Enhancing Skin Cancer Detection: A Study on Feature Selection Methods for Image Classification

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Visually similar images can be easily identified by the human eye; however, expert knowledge is required to accurately interpret medical images, particularly those depicting skin affected by cancer. As skin cancer is becoming more commonplace worldwide, there is a growing need for qualified specialists to help with its diagnosis. Several intricate genetic abnormalities lead to cancer, one of the most serious illnesses. Skin cancer is the most frequently diagnosed type of cancer. The present research examines two main methods: segmentation and feature extraction, since early identification is essential to enhancing treatment results. Our research focuses on identifying malignant melanoma, which is caused by an overabundance of melanocytes in the dermis layer of the skin. We used the well-known dermatological approach known as Asymmetry, Border, Color, and Differential (ABCD) dermo copy to aid in early identification. Asymmetry (differences in shape and structure), border irregularity (uneven or jagged borders), color variation (differing pigmentation inside the lesion), and differential structure (development in size and appearance over time) are the criteria used in this technique to analyze skin lesions. CNN-based deep learning models are used for image pre-processing, segmentation, feature extraction, and classification in the organized process of the suggested framework. Additionally, sophisticated digital image processing methods like size estimates, color identification, border analysis, and symmetry detection are included. By using CNNs to collect texture-based information, feature extraction is improved and skin lesions can be precisely categorized. We suggest using a Backpropagation Neural Network (BPNN) to increase classification accuracy and make efficient decisions when distinguishing between benign and malignant skin diseases. To overcome this difficulty, machine learning classifiers have surfaced as a viable way to automate the classification of images for skin cancer. In this paper, deep Convolutional Neural Networks (CNNs) are used to construct a predictive model for skin cancer diagnosis. Using the HAM10000 dataset, the suggested method produced a 92% accuracy rate.

Keywords: Skin Cancer, Image processing, Convolutional Neural Network, ABCD technique

Introduction:

Skin cancer occurs when unrepaired DNA damage leads to mutations, causing the development of abnormal cells in the epidermis, the outermost layer of the skin, as illustrated in Figure 1. Mutations in skin cells can cause cancer. Each year, approximately 800,000 new cases of skin cancer are reported globally, resulting in around 2,100 fatalities. The primary causes of skin cancer are exposure to ultraviolet (UV) radiation from the sun and UV tanning beds [1].

Figure 1. Skin cancer [2]

Melanoma, Squamous Cell Carcinoma (SCC), and Basal Cell Carcinoma (BCC) are the three main types of skin cancer. As shown in Figure 2, the first two skin tumors are classified as non-melanoma skin cancers. The most prevalent type of skin cancer in both men and women is non-melanoma. Basal cell carcinomas (BCCs) most commonly develop on sun-exposed areas of the skin, particularly the face, ears, neck, scalp, shoulders, and back. If not detected and treated early, basal cell carcinomas (BCCs) can become locally destructive. In rare cases, they may spread (metastasize) and become life-threatening.

Figure 2. Basal Cell Carcinoma [3]

Squamous cell carcinoma (SCC) are the second most common type of skin cancer, with an estimated 1.8 million population diagnosed annually in the United States. If not identified and treated promptly, SCCs can sometimes overgrow and spread, causing up to 15,000 deaths invasive SCCs each year. SCCs are common in sun-exposed areas like the ears, face, scalp, neck, and hands, where the skin frequently displays signs of sun damage, such as wrinkles and age spots [4].

Every year, skin cancers cause approximately 2,100 deaths worldwide. A less frequent but much more deadly form of skin cancer is Malignant Melanoma (MM). The incidence of skin cancer varies by ethnicity, with White individuals having a rate of 9.2 per 100,000, Hispanic individuals at 1.9 per 100,000, and Black and Asian individuals ranging from 0.7 to 1.2 per 100,000. According to reports, MM has emerged as the "most significant cancer of the twenty-first century." Over time, the lifetime risk for MM has gone up. Longer life expectancy, higher activity in UV-intense areas, and increased lifetime exposure to ultraviolet radiation (UVR) as a result of depleting ozone could all be contributing factors to this upward trend [5].

