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DermLens: The Enhanced Skin Lesion Classification Using Deep Learning

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ABSTRACT

Skin lesion classification plays a critical role in the early detection and accurate diagnosis of dermatological diseases, particularly melanoma, one of the most life-threatening skin cancers. Though widely used, traditional CNN-based models often face challenges handling complex cases, leading to misclassification and reduced diagnostic reliability. To overcome these limitations, this research integrates MobileNetV2 and Inceptionv3, two highly efficient and lightweight deep learning architectures trained on the HAM10000 dataset—a benchmark dataset containing diverse and well-labelled skin lesion images. By leveraging these advanced models, the proposed framework enhances classification precision, ensuring more accurate and reliable identification of seven skin lesions. The model can recognise complex patterns in lesion images by optimising feature extraction during training, improving diagnostic results. Regarding classification accuracy, comparative tests on the HAM10000 dataset show that our method performs noticeably better than conventional CNN-based models, making it a reliable and scalable AI-driven option for automated dermatological analysis. The findings demonstrate how deep learning can transform skin disease identification by providing a precise, effective, and interpretable framework to help medical practitioners make quicker and better clinical judgments.

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1.0 INTRODUCTION

With more than 1.5 million new cases reported each year, skin disorders, particularly melanoma and non-melanoma skin cancers, have grown to be a significant global health concern. The rising incidence of these illnesses emphasises how important it is to identify them early and classify them accurately to increase treatment efficacy and lower death rates. The leading causes include environmental contaminants, hazardous compounds including nitrates and arsenic, and extended exposure to ultraviolet (UV) radiation. Due to the substantial visual similarity between different skin disorders and the slight differences in texture, colour, and structure, it is still difficult to distinguish between distinct skin lesions, even with breakthroughs in medical diagnostics.

Dermatologists and medical researchers have traditionally extracted features for diagnosing skin diseases using standard image-processing techniques. However, the emergence of artificial intelligence (AI), intense learning, has revolutionised medical imaging by making it possible for highly accurate automated diagnostic systems, which lessen the strain for medical practitioners. Among deep learning techniques, Convolutional Neural Networks (CNNs) have demonstrated exceptional efficacy in accurately diagnosing skin lesions. Cutting-edge models like MobileNetV2 and InceptionV3 are excellent at maximising classification performance, extracting hierarchical visual features, and producing quicker, more accurate diagnostic results.

This study uses MobilenetV2 and InceptionV3 to improve skin lesion classification. It intends to increase the precision of automated skin disease diagnosis by training and evaluating these models on the HAM10000 dataset, which consists of various skin lesion photos. The dataset is a valuable standard for assessing deep learning models in dermatological applications because it includes pictures of seven distinct skin lesions. This method uses a fuzziness-based classification technique and sophisticated CNN architectures to improve the process further.

Test samples are divided into three groups based on their level of uncertainty: low, medium, and high fuzzy cases. This approach guarantees that well-defined patterns make a more significant contribution to decision-making, resulting in diagnostic results that are more trustworthy and comprehensible. Comparative tests on the HAM10000 dataset show that this approach improves the resilience of AI-driven dermatological analysis and greatly increases classification accuracy. This study advances AI applications in dermatology and healthcare by combining deep learning and fuzzy logic to provide a novel approach to automated skin lesion classification.

2.0 RELATED WORKS

The capacity of deep learning-based skin lesion classification algorithms to accurately assess and classify dermatological pictures has led to their widespread use. Convolutional neural networks (CNNs), particularly architectures like VGG16, Inception ResNet V2, and DenseNet201, have been widely utilised for feature extraction and classification. These models use transfer learning, the process by which networks that have already been trained on big datasets like ImageNet are improved on smaller datasets like HAM10000. Nevertheless, despite their efficacy, CNN-based models frequently face difficulties with variations in picture quality and skin tone, texture, and lesion form, making precise categorisation challenging. Furthermore, there is a serious problem with data imbalance since training datasets do not adequately represent some uncommon skin illnesses, resulting in biased predictions favouring more prevalent lesions. A lack of explainability is another issue with many current systems, which makes it challenging for medical practitioners to understand model projections. This lack of transparency diminishes the reliability of AI-driven dermatological diagnostics.

Additionally, CNN-based models usually need a lot of processing power, making them impractical for real-time applications, especially in telemedicine or on mobile devices. The fact that these models frequently miss long-range dependencies in photos, which are crucial for differentiating between extremely complex or aesthetically identical skin conditions, is another significant drawback.

