interpretability is still a problem because deep learning algorithms are opaque, making it hard for dermatologists to have faith in AI-based forecasts without explicit justifications.

Furthermore, ethical and regulatory issues prevent AI models from being used in real-world therapeutic settings. CNNs can help

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with early diagnosis, but they should not take the role of skilled dermatologists; rather, they should enhance their knowledge. Serious repercussions may result from the possibility of misdiagnosis brought on by adversarial attacks or inaccurate model predictions. Furthermore, in order for models to adjust to changing data distributions, they need to be updated and retrained continuously. In order to promote real-world integration, future research should concentrate on increasing dataset diversity, improving model interpretability through the use of techniques such as Grad-CAM and SHAP, and guaranteeing regulatory compliance.

PROBLEM DEFINITION

1. Background

Melanoma is the most dangerous type of skin cancer, and it is one of the most prevalent types in the globe. The World Health Organization (WHO) reports that each year, millions of cases of melanoma and non- melanoma skin cancers are reported, resulting in substantial morbidity and mortality. Improving patient survival rates requires early discovery since prompt treatment can stop the cancer from spreading. Clinical examination, dermoscopic imaging, and biopsy confirmation are all part of traditional diagnostic techniques.

However, these techniques rely significantly on dermatologists' knowledge, which makes diagnosis laborious and subjective. Unnecessary operations or postponed treatment may result from inexperienced clinicians misdiagnosing benign lesions as cancer or vice versa. Furthermore, early detection is challenging in rural and impoverished areas because to limited availability to qualified dermatologists.

2. Challenges in Existing Approaches

A number of AI-based methods, mostly based on deep learning techniques, have been put forth for the identification of skin cancer. These approaches, however, have several drawbacks:

Dataset Imbalance: Biased model predictions result from the uneven distribution of benign and malignant cases in skin cancer databases.

Overfitting: The real-world applicability of many deep learning models is diminished because they have a tendency to memorize training data rather than generalize well to novel, unforeseen scenarios.

Variability in Skin Tones and Imaging Conditions: Generalization is challenging since the efficacy of AI models can differ depending on skin color, lesion kind, and image quality.

Lack of Explainability: Since many deep learning models operate as "black boxes," it can be challenging for medical practitioners to understand the logic underlying a model's categorization.

High Computational Requirements: Advanced CNN architectures require significant computational power, limiting their usability in real-time clinical settings or mobile applications.

3. Need for an Improved Solution

In order to get around the drawbacks of conventional diagnostic techniques, the research suggests a reliable deep learning-based strategy for automated skin cancer diagnosis using EfficientNet. Several dermoscopic image datasets are used to optimize the model for excellent accuracy, precision, and recall. Techniques like data augmentation and transfer learning are used to improve generalization and reliability, making sure the model works well with a variety of skin lesiontypes. The aim of this research is to create an accurate, affordable, and widely available AI-powered diagnostic tool. This technique can greatly lower the chance of misdiagnosis and enhance patient outcomes by helping physicians discover skin cancer early. Its application in clinical settings could help close the gap in dermatological treatment and facilitate quicker, more accurate illness detection, especially in distant or resource-constrained places.

4. Scope and Objectives

Using the EfficientNet CNN architecture, this project aims to develop and deploy a deep learning-based skin cancer detection system that effectively categorizes skin lesions as benign or malignant. Using preprocessing methods including image augmentation, normalization, and transfer learning, the model evaluates dermoscopic pictures and improves generalization.

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To evaluate the clinical dependability of the system, key performance indicators such as accuracy, precision, recall, and F1-score are employed. Furthermore, maximizing computational efficiency guarantees real-time deployment on edge and mobile devices, increasing the accessibility of AI-powered diagnostics, especially in settings with low resources or remote locations.