Reports indicate that skin cancer is less common in the South, suggesting a potential North-South gradient. It is observed more frequently in the North and less in the South, where the population tends to have lighter skin tones, and resides at higher elevations. The melanoma as shown in Figure 3 [6], originates from melanocytes i.e, the skin cells responsible for producing melanin, the pigment that gives skin its color. This type of cancer arises due to mutations in these cells. Sometimes melanomas can develop from moles, which they frequently mimic. Melanomas can develop even in areas of the body that are not typically exposed to the sun. Sunburn from prolonged, strong sun exposure is frequently the cause of melanoma. Using tanning beds also raises the chance of developing melanoma. Over 207,390 new patients of melanoma were estimated to develop skin cancer in the United States in 2021, with approximately 106,110 of those instances being invasive. Melanoma, as shown in Figure 3, is the most serious of the three most common types of skin cancer. An estimated 7,180 people were estimated to be died of melanoma in 2021 [7].

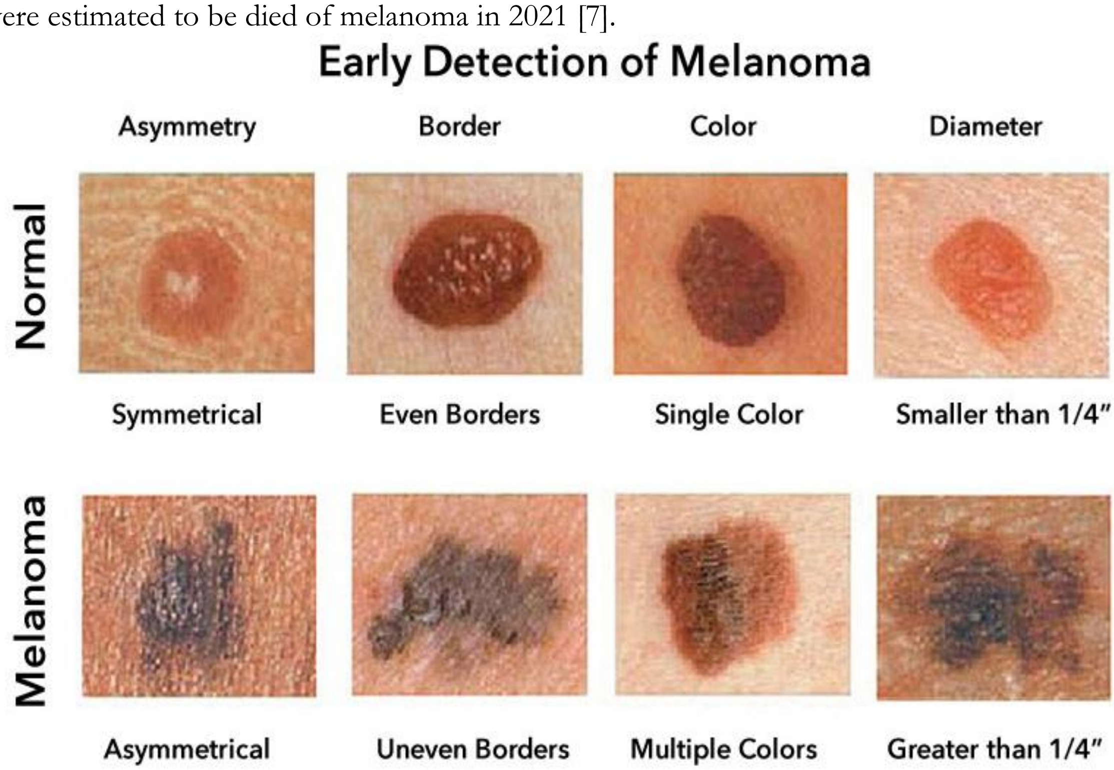

Figure 3. Melanoma Cancer [7]

Dermatologists utilize dermoscopy, a visual inspection technique with polarised light magnification, to assess patients. A patient's medical diagnosis is frequently influenced by their background, race, social customs, and sun exposure. Dermoscopy is the process of inspecting or examining skin lesions using equipment that consists of a polarisable light system and a high-quality magnifying lens. High-resolution digital single-lens reflex (DSLR) cameras or smartphone camera attachments are used to take dermoscopic pictures. Since the advent of numerous sizable publically accessible dermoscopic datasets containing various forms of benign and malignant skin lesions, the use of dermoscopic pictures for AI algorithms has emerged as a popular area of study [8].

Medical imaging, in particular, stands to be revolutionized by AI-enabled computer-aided diagnostics (CAD) technologies. In clinical practice, medical imaging, such as computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound, is widely utilized.