Researchers have explored ensemble learning approaches that combine multiple deep learning models to address these challenges to enhance classification accuracy and robustness. Effective ensemble strategies integrate architectures such as EfficientNet-B2, EfficientNet-B5, and ResNeSt101, which provide strong feature extraction capabilities while maintaining computational efficiency. These ensemble models significantly reduce misclassification rates and improve diagnostic reliability by employing methods like weighted averaging or voting mechanisms. However, despite these advancements, existing classification systems still face limitations. Achieving high accuracy across complex and overlapping skin lesions remains difficult, and ensuring generalizability across diverse patient demographics, skin tones, and imaging conditions is an ongoing challenge. Overfitting is another primary concern, as excessively fine-tuned models on limited datasets tend to perform poorly on real-world, unseen data. Additionally, many AI-powered dermatological tools lack intuitive and interactive interfaces, making them difficult to integrate into clinical workflows, particularly for non-expert users such as general practitioners or patients. The absence of real-time deployment capabilities further restricts the usability of these models in mobile-based applications and telemedicine services. Future advancements should focus on refining deep learning architectures, incorporating advanced data augmentation techniques, integrating additional clinical metadata for enhanced decision-making, and developing AI-assisted tools that are user-friendly and seamlessly adaptable for dermatological practice. By addressing these gaps, AI-driven skin lesion classification systems can achieve greater accuracy, reliability, and accessibility in real-world medical applications.

3.0 LITERATURE SURVEY

Skin lesion classification plays a vital role in medical image analysis, helping to catch skin diseases like melanoma early on. While traditional deep learning models, such as Convolutional Neural Networks (CNNs), have been the go-to for a while, recent strides in Transformer-based models, particularly Vision Transformers (ViTs), are proving even more effective. A 2023 IEEE paper presents an innovative method that combines fuzzy logic with ViTs to boost classification accuracy. The researchers suggest breaking the dataset into three categories based on how uncertain each sample is, which allows the model to tackle each subset more efficiently and enhance its learning. This method is especially useful in medical imaging, where some lesions look unclear or share traits with different classes. To further improve classification accuracy, the study recommends retraining classifiers mainly on samples with low fuzziness, minimising the influence of ambiguous samples that might add noise to the training. The proposed model was evaluated using the PAD-UFES-20 dataset, a well-known benchmark in dermatological image classification. The experimental results indicate that the fuzziness-based transformer model surpasses traditional deep learning methods by effectively managing uncertainty within the dataset. Future research could refine this approach by testing it on more datasets and enhancing the model's ability to generalise across various skin conditions (Yasmin *et al.,* 2023).

Arulmurugan *et al.* (2024) introduce an innovative approach to improve skin disease diagnosis. It combines Mini-batch Fuzzy C-Means (MBFCM) clustering with Convolutional Neural Networks (CNNs) to tackle the computational hurdles often faced by traditional FCM methods while boosting the effectiveness of CNNs in this field. MBFCM is well-regarded for its image segmentation capabilities, particularly because it can manage ambiguity effectively. However, traditional FCM can be pretty demanding in computation, especially when dealing with large datasets. To make things easier, the authors utilise a mini-batch strategy that lightens the computational load and speeds up convergence, making FCM more feasible for extensive medical image analysis. The MBFCM-CNN hybrid model is specifically designed to segment images of skin lesions, pinpoint areas of interest and improve the quality of the data fed into the CNN, which is responsible for extracting and classifying features. This leads to better diagnostic accuracy. The study also highlights the potential real-world applications of this method, such as facilitating early detection and treatment planning for dermatologists, particularly in areas where specialised healthcare is hard to come by. With its reduced computational demands, this approach is well-suited for use in resource-limited environments, like mobile health platforms. In summary, the paper showcases a significant step forward in medical image analysis by merging MBFCM clustering with CNNs, effectively addressing the computational challenges of traditional FCM and enhancing the performance of CNNs in diagnosing skin diseases.

