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A Deep Learning-Based Predictive Model for Pattern Recognition and Classification of Cancerous Skin

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Abstract

Detecting cancerous skin lesions early is essential for improving treatment outcomes and saving lives. However, traditional diagnostic methods often depend on expert judgment, which can be time-consuming and sometimes subjective. To address this challenge, our study introduces a deep learning-based predictive model designed to recognize patterns and classify cancerous skin lesions automatically using medical images. The model leverages convolutional neural networks (CNNs) to capture key visual features from dermoscopic images and employs advanced classification layers to distinguish between benign and malignant lesions with high accuracy. The model was developed and validated using a comprehensive and diverse dataset of dermoscopic images retrieved from the online repository. Through systematic fine-tuning, we optimized the network's performance with a particular focus on accuracy, precision, and recall, aiming to support dermatologists in clinical decision-making. The resulting outputs of this study demonstrates that the proposed model is both robust and effective in detecting various types of skin cancer, including melanoma, while maintaining a low rate of false positives. Compared to existing diagnostic -methods, the model achieved improved outcomes, recording a precision of 0.92, an accuracy of 89.21%, and a recall of 0.91. These results underscore the significant potential of deep learning to enhance early detection, reduce the reliance on invasive procedures, and ultimately contribute to better patient outcomes.

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1.0 Introduction

The skin is considered one of the body's largest organs (Yousef, *et al., 2017*). Composed of ectodermal tissue and potentially consisting of up to seven distinct layers (Brunke *et al*., 2022), it plays a crucial role in safeguarding the muscles, bones, ligaments, and internal organs. In addition to its protective function, the skin acts as a barrier against environmental elements, helps regulate body temperature, and enables us to perceive sensations such as touch, warmth, and cold.

Recent progress in deep learning, which is a subfield of machine learning has led to impressive breakthroughs in image recognition, particularly within medical imaging. Convolutional Neural Networks (CNNs), in particular, have shown strong capabilities in analyzing dermoscopic images by identifying subtle features and patterns that help distinguish between malignant and benign skin

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lesions. Leveraging these strengths, this study proposes a deep learning-based model designed to detect and classify cancerous skin lesions with improved accuracy.

Ultraviolet (UV) radiation, whether from sunlight or artificial sources like tanning beds is widely recognized as a leading cause of skin cancer (Abdar *et al*., 2021). Skin cancer is not only a serious public health concern but also the most commonly diagnosed form of cancer worldwide. It is generally classified into two main types: melanoma and nonmelanoma. Although less common, melanoma is the more aggressive and potentially life-threatening type (Abdar *et al*., 2021). It originates from melanocytes, the pigment-producing cells in the skin, which can begin to multiply uncontrollably and form malignant tumors. While melanoma can occur anywhere on the body, it most often appears in areas that receive frequent sun exposure, such as the face, neck, hands, and lips

Detecting melanoma early is crucial, as it is highly treatable in its initial stages. If left undiagnosed, however, it can spread to other parts of the body, often resulting in severe and potentially fatal consequences (Höhn *et al.*, 2021; Das *et al*., 2021). Melanoma presents in various forms, including nodular melanoma, superficial spreading melanoma, acral lentiginous melanoma, and lentigo maligna (Das *et al*., 2021; Brunke *et al*., 2022).

Despite melanoma's severity, the majority of skin cancer cases fall under the nonmelanoma category, which includes Basal Cell Carcinoma (BCC), Squamous Cell Carcinoma (SCC), and Sebaceous Gland Carcinoma (SGC) (Saarela & Geogieva, 2022). These types typically originate in the middle to upper layers of the epidermis. Fortunately, they tend to be less aggressive and are unlikely to metastasize (Pacheco & Krohling, 2021).

Traditionally, skin cancer has been diagnosed through a biopsy, where a sample of suspicious tissue is removed and examined under a microscope. While this method is accurate, it is also invasive, often uncomfortable, and can take time to deliver results (Keerthana & Venugopal, 2023).
Within this framework, deep learning which is a branch of machine learning inspired by the way the human brain interprets and processes information and offers promising advancements. These models excel at recognizing intricate patterns across different types of data, including images, text, and audio, enabling them to deliver highly accurate predictions. Convolutional Neural Networks (CNNs), in particular, have shown remarkable success in the field of image analysis.