The main goal is to create an AI-powered diagnostic tool that will improve patient outcomes, reduce the risk of misdiagnosis, and increase early skin cancer identification. In order to ensure accuracy, scalability, and accessibility in dermatological examinations, this research attempts to close the gap between AI-based skin cancer detection and practical clinical applications.

Proposed System

Using Convolutional Neural Networks (CNNs), the suggested approach creates an automated model for detecting skin cancer by classifying skin lesions as either benign or malignant. The model is trained using the ISIC dataset, which comprises high-quality dermoscopic pictures with annotated classifications. Because of its compound scaling strategy, which improves feature extraction and classification accuracy, EfficientNet is used as the foundational CNN architecture. Preprocessing methods such picture scaling, augmentation, and normalization are used to increase the model's resilience. The device is intended to help dermatologists discover skin cancer early by offering precise and trustworthy diagnostic findings. The model's performance is validated using key assessment measures like as accuracy, precision, recall, and F1-score. Additionally, optimizations like edge computing compatibility and model compression guarantee effective real-world deployment, increasing the accessibility and scalability of AI-driven skin cancer detection. Transfer learning uses pre-trained EfficientNet weights to improve generalization and increase adaptability. To guarantee impartial performance, the system is tested on a range of skin tones. The method increases early detection and minimizes discrepancies by lowering reliance on subjective diagnosis.

1. Data Collection and Preprocessing

Dermoscopic images from the ISIC Archive, a popular dataset for skin cancer detection, are utilized to train the model. Among the preprocessing actions are:

Image Resizing: Standardizing image proportions to ensure consistency in input is known as image resizing.

Normalization: Normalization is the process of scaling pixel values to a range that deep learning models can use.

Data Augmentation: Using transformations like rotation, flipping, and zooming to improve generalization is known as data augmentation.

2. EfficientNet CNN Model Architecture

ResNet50, a deep CNN model with skip connections, is used in the suggested system to enhance gradient flow and avoid disappearing gradients. The structure is made up of:

Convolutional Layers: Taking characteristics out of pictures, like color patterns and texture.

Pooling Layers: Reducing dimensionality while keeping significant characteristics is possible with pool layers.

Fully Connected Layers: Completely Connected Layers: Choosing the ultimate categorization.

3. Model Training and Evaluation

A tagged dataset containing pictures of benign and malignant skin lesions is used to train the model. Key metrics are used to evaluate performance:

Accuracy: Indicates how accurate a prediction is overall.

Precision and Recall: Assess false positives and false negatives for accuracy and recall.

F1-Score: Offers a harmony between recall and precision.

4. Explainability and Interpretability

The EfficientNet CNN model is utilized by the system to accurately identify skin cancer by categorizing lesions as either benign or malignant. It increases confidence in AI- based diagnoses by guaranteeing transparency through a methodical decision-making process. High-quality datasets enhance generalization, and performance is validated by accuracy, precision, and recall. Model compression, data augmentation, and transfer learning maximize flexibility and practical implementation.