Their study (Reka *et al.,* 2024) utilises the HAM10000 dataset, which features 10,015 dermoscopic images sorted into seven skin lesions. They apply data augmentation techniques like geometric transformations and colour space adjustments to make the dataset more robust and varied. The study investigates two main QML models: the Quanvolutional Neural Network (QNN) and the Quantum Support Vector Classifier (QSVC). The QNN merges quantum computing concepts with classical convolutional neural networks by adding quanvolution layers that apply quantum transformations to the input data, allowing for the extraction of intricate features. On the other hand, the QSVC model pulls features from the MobileNet pre-trained network, using quantum computing to tackle classification tasks. When comparing the performance of these QML models to several well-known classical pre-trained models, the QNN stands out, primarily when it employs the RY qubit rotation alongside the Pauli-Z gate in the quanvolutional layer, achieving a classification accuracy of 82.86%. This performance surpasses all other models assessed in the study. Meanwhile, the QSVC reaches a classification accuracy of 72.5%, which is on par with the classical pre-trained models.

Karthik *et al.* (2024) introduce an innovative method to enhance the accuracy of skin cancer diagnoses through cutting-edge image classification techniques. Skin cancer poses a significant global health challenge, making early and accurate detection vital for effective treatment. Traditional diagnostic methods often fall short when faced with skin lesions' diverse and intricate nature, highlighting the need for more advanced computational strategies. In this study, the authors proposed a hybrid classification system that combines two unique neural network architectures: the Swin Transformer and the Dense Group Shuffle Non-Local Attention (DGSNLA) Network. The Swin Transformer, a type of Vision Transformer, excels at capturing hierarchical representations of images, which is particularly beneficial for medical image analysis. Meanwhile, the DGSNLA Network is a specially designed convolutional neural network that merges DenseNet169, Group Shuffle Depth-wise (GSDW) blocks, and an Enhanced Non-Local Attention (ENLA) block. This combination effectively combines global and local features, resulting in a richer representation. To assess the performance of this hybrid model, the researchers utilised the HAM10000 dataset, a well-known collection of dermoscopic images that serves as a benchmark for skin lesion classification algorithms. The findings revealed a notable enhancement compared to traditional methods, underscoring the model's capability to classify skin lesions accurately. In summary, this study presents a groundbreaking hybrid deep learning framework that harnesses the advantages of both transformer-based and convolutional neural network architectures for skin cancer classification. Integrating the Swin Transformer with the DGSNLA Network enables robust feature extraction and representation, ultimately improving diagnostic accuracy.

Debelee (2023) points out the increasing rates of skin cancer worldwide and stresses the urgent need for practical diagnostic tools to help with early detection and timely intervention. The authors thoroughly analyse various cutting-edge machine learning algorithms, such as Decision Trees, Support Vector Machines (SVM), Random Forests, and K-Nearest Neighbours (KNN), assessing their ability to identify and classify different skin lesions. This research underscores the critical role of incorporating machine learning into skin lesion assessments, which could significantly propel advancements in dermatological science, leading to diagnostic systems that are more accurate and faster for dermatologists and patients. Additionally, the authors explore how machine learning models can leverage patient metadata alongside lesion images, further boosting their predictive capabilities. This comprehensive approach aligns perfectly with the growing trend towards precision medicine in dermatology. The paper highlights that integrating machine learning techniques into skin lesion detection and classification can enhance diagnostic accuracy and improve treatment outcomes.

4.0 EXISTING SYSTEM

Current skin lesion classification systems rely on deep learning models, specifically Convolutional Neural Networks (CNNs), to evaluate and classify dermatological images. Popular architectures like VGG16, Inception ResNet V2, and DenseNet201 have shown strong feature extraction capabilities. These architectures use transfer learning to refine pre-trained models on specialised datasets like HAM10000. Even while these models have demonstrated encouraging accuracy, they still have many problems, such as trouble differentiating between ambiguous lesions, picture quality variations, and skin tone, texture, and shape. Another serious problem is data imbalance, which occurs when predictions that favour more prevalent lesions are skewed due to underrepresented skin disorders. Furthermore, medical experts find it challenging to trust and comprehend CNN-based models' decision-making process due to their frequent lack of interpretability. Their high computational requirements further limit their real-time applicability, especially in telemedicine or mobile systems. Many models still have trouble identifying long-range relationships in images, which is important for distinguishing between superficially identical or extremely complex skin diseases, even with improved training methods. Problems like overfitting, suboptimal accuracy for some complex lesions, and limited generalizability across a variety of patient demographics still exist, even though ensemble learning techniques combining models such as EfficientNet-B2, EfficientNet-B5, and ResNeSt101 have been investigated to improve classification performance. Furthermore, the lack of real-time deployment capabilities limits usability in mobile-based apps and telemedicine. At the same time, the absence of interactive and user-friendly interfaces makes it difficult to integrate into clinical workflows, especially for non-specialists. To overcome these constraints, deep learning architectures must be improved, data augmentation methods must be enhanced, clinical metadata must be included, and easily interpretable AI-assisted tools must be developed.