This study centers on the development of a deep learning model designed to detect cancer-related features in skin images and classify them into clinically relevant categories. By leveraging a comprehensive, annotated dataset of dermoscopic images, the model is trained to distinguish between different forms of skin cancer, such as melanoma, basal cell carcinoma, and squamous cell carcinoma. The model's performance is measured using established evaluation metrics, including accuracy, precision, recall, F1-score, and the Area Under the ROC Curve (AUC-ROC). These results underscore the model's potential as a dependable tool to support dermatological diagnosis.

Ultimately, the goal of this research is to bridge the gap between advanced computational methods and practical clinical application, offering an efficient and scalable solution for the early identification and classification of skin cancer.

2.0 The Skin Problems

Skin conditions ranging from common issues like acne to more serious illnesses such as melanoma affect millions of individuals globally. Early diagnosis plays a vital role in ensuring timely and effective treatment. However, conventional diagnostic approaches, which typically involve physical examinations and biopsies, can be slow, costly, and sometimes influenced by subjective judgment. Thanks to recent progress in medical imaging and artificial intelligence (AI), automated detection systems are becoming valuable assets in the accurate and efficient diagnosis of skin diseases.

2.1 Common Skin Problems and Their Impact

Skin diseases can be broadly classified into four main categories: infectious, inflammatory, allergic, and malignant. Among the most common conditions is acne, which is a widespread dermatological issue typically caused by blocked pores and bacterial infections. Another frequently encountered condition is eczema, a chronic inflammatory disorder marked by redness, itching, and skin irritation. Psoriasis also ranks high among troubling skin diseases—an autoimmune condition that accelerates skin cell turnover, often leading to scaling, redness, and inflammation.
According to research, skin disorders are the third most common category of disease and are a leading cause of illness among returning travelers. It's estimated that around 8% of individuals experience skin-related issues while traveling (Brigid & Brien, 2009).
One of the more serious and potentially life-threatening skin conditions is skin cancer, which

includes melanoma, basal cell carcinoma, and squamous cell carcinoma. Also falling under serious skin conditions are fungal and bacterial infections like ringworm and cellulitis. These require prompt medical attention, as they can have a considerable impact on a person's health and overall quality of life.

2.2 Advanced Technologies in Skin Problem Detection

The integration of technology in dermatology has improved diagnostic accuracy and efficiency. Some of the key advancements include:

i. *Machine Learning & Deep Learning* – Algorithms trained on vast datasets can identify patterns and classify skin conditions with high precision.

ii. *Computer Vision & Image Processing* – AI-driven image analysis can detect abnormalities in skin texture, color, and structure.

iii. *Mobile Applications & Tele-dermatology* – Smartphone-based diagnostic tools enable remote consultations and preliminary assessments.

iv. *Wearable Sensors* – Devices that monitor skin health parameters such as moisture levels, temperature, and UV exposure.

2.3 Deep Learning Concept for the Detection of Skin Problems

Deep learning techniques, particularly CNNs, have shown some remarkable success in dermatological diagnosis. CNNs process high-resolution images to differentiate between benign and malignant lesions, reducing diagnostic errors. Studies have demonstrated that AI-based models can achieve dermatologist-level accuracy in detecting skin cancer, psoriasis, and other dermatological conditions.

There are a number of key benefits of deep learning in skin problem detection, such benefits include: Automated and objective diagnosis, early detection leading to better treatment outcomes, reduced need for invasive procedures, scalability for widespread use in telemedicine and so on. However, challenges such as data bias, model interpretability, and regulatory approval must be addressed before widespread clinical implementation.

3.0 Review of Related Studies

In recent years, numerous studies have focused on developing computer-based methods for analyzing malignant skin lesions through medical images. Despite these efforts, challenges remain due to the complexity and variability often present in the datasets used for such analysis. To tackle these issues, Ali *et al*. (2021) introduced a deep learning-based model designed to accurately classify skin lesions as either benign or malignant.

Their approach involved several preprocessing steps, including image enhancement, normalization, and data augmentation, to improve model performance. The extracted features were then processed using a custom-designed Convolutional Neural Network (CNN), which was evaluated against several well-known pretrained models such as AlexNet, ResNet, VGG-16, DenseNet, and MobileNet. According to their findings, the proposed model achieved high training accuracy with minimal error. When compared with selected transfer learning architectures, the CNN developed by Ali et al. demonstrated strong reliability and promising results.