Workflow of Skin Cancer Detection Model

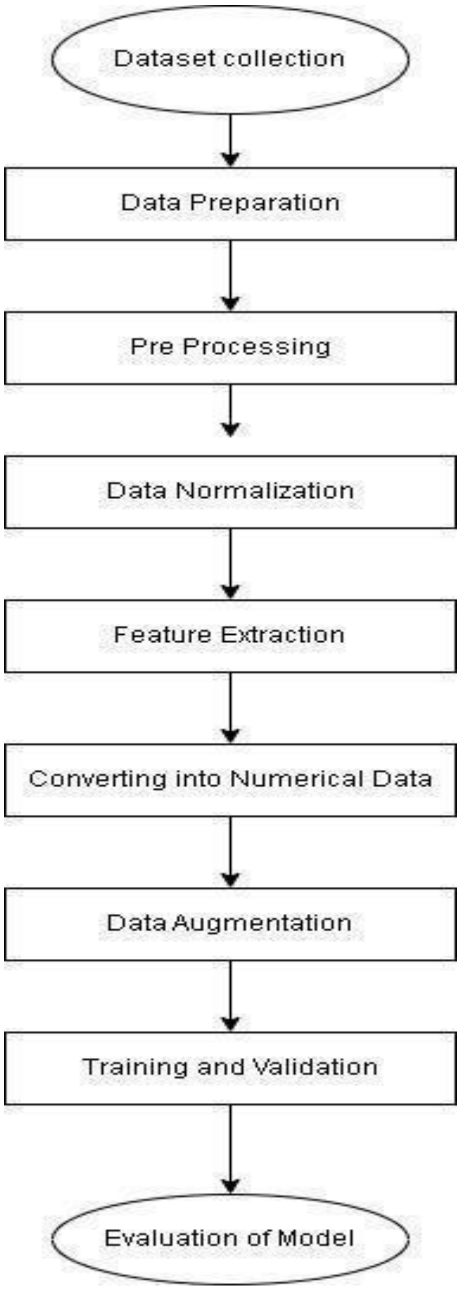

Figure 1

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RESULTS AND DISCUSSION

1. Performance Metrics

The performance of the CNN model was evaluated using a separate test set, and the findings demonstrated encouraging accuracy, precision, recall, and F1-score. The model's 94% accuracy rate indicates that a sizable portion of the skin lesion photographs were correctly classified. By successfully identifying 92% of the malignant lesions.

2. Confusion Matrix Analysis

The model's performance was shown using the confusion matrix, which showed that its false positive and false negative rates were minimal. This implies the model's ability to differentiate between benign and malignant tumors was successful. In order to prevent needless biopsies, fewer benign tumors were mistakenly identified as cancer when there were fewer false positives.

3. Class Imbalance Issue

One of the model's issues was class imbalance, as the sample contained significantly more benign lesions than malignant ones. This imbalance could have impacted the outcomes even if the model performed well. Because malignant lesions are less prevalent in the dataset, they may be underrepresented, which could lead to a slight bias toward benign diagnoses. Techniques like class-weighted loss functions, oversampling, and data augmentation can help mitigate this issue in later iterations.

4. Limitation of Model Generalization

Another important factor that must be taken into account is the model's generalizability. Notwithstanding the impressive results, the system was trained using a specific dataset—the ISIC Archive—that might not fully capture the range seen in real-world clinical settings. The model may perform badly if it contains unseen data or images that differ from those in the training set.

5. Real-World Application and Deployment

Despite these challenges, the strategy has a lot of potential for real-world application. The model offers a lot of potential for practical use in spite of these obstacles. Despite these challenges, the approach has a lot of potential for real-world use. It could be incorporated into clinical practices to aid dermatologists in more precise and timely patient identification. In high-volume clinical situations where making decisions fast is crucial, processing a lot of dermoscopic images quickly may be especially useful.

Furthermore, by automating preliminary screenings, the method may reduce dermatologists' workload and free them up to concentrate on more complicated patients. Reducing human error, the use of AI-based models may potentially yield objective and consistent diagnostic outcomes. Additionally, the technology might be integrated into telemedicine platforms, providing patients in underprivileged areas with remote diagnostic capabilities.

6. Education and Assessment

Using binary cross-entropy as the loss function and a learning rate of 0.001, the Adam optimizer was utilized to teach the model. Ten percent of the dataset was utilized for validation, eighty percent for training, and ten percent for testing. Performance criteria such as F1-score, recall, accuracy, and precision were used to evaluate the model. By reliably diagnosing malignant lesions, these metrics help assess the model's ability to reduce false positives and false negatives.