In the field of dermatology, dermoscopy and confocal microscopy techniques enable more detailed in vivo visualization of disease characteristics and improved risk classification. [9]. Deep learning has offered many end-to-end solutions for identifying anomalies across a variety of medical imaging picture modalities, including skin lesions, foot ulcers, lung cancer, esophageal cancer, brain tumors, and breast cancer.

Melanoma, the most severe form of skin cancer, is caused by an excess of melanin pigments, leading to changes in skin color and texture, often appearing as a dark patch. Data indicates a concerning rise in melanoma cases, as this cancer spreads rapidly. However, in addition to the fact that not all melanomas have the same characteristics, visual analysis is constrained by human visual skills, perception, and sensitivity. The information in the images is especially important, as the tumor represents an abnormal proliferation of human cells that grow uncontrollably [10]. The tumor can be detected by the range of colors and textures of the human tissues under examination. Visual patterns with brightness, color, slope, size, and other characteristics are called textures. These textures can be properly classified when divided into sub-images based on regions of interest.

With the increasing prevalence of skin cancer and low awareness, a system for identifying and classifying skin cancer from images is essential. Estimates suggest that nearly 40% to 50% of fair-skinned individuals who live to age 65 will develop at least one case of skin cancer. Diagnosing skin cancer can be challenging as it depends on human eyesight and clinical expertise. Therefore, software capable of distinguishing melanoma from benign lesions in its earliest stages is necessary. This softwares can assist dermatologists in the diagnosis of skin cancer. Since dermoscopic images include imaging technology that increases diagnostic accuracy and may lower the human death rate. However, interpreting these images requires human expertise, as they can be complex on their own. Individuals whose melanoma is detected and treated before spreading to the lymph nodes have a five-year survival rate of 99%. Almost all patients can be successfully treated if skin cancer is detected at an early stage. Healthcare organizations, particularly those in developing nations, can benefit from this cancer categorization model by using it to enhance patient care and lower expenses.

Objectives and Novelty Statement:

The primary objective of this research is to use deep Convolutional Neural Networks (CNNs) to create an accurate and effective skin cancer detection system. The research's objectives are to:

- Use cutting-edge image processing and machine learning approaches to increase the early diagnosis of malignant melanoma.

- Improve classification accuracy by using feature extraction techniques and an optimized CNN architecture.
- Provide a dependable and automated diagnostic tool to lessen reliance on dermatologists.

This research is novel because it combines CNN-based feature extraction with the ABCD dermoscopy technique to produce better classification performance. Furthermore, the suggested method offers a thorough and reliable framework for skin cancer detection by fusing deep learning with conventional GLCM texture analysis.

Related Work:

Author in [11] obtained classification results for three types of injuries by combining resilient Convolutional Neural Networks (CNNs) into a structure. Experimental results showed that the classification of the three classes achieved an average area under the receiver operating characteristic curve (AUC) of 89.10%. To tackle the emerging challenges in the field of skin lesion image processing lesion segmentation (task 1), lesion dermoscopic feature extraction (task 2), and lesion classification (task 3) is utilized. Another study [11], presented two deep learning techniques. In this study the ISIC 2017 dataset was used to assess the suggested deep learning frameworks. The results of the experiments demonstrated the potential accuracy of these frameworks: 75.30% for task 1, 84.80% for task 2, and 91.20% for task 3. Author in [12], suggested a strategy considering the ABCD (Asymmetry, Edge, Color, and Diameter) methodologies. The metric TDS (Total Dermoscopy Score) was computed to carry out the classification to detect melanoma. The results showed a 90.45% accuracy rate. Another author [13] proposed feature extraction that appear in the lesion image by utilizing the Grey Level Co-occurrence Matrix (GLCM) technique. A statistical technique called GLCM examines an image's texture by taking into account the spatial relationship between pixel intensities. It calculates the frequency at which pairs of pixel values appear in a specific spatial relationship to identify patterns of texture contrast, correlation, energy, and homogeneity. During the detection phase, a team of classifiers determine whether a malignant tumor was present.