Deep learning models often face difficulties when analyzing skin lesions with complex visual features, such as indistinct edges, presence of artifacts, low contrast against surrounding skin, or when constrained by limited training data. To address these challenges, Brunke *et al*. (2022) and Adegun & Viriri (2020) proposed a novel framework for both the classification and segmentation of skin lesions aimed at improving skin cancer detection. Their approach adheres to a conventional CNN architecture, with a Fully Connected Network (FCN) enhanced by a series of interconnected subnetworks. These subnetworks utilize skip pathways, including both long and shortcut connections, to better retain and integrate features across network layers. Additionally, hyperparameter optimization techniques were employed to minimize model complexity and improve computational efficiency. Experimental evaluations demonstrated high levels of accuracy, recall, and Area Under the Curve (AUC) scores.

Further efforts to enhance machine learning performance on images of infected skin were detailed by Adegun & Viriri (2020) and Vidya & Karki (2020). These studies focused on feature extraction using established dermatological criteria such as the Asymmetry, Border irregularity, Color variation, and Diameter (ABCD) rule, alongside Gray-Level Co-occurrence Matrix (GLCM) and Histogram of Oriented Gradients (HOG) techniques. The process began with preprocessing to improve lesion visibility and reduce noise from artifacts, skin tone variations, and hair. Lesions were then segmented using the Geodesic Active Contour (GAC) method, allowing for more precise isolation of the affected region—crucial for accurate feature extraction.

ABCD scoring was used to assess symmetry, border definition, color distribution, and diameter of lesions, while HOG and GLCM were applied to capture textural characteristics. These extracted features were then passed to various classifiers for distinguishing between benign and malignant (melanoma) lesions. Among the models tested, Support Vector Machine (SVM) outperformed the others, achieving a notable accuracy of 97.8% and an AUC of 0.94. K-Nearest Neighbor (KNN) also performed well, with a sensitivity of 86.2% and specificity of 85%, although it lagged slightly behind SVM in overall performance.

In a related investigation, Afza *et al*. (2022) proposed an innovative method for multiclass classification of skin lesions, utilizing an advanced feature fusion strategy rooted in deep learning. Their workflow consists of five key stages: image acquisition and enhancement, deep feature extraction through transfer learning, optimal feature selection using a hybrid Whale Optimization Algorithm combined with Entropy Mutual Information (EMI), feature fusion via a modified canonical correlation approach, and final classification using an Extreme Learning Machine (ELM). The hybrid feature selection technique played a crucial role in enhancing both computational speed and model accuracy.

Similarly, Bechelli and Delhommelle (2022) conducted a comparative study to evaluate the performance of various machine learning algorithms in classifying skin tumors. Their analysis included traditional models such as logistic regression, linear discriminant analysis, k-nearest neighbors, decision trees, and Gaussian Naïve Bayes. They also assessed several deep learning approaches, testing both custom-built CNNs and well-established pretrained models like VGG16, Inception, and ResNet50. Results showed that deep learning models consistently outperformed classical machine learning techniques, achieving classification accuracies as high as 0.88. In contrast, traditional models hovered around 0.72 in accuracy, though this could be improved slightly to 0.75 with the use of ensemble methods.

4.0 Material and Methods

4.1 Data Collection

In this study, the predictive model was developed using a publicly available secondary dataset obtained from Kaggle, an open-access data platform. The dataset explored in this study comprises 2,357 dermoscopic images representing both malignant and benign skin conditions, originally curated by the International Skin Imaging Collaboration (ISIC). The images were categorized according to ISIC's standardized classification system. Efforts were made to balance the number of samples across categories, although slightly higher counts were observed in the melanoma and nevus (mole) classes. Overall, the dataset spans nine diagnostic categories: actinic keratosis, basal cell carcinoma, dermatofibroma, melanoma, nevus, pigmented benign keratosis, seborrheic keratosis, and squamous cell carcinoma. A visual representation of this dataset is provided in Figure 1.

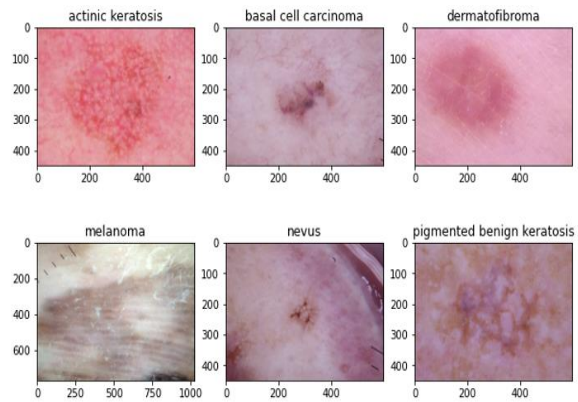

Figure 1. Excerpts of the dataset retrieved from Kaggle

4.2 Data Pre-processing

The data retrieved from Kaggle was preprocessed to make it suitable for training. Attributes with no tangible contribution to learning were dropped using the appropriate library in python. The model created has been evaluated to determine its accuracy, precision, and recall. The preprocessing operation that has been adopted in this study is image augmentation, which includes, image rotation and image shift. The pre-augmentation and post augmentation dataset is illustrated in Figure 4 and Figure 5 respectively.