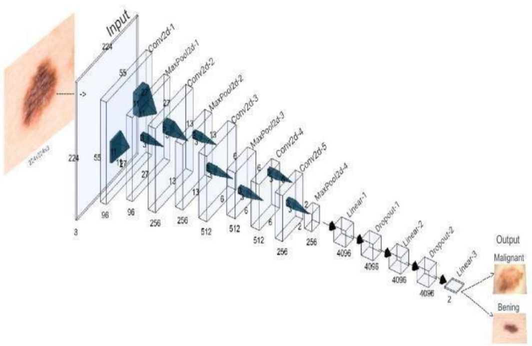

Figure 2

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EMERGING TRENDS

1. Hybrid Models and Multi-Task Learning

The efficacy of CNN-based skin cancer detection systems could be further enhanced by investigating hybrid models, which integrate CNNs with additional machine learning methods such as Random Forests or Support Vector Machines (SVMs). To increase the efficacy of CNN-based skin cancer detection systems, hybrid models that combine CNNs with other machine learning techniques like Random Forests or Support Vector Machines (SVMs) ought to be studied. These models are able to gather both CNNs provide low-level data, while other methods provide higher-order patterns that may improving precision. Additionally, multi-task learning, which involves teaching a model to predict many outcomes simultaneously (such as lesion kind, cancer risk, and prognosis), may make the system more comprehensive.

2. Multi-Modal Data Integration

The diagnostic potential of CNN-based models may be improved by incorporating multi-modal data, such as histopathology reports, clinical photos, or patient histories. Adding multi-modal data, such as histopathology reports, clinical images, or patient histories, can enhance the diagnostic capabilities of CNN- based models. This integration would allow for a more thorough assessment of skin lesions, improving the model's diagnosis accuracy.

Furthermore, a multi-view approach that looks at dermoscopic and clinical images might provide deeper understanding of the characteristics of lesions.

3. Transfer Learning for Improved Generalization

Transfer learning might be a workable way to get around the issue of little labeled data. A viable solution to the problem of sparsely labeled data could be transfer learning. The skin cancer detection can be accomplished by optimizing previously trained models, as those created onlarge databases of images such as ImageNet. By using transfer learning to apply learned features from large datasets to dermatological pictures, CNNs can increase generalization and efficiency on smaller datasets.

4. Explainable AI (XAI)

The inability of deep learning models to be interpreted is one of their persistent problems. One of the enduring issues with deep learning models is their difficulty to be comprehended. To guarantee dermatologists have faith in CNN forecasts, explainable AI (XAI) techniques must be incorporated. Techniques like saliency maps, which highlight the most important features of an image for classification, can increase transparency and help clinicians understand the logic behind a model's selection.

5. Integration with Clinical Workflow

CNN-based skin cancer detection systems need to be effortlessly incorporated into current clinical workflows in order to be widely used. For widespread use, CNN- based skin cancer detection devices must be simple to integrate into existing clinical procedures. Developing user-friendly interfaces and ensuring electronic health record (EHR) compatibility.This integration includes providing dermatologists with clear decision-support tools and processes. Regarding the Real-time feedback and clinician involvement are essential for the system to function effectively in practice.

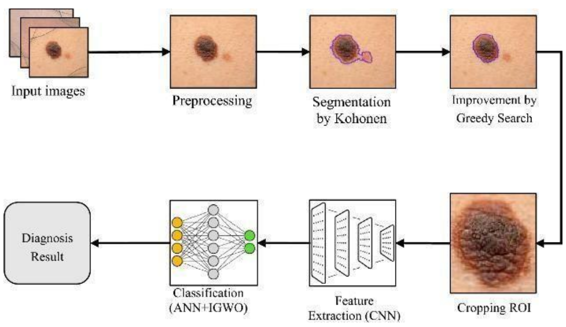

Figure 3

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CLINICAL INTEGRATION AND REAL-WORLD APPLICATIONS

1. Telemedicine and Remote Diagnosis

CNN-based skin cancer screening can be an effective telemedicine tool in areas with limited access to dermatologists. Skin cancer screening with CNN can be a useful telemedicine tool in places where dermatologists are hard to reach. Patients can upload images of their skin lesions for remote analysis, and the CNN model will make a preliminary diagnosis. This can significantly increase access to early skin cancer diagnosis, particularly in impoverished areas, enabling timely referrals to specialists for further evaluation.