Images from the ISIC library were used for various studies. The accuracy of skin cancer detection offered by the suggested approach is more than 88.00%. Researchers [14] suggested an SVM-based skin cancer detection framework for early skin cancer detection. Using filtering pictures, the dermoscopic image of skin cancer was acquired and subjected to several pre-processing techniques. Specific features from the image were selected using the GLCM method to assist in building the classifier. Whether the photograph showed a malignant or non-cancerous tissue was evaluated by the classification. The suggested structure has a 91% accuracy rate.

Author in [15] researched the use of picture texture analysis for breast cancer subtype detection. The analysis took into account the magnetic resonance images' pixel intensity distribution. The GLCM matrix's entropy parameters produced noteworthy contributions to image classification, which may be helpful for breast cancer treatment and therapeutic monitoring. Using cutting-edge methods like Diffusion Tensor Imaging. Author in [16] recently suggested a solution to a problem in magnetic resonance imaging diagnosis: separating ambiguous images that appear to be glioblastoma multiforme from solitary metastases using 3D textural resources with GLCM. Researchers in [17] demonstrated a promising method for medical diagnostics by applying GLCM and Local Standard Descriptor parameters to brain magnetic resonance images. To diagnose breast cancer, an author [18] employed machine learning techniques in the Wisconsin Breast Cancer database, including Support Vector Machine (SVM), Decision Tree, Naive Bayes, and K nearest neighbors. The SVM has the highest accuracy, 91.13%, according to the data. Yoon et al. [19] chose parameters for texture analysis in magnetic resonance imaging in a recent study on lung cancer. Linear regression was used to determine the relationship between tumor size and area. The MRI pictures were checked using a contrast material injection, and throughout a 120–180 s time window, improvements were noted in the chosen texture parameters.

Another author demonstrated two probabilistic and predictive models for identifying liver cancer in humans from computed tomography images [20]. Using a variety of classification models, including Linear Discriminant Analysis (LDA), Logistic Regression (LR), and a predictive model that uses Multilayer Perceptrons (MLP), Haralick [21] computed parameters in the GLCM of images of the liver with and without injury to estimate the likelihood that a patient has liver cancer or not. When compared to LDA (91%) and MLP (92.40%), it was demonstrated that logistic regression (92.67%) produced the best accuracy. In another research author [22] used SVM (Support Vector Machine) to classify data extracted from brain images to characterize benign or malignant tumors. To evaluate the performance of these resources, several texture methods were used, such as the histogram, Gray Level Co-occurrence Matrix (GLCM), and gray level execution length matrix (GRLM), all analyzed separately. Performance results ranged from 82.97% to 91.83%. In [23], author demonstrated an efficient proposal to identify normal and abnormal tissues from MRI images of the brain. According to the testing data, one was classified with a sensitivity of 89.72%, a specificity of 90.20%, and an accuracy of 91.51%. Using the information on the texture, color, contrast, and GLCM of the examined images, machine learning techniques were applied. A technique developed by a researcher [24] generates a set of compact representations of infrared breast images, effectively distinguishing between benign and malignant cases, achieving competitive results with an AUC of 0.989. Numerous works for detecting skin cancer are highlighted in the reviewed literature, including deep learning models, feature extraction methods like GLCM, and diagnostic frameworks that use SVM and decision trees. Although previous researches have shown encouraging results, such as utilizing ABCD methodology and SVM-based frameworks to achieve classification accuracies of up to 91%, these approaches frequently lack the thorough integration of numerous techniques to improve diagnostic accuracy. To improve detection accuracy and reliability, our study builds upon these foundations by fusing the advantages of GLCM texture analysis, ABCD dermoscopy, and CNN-based deep learning. By offering a more reliable framework for early melanoma diagnosis, this hybrid approach overcomes the drawbacks of earlier techniques.

Methodology:

In this section, the methodology is outlined. We propose a model for skin cancer detection that will be based on a convolutional neural network (CNN). The architecture of the proposed model design was created using draw.io. Draw.io, now known as **diagrams.net**, is a free, web-based tool for creating diagrams and flowcharts. It provides a user-friendly interface for designing various types of visuals, including organizational charts, network diagrams, and software architectures. It allows users to draw and design complex structures with ease, offering a wide range of shapes, templates, and customization options. Draw.io can be used online or offline, and it integrates with cloud storage services like Google Drive, OneDrive, and Dropbox for easy sharing and collaboration. Figure 4 presents the layers of our proposed model.

Input Layer:

The input layer receives the preprocessed images, each with a size of 224 × 224 pixels, as the initial data for the model.