5.0 PROPOSED SYSTEM

By merging MobileNetV2 with InceptionV3, the proposed system enhances skin lesion categorisation and ensures high precision, computational economy, and reliable recognition of seven unique skin lesion types. Employing advanced data preprocessing and augmentation methods effectively addresses challenges such as data imbalance, feature misrepresentation, and intra-class variation in lesion appearance. It was trained using the HAM10000 dataset. By leveraging the light-weighting structure of MobileNetV2 and depth-wise separable convolutions for minimising the computational load at the expense of preserving essential visual information, this system finds a balance between speed, efficiency, and accuracy in comparison to traditional CNN-based systems that struggle to extract features. With multi-scale feature extraction, classification performance is further improved by InceptionV3. The model can extract global and detailed lesion features by doing so, making it suitable for real-world medical purposes. To ensure a well-balanced dataset and reduce classification bias, the training process includes scaling, normalisation, and augmentation strategies such as rotation, zooming, and shifting. The model is resilient in detecting unseen dermatological examples due to transfer learning and optimisation techniques, enhancing its capacity for generalisation. Rigorous validation confirms its accuracy, stability, and reliability, automating and accelerating the classification of skin diseases and reducing dependency on human examination. Even with a change in background, lighting, and lesion image, the process has high classification accuracy with an assurance of objective results. It is advantageous in clinical, telemedicine, and mobile diagnosis due to its efficiency in computing and ability to make fast inferences. Due to the employment of deep learning, this intelligent solution assists dermatologists in enabling faster, more precise decisions and earlier detection, diagnosis, and treatment planning of various skin diseases by filling the gap between computer-based dermatological examination and realistic medical experience.

6.0 DESIGN ARCHITECTURE

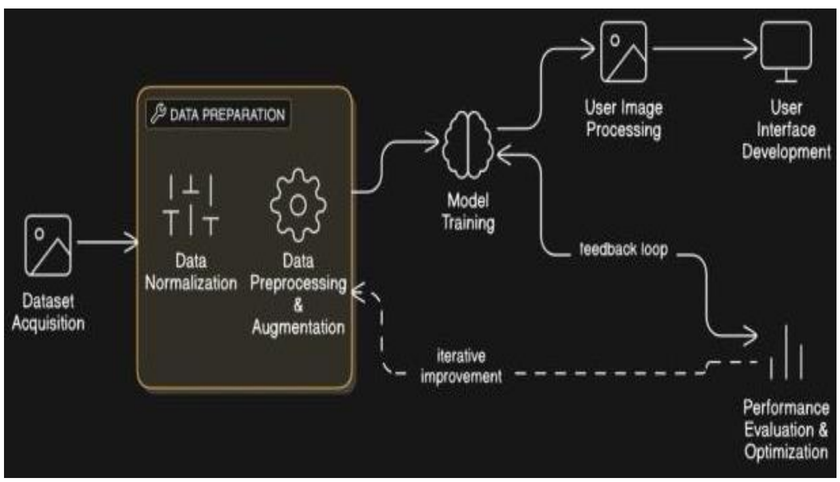
Skin diseases, especially melanoma and other critical dermatological conditions, require accurate and early detection to ensure timely medical intervention and better patient outcomes. With the rising incidence of skin-related ailments, automated diagnostic solutions powered by artificial intelligence (AI) and deep learning have become essential for assisting dermatologists in precise assessments. The HAM10000 dataset, a widely used dermatological image dataset containing seven distinct skin lesion types, is crucial in training deep learning models. The dataset is systematically downloaded, categorised, and structured to ensure organised processing, minimising misclassification risks and improving learning efficiency. Proper dataset preparation enhances model performance, allowing it to generalise well across real-world cases. Preprocessing techniques such as resizing, normalisation, and augmentation are applied to refine image quality and reduce biases. Augmentation techniques like height and width shifting, rotation, and zooming enhance dataset diversity, enabling the model to recognise lesions under different conditions. The dataset is then split into an 80:20 ratio for training and validation, ensuring the model learns effectively while maintaining generalisation capability. Balancing the dataset by selecting an equal number of images for each lesion type prevents bias, making the classification process more accurate and reliable.