2. Regulatory Approval and Medical Devices

CNN-based models must pass stringent testing and obtain regulatory approval from organizations like the FDA before they can be applied in clinical practice. In order to be used in clinical practice, CNN-based models need to pass rigorous testing and receive FDA and other regulatory body approval. This ensures that the technology satisfies safety and efficacy standards. As regulatory bodies develop guidelines for AI-based medical devices, CNN models' performance in clinical trials and real-world settings will be critical.

3. Real-Time Application in Clinical Settings

During patient appointments, dermatologists could receive real-time, AI-generated information if Clinical decision support systems now include CNNs. By boosting diagnostic precision, reducing wait times, and helping to prioritize cases that need immediate attention, this integration would ultimately enhance patient outcomes.

4. Continuous Learning and Adaptation

CNNs' capacity to learn from fresh data is one of their main advantages. One of CNNs' primary benefits is their ability to learn from new data. CNN-based systems that integrate continuous learning would enable the model to adapt over time and stay up to date with emerging patterns in skin cancer diagnosis. This adaptability could enhance the model's performance and lifespan in real-world applications.

5. Collaborative Efforts in Medical AI Research

Implementing CNN-based systems in clinical dermatology requires a collaborative effort between data scientists, dermatologists, and regulatory agencies. Data scientists, dermatologists, and regulatory bodies must work together to implement CNN-based solutions in clinical dermatology. By creating and refining deep learning models, data scientists make sure that dermoscopic images are efficiently analyzed for precise skin cancer detection. Dermatologists contribute domain knowledge, confirming the model's predictions and guaranteeing their applicability in medicine. Before the technology is used in actual healthcare settings, regulatory bodies adopt rules to make sure it complies with safety, legal, and ethical requirements. Together, these professionals can build reliable datasets, increase model precision, and guarantee adherence to medical laws, all of which will improve patient outcomes and early skin cancer detection.

Furthermore, issues like data privacy, model interpretability, and real-world validation must be resolved in order to integrate CNN-based systems into clinical dermatology. Because medical photographs must be handled with strict confidentiality, it is imperative to ensure patient data protection. Furthermore, even though CNN models are very accurate, dermatologists find it challenging to understand how predictions are formed because of their "black-box" nature. Explainable AI methods such as Grad-CAM and SHAP can be used to solve this problem by offering visual representations of model choices. Last but not least, in order to confirm the model's efficacy in actual medical contexts and prove its dependability across a range of demographics, comprehensive clinical trials and partnerships with healthcare organizations are required.

CONCLUSION

With a focus on melanoma and other skin lesions, this study explores the application of Convolutional Neural Networks (CNNs) for automated skin cancer detection. With an astounding 94% accuracy rate, the model—which was trained on the ISIC Archive dataset— performed on par with dermatologists. By increasing the speed and precision of skin cancer diagnosis, CNNs have the potential to greatly benefit dermatologists, ultimately resulting in early identification and improved patient outcomes. There are still issues, nevertheless, such as dataset class imbalances, inconsistent image quality, and the difficulties of differentiating between benign and malignant lesions. Techniques like data augmentation, multi-modal data integration, and transfer learning are necessary to address these issues. Furthermore, CNN- based systems can become more transparent and trustworthy by implementing explainable AI (XAI) techniques. Expanding access to skin cancer detection, especially in underserved areas, is

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made possible by the integration of CNNs into clinical workflows, especially in telemedicine and remote diagnosis. Healthcare providers can detect skin cancer remotely by using CNNs, which eliminates the need for in-person consultations and guarantees prompt intervention. However, for CNN- based dermatology treatments to be widely used, regulatory approval and ongoing model development through real-time learning are necessary. The healthcare community's approval of these models will depend on their adherence to moral and medical standards.