Convolutional Layers:

To efficiently capture crucial features including edges, forms, and textures, the CNN design has three convolutional layers, each with a 3 × 3 kernel size. To enhance model learning capabilities and incorporate non-linearity, the Rectified Linear Unit (ReLU) activation function was employed following each convolutional operation. The equation of the layer is given below [24]:

$$Y_{ij}^{k} = \Sigma_{m=0}^{M-1} \Sigma_{n=0}^{N-1} X_{i+m,j+n}.W^{k} + b^{K} \qquad (1)$$

Here X is the input image. W is the filter and b denotes the bias term. The M and N used here are for the height and width of the filter.

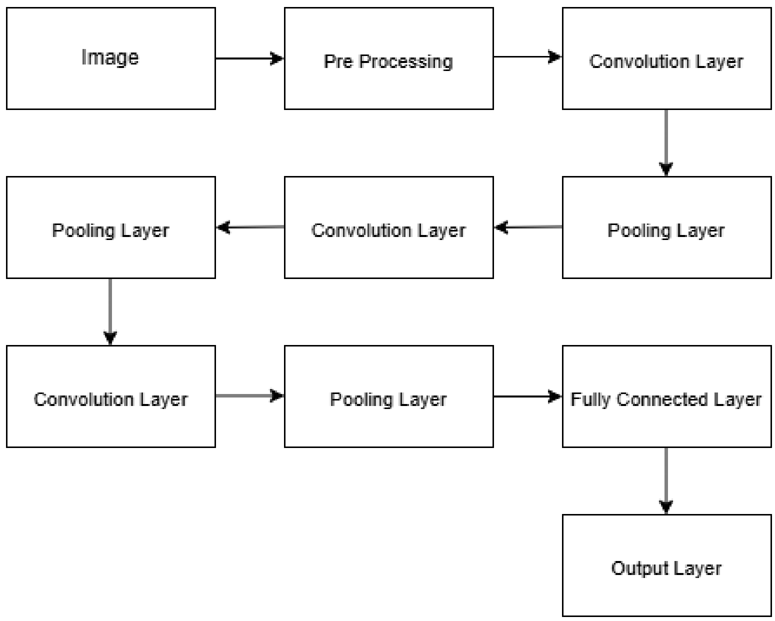

Figure 4. Architecture of the proposed model

Pooling Layers:

Following each of the three convolutional layers, max pooling with a 2 × 2 kernel size is used to minimize the spatial dimensions of the feature maps without sacrificing significant information. By doing this, overfitting is avoided and computing complexity is decreased. The equation of the layer is given below [24]:

$$Y = f(WX + b) \qquad (2)$$

Here X is the input vector. W is the weight matrix. B is the bias vector and f is the activation function ReLu.

Fully Connected Layer:

The collected features wer flattened and then run through fully connected layers after going through several convolutional and pooling layers. These layers aid in the final categorization by learning intricate feature representations. The equation of the layer is given below [25]:

$$Y_{i} = \Sigma N_{j=1}^{Ezi}\, e^{EZ} \qquad (3)$$

Here Z is the input vector. N is the number of classes and I is the index of the current class.

Output Layer:

Multi-class classification is made possible by the final output layer, which generates class probabilities for every type of skin lesion using the SoftMax activation function.

Dataset:

The algorithm was trained on the HAM10000 dataset is shown in Figure 5, which includes seven different kinds of skin lesions. To increase the diversity of the dataset, the images were reduced to 224 × 224 pixels for consistency and go through many preprocessing stages, including data augmentation techniques like rotation, flipping, zooming, and shearing. By mimicking the variability found in lesion images in the real world, this procedure prevents overfitting.

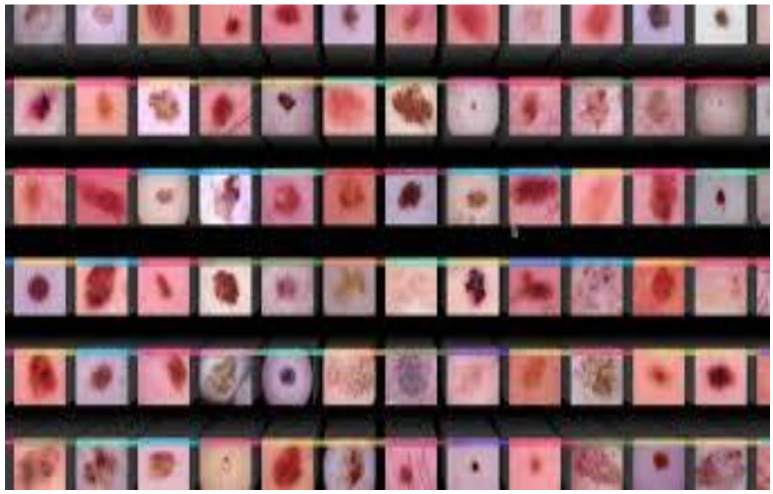

Figure 5. HAM10000 dataset [25]