Image Rotation

One of the most widely used data augmentation techniques is image rotation. Rotating an image doesn't change its underlying information after all, however, a skin cancer image looks the same no matter which angle you view it from. Because of this, we applied rotation to generate multiple versions of each image at different angles, effectively increasing the amount of training data available for the model.

4.3 Convolutional Neural Network

The proposed CNN architecture consists of two dense layers and three convolutional blocks. The last dense layer has seven neurons since the dataset has seven classifications. Each convolutional block consists of a convolutional layer and a max pooling layer. Figure 2 shows the CNN architecture.

4.4 The CNN Architecture

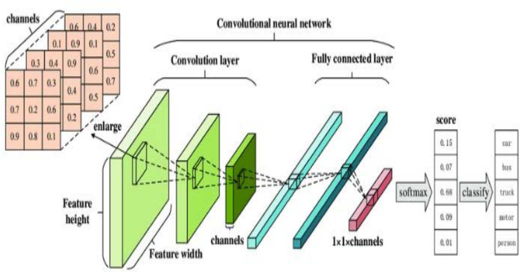

Figure 2. The CNN structure adapted from Fuadah *et al.*, 2020

The convolution operation extracts the features in the skin images as it is the role of the convolutional layer to extract spatial features from an input image. The output feature map was computed based on equation 1.

$$Y(i,j) = \sum_{m}\sum_{n} X(i-p, j-q)\,.\,K(p,q) \tag{1}$$

where
Y(I,j) represent the output feature map
X (i – p, j – q) represent the input image
K (p , q) represent the convolution kernel (filter)

4.5 Convolutional Layer

Convolutional layers are at the heart of convolutional neural networks (CNNs). Convolution itself is simply the process of applying a filter to an input to produce an activation. By sliding the same filter over an input repeatedly, CNNs create a feature map that highlights where and how strongly a certain feature appears in the input like an image. What makes CNNs especially powerful is their ability to learn many filters in parallel, all tailored to the specific patterns found in the training data, and all within the framework of the predictive task at hand.

Prior to the time CNNs gained popularity, tackling computer vision problems meant manually extracting features from data. This approach was not only inefficient but also struggled to achieve high accuracy. In contrast, CNNs have brought significant improvements in both efficiency and accuracy across various applications, with object detection being one of the most prominent examples (Ajit *et al.*, 2020).

4.6 Max Pooling

Max pooling functions by scanning over sections of a feature map and selecting the highest value from each region, effectively creating a down-sampled version of the original. This approach helps to reduce dimensionality while preserving the most significant features.

In addition, global pooling layers play a vital role in Convolutional Neural Networks (CNNs). These layers summarize information across the entire spatial dimension of a feature map, producing a fixed-length output vector. Techniques such as global average pooling and global max pooling are frequently used in modern CNN architectures to transform feature maps of varying input sizes into a consistent output format (Christelyn *et al.*, 2019). It's important to highlight that both max pooling and global pooling operate locally or across full spatial domains without taking broader spatial relationships into accounts; they treat each region or entire map independently during computation.

4.7 Experimental Setup

In this study, we used a Python programming environment to implement the selected feature extraction algorithms. The CNN model was built using Keras with TensorFlow as the backend, all within the Anaconda IDE. A summary of the hyperparameter settings is provided in Table 1, and the overall model structure is illustrated in Figure 3.