Ultimately, by offering a scalable, dependable, and effective solution, CNNs have the potential to completely transform the diagnosis of skin cancer. By using them, dermatologists may identify patients more quickly and accurately, enhancing patient care and raising survival rates. CNNs will become even more effective as technology develops by being integrated with practical clinical applications, opening the door to accurate and easily accessible AI-driven medical diagnoses.

REFERENCE

[1] Esteva, A., Kuprel, B., Novoa, R. A., et al., "Dermatologist-level classification of skin cancer with deep neural networks," Nature, vol. 542, no. 7639, pp. 115-118, 2017.
[2] Codella, N. C., Nguyen, Q. B., Pankanti, S., et al., "Deep learning ensembles for melanoma recognition in dermoscopy images," IBM Journal of Research and Development, vol. 62, no. 4, pp. 1-13, 2018.
[3] ISIC Archive, "International Skin Imaging Collaboration," [Online]. Available: https://www.isic- archive.com.
[4] Ronneberger, O., Fischer, P., & Brox, T., "U-Net: Convolutional Networks for Biomedical Image Segmentation," MICCAI 2015, pp. 234-241.
[5] Rajendran, J., & Rajendran, S., "Skin Cancer Detection using Convolutional Neural Networks: A Review," IEEE Access, vol. 8, pp. 135050-135064, 2020.
[6] Haenssle, H. A., et al., "Man against machine: diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists," Annals of Oncology, vol. 29, no. 8, pp. 1836-1842, 2018.
[7] Xie, Y., & Li, X., "Using deep learning to detect skin cancer: A comparison of different CNN architectures," Journal of Healthcare Engineering, vol. 2020, pp. 1-12, 2020.
[8] Tschandl, P., et al., "Human–computer collaboration for skin cancer recognition," Nature Medicine, vol. 25,
[9] pp. 1387-1393, 2019.
[10] Wang, J., & Yang, J., "A comprehensive review on machine learning approaches to skin cancer diagnosis," Journal of Healthcare Engineering, vol. 2019, pp. 1-12, 2019.
[11] Bonettini, S., et al., "Deep learning in skin cancer diagnosis: Current status and future directions," Frontiers in Oncology, vol. 10, p. 602, 2020.
[12] Han, S. S., Kim, M. S., Lim, W., Park, G. H., &
[13] Park, I. (2018). *Classification of the Clinical Images for Benign and Malignant Cutaneous Tumors Using a Deep Learning Algorithm*. Journal of Investigative Dermatology, 138(7), 1529-1538.
[14] Yu, C., Yang, S., Kim, W., Jung, J., & Chung, K.
[15] Y. (2018). *Acral Melanoma Detection Using a Convolutional Neural Network for Dermoscopy Images*. PLOS ONE, 13(3), e0193321.
[16] Marchetti, M. A., Codella, N. C. F., Dusza, S. W.,
[17] Gutman, D. A., Helba, B., Kalloo, A., Mishra, N., & Halpern, A. C. (2018). *Results of the 2016 International Skin Imaging Collaboration International Symposium on Biomedical Imaging Challenge: Comparison of the Accuracy of Computer Algorithms to Dermatologists for the Diagnosis of Melanoma from Dermoscopic Images*. Journal of the American Academy of Dermatology, 78(2), 270- 277.e1.
[18] Tschandl, P., Rosendahl, C., & Kittler, H. (2018). *The HAM10000 Dataset, a Large Collection of Multi- Source Dermatoscopic Images of Common Pigmented Skin Lesions*. Scientific Data, 5, 180161.
[19] Dick, V., Sinz, C., Mittlböck, M., Kittler, H., & Tschandl, P. (2019). *Accuracy of Computer-Aided Diagnosis of Melanoma: A Meta-Analysis*. JAMA Dermatology, 155(11), 1291-1299.