Results and Discussion:

The proposed model achieved an accuracy of 92%, with a low loss, demonstrating its robustness, as shown in Figure 6. To make sure the model generalizes well across various dataset subsets, cross-validation was employed. The contribution of the ensemble method to the overall performance was also evaluated using CNN.

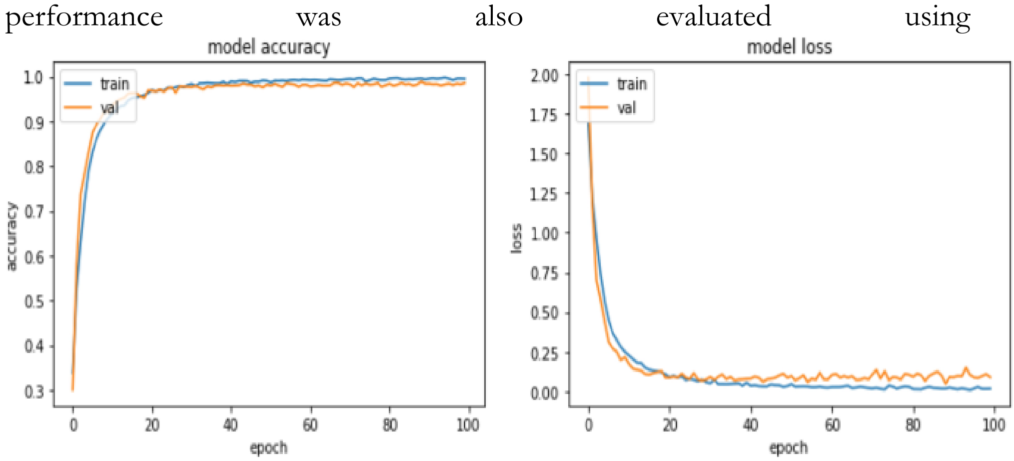

Figure 6. Accuracy of the Proposed Model

Table 1 below shows the accuracy, precision, recall, and F1 score. These metrics demonstrate the models' accuracy and robustness on the dataset. The proposed model, illustrates the model's effectiveness and robustness in classifying skin cancer images from the dataset. The model achieved an accuracy of 92%, indicating that it correctly classified 92% of the images. Precision, which measures the proportion of true positive predictions out of all instances predicted as positive, was 81%, meaning the model was correct 81% of the time when predicting skin cancer. The recall of 90% shows that the model identified 90% of the actual positive cases of skin cancer. Finally, the F1-score, which balances precision and recall, was 85.71%, indicating a strong balance between the two metrics. Together, these metrics demonstrated the model's reliable and robust performance in accurately detecting skin cancer from the dataset.

Table 1. Performance metrics of the proposed model

Metrics	Values (%)
Accuracy	92
Precision	81
Recall	90
F1-score	85.71
Accuracy	92

Comparison of Results with Existing Models:

A comparison between the proposed approach and existing CNN-based techniques for skin cancer detection is shown in Table 2. The suggested model outperforms earlier models that claimed accuracy rates ranging from 80% to 91%, with an improved accuracy of 92%. The proposed model, which achieved an accuracy of 92%, outperforms all the other models in the table. This improvement in accuracy highlights the effectiveness of the proposed model, which benefits from optimized CNN architecture and the integration of GLCM feature extraction and the ABCD dermoscopy approach.