Deep learning architectures such as MobileNetV2 and InceptionV3 are employed to achieve highly efficient skin lesion classification due to their superior feature extraction capabilities. MobileNetV2 is chosen for its lightweight design and computational efficiency, making it ideal for mobile and cloud-based healthcare applications, while InceptionV3 is designed to capture intricate image details, enhancing classification accuracy. The training involves loading the preprocessed dataset into these models, allowing them to learn hierarchical patterns that differentiate skin lesion types. Optimisation techniques such as dropout layers, batch normalisation, and adaptive learning rate adjustments prevent overfitting and ensure stable model convergence. Performance metrics, including accuracy, precision, recall, and F1-score, are continuously monitored to assess the effectiveness of the models. A comparative evaluation of MobileNetV2 and InceptionV3 helps determine the optimal model for real-world applications. Iterative refinements, including hyperparameter tuning and additional data augmentation strategies, further improve the model’s robustness. By leveraging the strengths of both models, this system achieves a high level of precision in classifying skin lesions, offering a scalable and reliable AI-powered dermatological analysis solution.

Once the models are fully trained and optimised, an efficient image preprocessing pipeline is implemented to handle real-time user input, ensuring seamless classification of newly uploaded images. Input images undergo preprocessing steps such as resizing to 224x224 pixels, normalisation, and format conversion to ensure consistency with training data. This structured preprocessing approach ensures high classification accuracy in real-world scenarios by reducing discrepancies in image quality. To make the system accessible and user-friendly, an interactive web-based interface is developed using Streamlit, allowing users to upload images and receive instant classification results. Streamlit provides a lightweight and intuitive platform, ensuring a smooth and responsive user experience. This application bridges the gap between AI-driven dermatological analysis and practical usability, making skin disease detection more accessible to healthcare professionals and the general public. By integrating deep learning with an interactive interface, this system demonstrates the potential of AI-driven healthcare applications in revolutionising dermatological diagnostics, ultimately improving early detection, diagnosis, and treatment planning for various skin conditions.

Figure 1

Architecture Diagram



7.0 CONCLUSION

This skin lesion classification system integrates deep learning with a user-friendly interface to enhance automated dermatological analysis. Using the HAM10000 dataset and a systematic procedure that includes preprocessing, model training, picture augmentation, and dataset preparation, it successfully diagnoses seven kinds of skin lesions. MobileNetV2 and InceptionV3 optimise efficiency and precision, ensuring robust classification even for complex cases. The method leverages an 80-20 training-validation split to promote generalisation and maintains consistency through a structured image preprocessing pipeline. Streamlit provides an interactive interface, enabling smooth image uploads and real-time classification, making it accessible to medical specialists and everyday users. Accuracy and dependability are guaranteed for real-world deployment by rigorous testing, which includes unit, integration, and user acceptability testing. Future developments can further increase its efficacy, including real-time feedback systems, sophisticated deep learning structures, and dataset extension. This technology helps detect skin diseases early, facilitating prompt medical intervention and improved patient outcomes by bridging the gap between AI-driven healthcare and proper usage.

Figure 2

Confusion Matrix

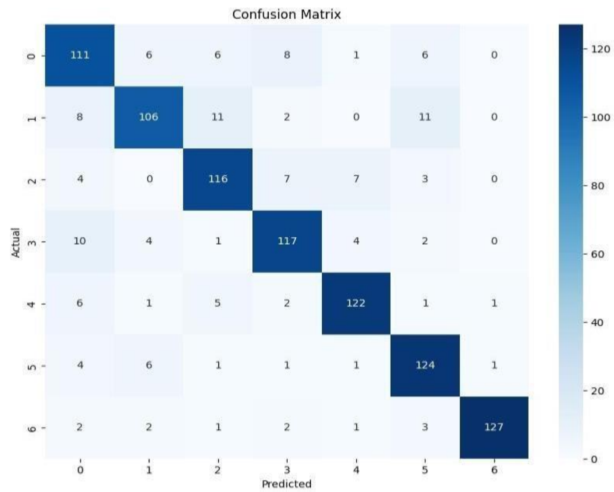


Figure 3

Accuracy Score

	precision	recall	f1-score	support
0	0.77	0.80	0.78	138
1	0.85	0.77	0.81	138
2	0.82	0.85	0.83	137
3	0.84	0.85	0.84	138
4	0.90	0.88	0.89	138
5	0.83	0.90	0.86	138
6	0.98	0.92	0.95	138
accuracy			0.85	965
macro avg	0.86	0.85	0.85	965
weighted avg	0.86	0.85	0.85	965

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