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
rescaling (Rescaling)        (None, 180, 180, 3)       0
_________________________________________________________________
conv2d (Conv2D)              (None, 180, 180, 32)      896
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 90, 90, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 90, 90, 64)        18496
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 45, 45, 64)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 45, 45, 128)       73856
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 22, 22, 128)       0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 22, 22, 256)       295168
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 11, 11, 256)       0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 11, 11, 512)       1180160
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 5, 5, 512)         0
_________________________________________________________________
flatten (Flatten)            (None, 12800)             0
_________________________________________________________________
dense (Dense)                (None, 1024)              13108224
_________________________________________________________________
dense_1 (Dense)              (None, 9)                 9225
=================================================================
Total params: 14,686,025
Trainable params: 14,686,025
Non-trainable params: 0
_________________________________________________________________
```

Figure 3. Summarized model settings.

We split the dataset so that 80% was used for training and the remaining 20% for testing. When it came to hyperparameter tuning, we chose the “Adam” optimizer. This optimizer is responsible for adjusting the model’s weights to minimize the loss function during training.

Table 1: Hyperparameter Settings

Hyperparameter	Value
Number of Iterations	30
Optimizer	Adam
Activation Function in the input layer	Rectified Linear unit
Activation Function in the output layer	Softmax
Loss function	Categorical Cross Entropy

4.8 Augmentation

The whole idea behind augmentation is to make the model stronger and perform better, help the model generalize well to a new set of data, and cut down on overfitting. Figure 4 shows the dataset prior to augmentation, while Figure 5 shows the dataset after augmentation.

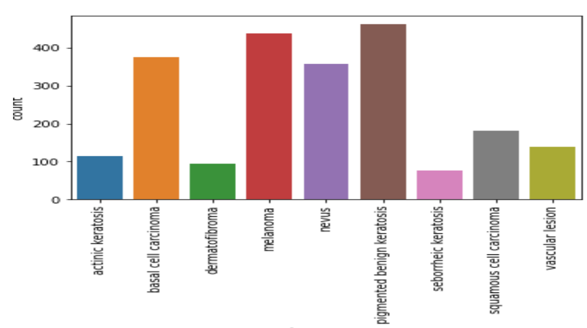

Figure 4. Data visualization before augmentation

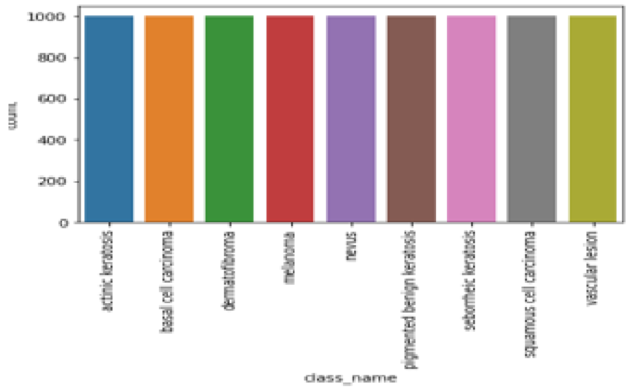

Figure 5. Data visualization after augmentation

4.9 Performance Evaluation

Model performance evaluation is simply the process of checking how well a predictive or analytical model does its job, using certain measurements. The developed model was evaluated in terms of accuracy, precision, recall, F1-score, and loss. The Mathematical formulae are as given.

$$Accuracy = \frac{TN + TP}{TN + FP + TP + FN} \quad (2)$$

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

$$F1 - score = \frac{2 * Precision * Recall}{Precision + Recall} \quad (5)$$

Where TP denotes True Positive, TN represent True Negative, FN is the number of False Negative and FP represents False Positive.

5.0 Results and Discussion

5.1 Results

The model performance during the training process is illustrated in Figures 6 and 7.

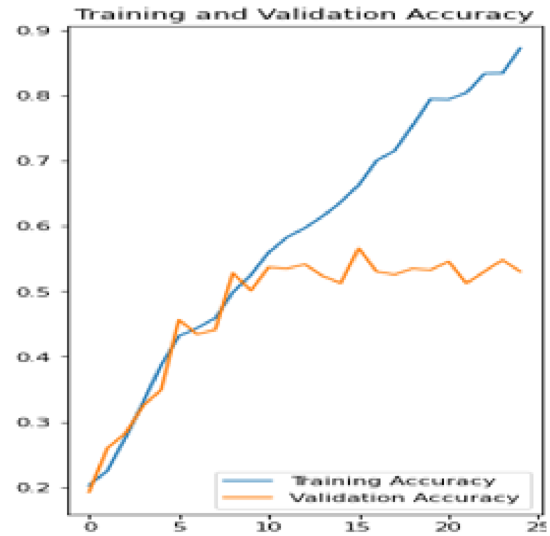

Figure. 6. Illustration of model accuracy

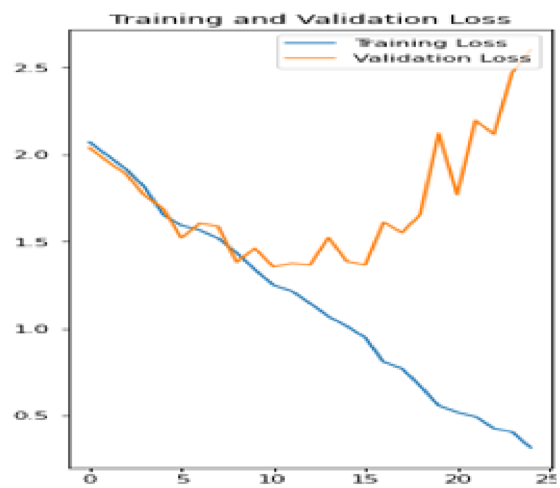

Figure 7. Illustration of model loss

In some applications, the focus is mainly on one specific class, often the minority class. This is especially common in text classification tasks where the data is highly imbalanced. The class of interest is usually referred to as the *positive* class, while all others are grouped as *negative*. In such cases, relying on accuracy alone can be misleading. For instance, if 99% of samples are normal, a model could simply label everything as normal and still achieve 99% accuracy, without actually solving the problem.

That's why additional metrics like precision, recall, and the F1-score are essential. Precision and recall, in particular, provide a clearer picture by showing how accurate and how complete the model's predictions are for the positive class. The results of the performance metrics are represented in Table 2.