Table 2. Comparison with Different Models

Models	Accuracy
CNN [26]	90.27%
CNN [27]	90.11%
CNN [28]]	80%
CNN [29]	91%
Proposed Model	92%

Discussion:

The proposed model for skin cancer detection achieved an impressive accuracy of 92%, which marks a substantial improvement over many existing CNN-based models in the field. This elevated accuracy rate signifies that the model has successfully learned to distinguish between malignant and benign skin lesions, making it a promising tool for the early detection of skin cancer. Early detection is crucial for skin cancer treatment as it directly influences survival rates, and an accurate model can lead to better outcomes by enabling timely intervention. Moreover, the robustness of the model is highlighted by its low loss, which suggests that the model is well-optimized and able to minimize training errors. This not only demonstrates the accuracy of the model but also its ability to generalize well to unseen data, ensuring its reliability for use in real-world applications.

The performance of the model was further validated through key metrics including precision, recall, and F1-score. Precision, with a value of 81%, indicates that when the model predicts a positive case, it is correct 81% of the time. This highlights that the model is efficient at reducing false positives, which is crucial for minimizing unnecessary treatments or interventions. Recall, on the other hand, stands at 90%, signifying that the model is able to correctly identify 90% of actual positive skin cancer cases. This ability to detect most of the positive instances is essential for skin cancer detection because missed cases could result in delayed treatment and worse patient outcomes. The F1-score of 85.71% reflects a solid balance between precision and recall, further supporting the model's overall reliability and robustness.

To ensure that the model performs well across diverse subsets of data and is not overfitting to a specific training set, cross-validation techniques were employed. Cross-validation is a widely-used technique in machine learning, where the dataset is divided into multiple subsets, and the model is trained and evaluated on different combinations of these subsets. This process helps mitigate overfitting by ensuring that the model's performance is not overly reliant on any single portion of the data. It also provides a more generalized view of the model's ability to classify skin cancer images accurately across different conditions and variations within the dataset. The successful application of cross-validation further affirms the reliability and robustness of the proposed model.

An important aspect of this work is the integration of advanced techniques like Gray Level Co-occurrence Matrix (GLCM) feature extraction and the ABCD dermoscopy approach. GLCM allows the model to capture texture-based features from the skin lesions, which can be crucial for distinguishing between malignant and benign growths. The ABCD dermoscopy approach, which is commonly used in dermatology, adds an extra layer of diagnostic expertise by evaluating asymmetry, border irregularity, color variation, and diameter. The fusion of these techniques with the CNN architecture likely contributed significantly to the model's enhanced performance. The CNN architecture itself was optimized, with careful attention to hyperparameters and layers, allowing the model to learn from complex patterns in the data, thus improving the accuracy of predictions.

When compared to existing CNN-based models, the proposed model demonstrates superior performance. As shown in Table 2, the proposed model outperforms several other CNN models that reported accuracy rates ranging from 80% to 91%. For example, the models in references [26], [27], and [29] achieved accuracy rates of 90.27%, 90.11%, and 91%, respectively, while the proposed model achieved 92%. This increase in accuracy indicates the effectiveness of combining GLCM feature extraction and ABCD dermoscopy techniques with the CNN framework. The integration of these features likely enabled the model to capture more meaningful information from the skin lesions, leading to more accurate predictions.

One of the main advantages of the proposed model lies in its ability to outperform existing models by integrating specialized techniques that have shown to be effective in the domain of dermatology. Models like CNN [26] and CNN [27], while highly accurate, still fall short of the proposed model's performance. The improved results can be attributed to a combination of optimized architecture and the inclusion of additional features like texture analysis and dermoscopic characteristics, which provide a deeper understanding of the skin lesions. The proposed model's superior performance, as evidenced by its higher accuracy, demonstrates the potential of this approach to become a state-of-the-art tool in the early detection of skin cancer.

The proposed model demonstrates exceptional accuracy and robustness in classifying skin cancer images, significantly improving upon existing CNN-based models. The integration of advanced feature extraction techniques like GLCM and ABCD dermoscopy, along with careful architectural optimization, has resulted in a model that can reliably detect skin cancer, offering a valuable resource for early detection and diagnosis. Future work can further explore the incorporation of additional imaging modalities or the use of a larger, more diverse dataset to continue improving the model's accuracy and generalizability.

Conclusion:

The purpose of this research was to investigate and apply cutting-edge machine learning methods for the identification of skin cancer, including Convolutional Neural Networks (CNNs). To create a deep-learning model that can distinguish between benign and malignant skin disorders, we used the HAM10000 dataset, which includes pictures of seven distinct kinds of skin cancer. The model's high accuracy of 92% is remarkable and it is applicable for practical clinical use.

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