Table 2. Performance evaluation

Model	Accuracy	Precision	Recall	F1-score
CNN	85.01%	0.9	0.89	0.9
CNN + Grid Search	89.21%	0.92	0.91	0.86

5.2 Discussion

The figure 3 and figure 4 in Section 4.1 illustrates the model accuracy and loss during the training process. Figure 3 continue to rise in accuracy to the point close to 90% as shown, while in Figure 4, the loss as shown in the graph keep descending as the model learns. Generally, in a machine learning, training loss indicates how such model fits the data it was trained on.

Hyperparameter tuning is an essential process in optimizing CNNs to achieve the best possible performance. Determining the right combination of hyperparameters such as learning rate, and batch size, can drastically affect the accuracy and efficiency of a CNN. Grid Search is a widely used technique for hyperparameter tuning, as it systematically works through multiple combinations of parameters, evaluating the performance of each to identify the optimal set. Applying Grid Search in CNN hyperparameter tuning involves exhaustively searching through a manually specified subset of the hyperparameter space.

This approach provides a structured framework for model selection, helping to improve the generalization of the network by navigating through the complex landscape of parameter sensitivities and interactions. Improved model generalization leads to higher accuracy. However, Grid Search is computationally expensive and time-consuming since it evaluates all possible parameter combinations. It is critical to conduct this process efficiently by narrowing down the search space based on prior knowledge or exploratory analysis. Low performance for CNN model has been attributed to the absence of hyperparameter optimization.

This study demonstrates that applying grid search to optimize a CNN model can lead to noticeable performance gains. When compared with related works discussed in the literature, the model developed here achieved significantly improved accuracy, which is largely due to the careful tuning of hyperparameters through grid search. Additionally, data augmentation played a crucial role in enhancing the model's effectiveness, as highlighted in the study. Taken together, the use of CNNs alongside grid search proves to be a highly effective approach, especially for tackling the challenges associated with skin cancer classification.

6.0 Conclusion

This study developed a deep learning-based predictive model for the detection and classification of cancerous skin lesions. The study achieved this through an optimized CNN with an advanced feature extraction technique. The developed model demonstrates a better accuracy when compared to traditional diagnostic methods. The integration of a large and diverse dataset ensures its effectiveness across different skin types and cancer stages, making it a reliable technique and very useful for an early detection.

The results highlight the strength of deep learning in skin cancer diagnosis by reducing human error, minimizing the need for invasive procedures, and enabling faster decision-making. This advancement has significant implications for dermatology and medical imaging, as it can assist healthcare professionals in improving diagnostic precision and patient outcomes.

Future work will focus on further enhancing the model's interpretability, integrating multi-modal data for improved classification, and exploring real-time deployment in clinical settings. With continued advancements, AI-driven diagnostic tools have the potential to transform cancer detection and contribute to more efficient and accessible healthcare solutions.

Authors Contributions

Adeleke Raheem Ajiboye (Installations of tools, implementation of relevant algorithms and libraries)

Shefiu Olusegun Ganiyu (Retrieval of required secondary dataset and pre-processing)

Suhura Ikeoluwa Olatinwo (Review of relevant literatures and structural representation of the network)

Ganiyat Bolanle Balogun (Writing, Formatting and Editing)

Conflict of Interest

The authors have no conflict of interest to declare.

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