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Development of Skin Lesion Classification System Based on Watershed Algorithm and Custom CNN

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ABSTRACT

Skin cancer poses a substantial health threat worldwide, underscoring the importance of timely identification and precisecategorization for effective treatment. This paper presents a comprehensive framework for skin cancer image analysis,encompassing preprocessing, segmentation, and classification of nine types of skin cancer using a custom ConvolutionalNeural Network (CNN) model. The preprocessing stage addresses missing or corrupted regions in images using inpainting algorithms, enhancing image quality and completeness. After that, a dataset obtained from the International Skin Imaging Collaboration (ISIC) on Kaggle is segmented using the watershed technique. Accurately identifying tumor locations throughout the segmentation process makes feature extraction for classification easier later on. Deep learning techniques play a pivotal role in this framework, enabling automatic feature extraction and learning from raw image data. The use of CNNs enables the development of a personalized model specifically designed to accurately identify nine types of skin cancer. The evaluation process of our skin cancer classification system includes the assessment of variousmetrics, such as predicting cancer types and confidence scores. Through this evaluation, the model assigns prediction values to all nine types of skin cancer, ultimately identifying the specific type based on the highest prediction value. This comprehensive assessment highlights the system's potential as a valuable aid for dermatologists in accurately diagnosing and effectively treating skin cancer cases.

KEYWORDS

Skin cancer, Dataset, Preprocessing, Segmentation, CNN, Evaluation metrics

1. INTRODUCTION

A common and often deadly condition, skin cancer is a broad group of malignancies that originate from several types of skin cells. Among these, nine distinct types stand out, each with its unique characteristics and clinical implications. Actinic keratosis, basal cell carcinoma, nevus, pigmented benign keratosis, seborrheic keratosis, dermatofibroma, melanoma, and vascular lesions are a few of them [1].

Melanoma, squamous cell carcinoma, and basal cell carcinoma are the more serious forms of skin cancer since they have the ability to spread and result in severe morbidity and mortality if treatment is not received [2]. These cancers arise from abnormal growth or mutations in skin cells, often triggered by UV radiation exposure or genetic predisposition [3].

On the other hand, dermatofibroma, nevus, pigmented benign keratosis, seborrheic keratosis, actinic keratosis and vascular lesions are generally classified as non-cancerous or benign skin conditions. While they may present as abnormal growths or lesions on the skin, they typically do not pose the same level of risk as cancerous skin lesions. However, it's essential to monitor these lesions for any changes or signs of malignancy, as certain benign conditions may mimic or evolve into malignant tumors over time.

Understanding the distinctions between cancerous and noncancerous skin lesions is critical for accurate diagnosis, treatment planning, and patient management. Dermatologists rely on a combination of clinical examination, dermoscopy, histopathological analysis, and molecular testing to differentiate between benign and malignant skin lesions accurately [4],[5].

It is critical to create algorithms that can reliably identify these nine types of skin lesions into groups corresponding to cancer and non-cancerous conditions in the context of automated skin cancer detection [6]. In order to help dermatologists make timely and well-informed therapeutic decisions, researchers hope to build models that can recognize minor traits and patterns indicative of malignancy by utilizing machine learning and deep learning approaches.

Based on this understanding, this paper recommends an extensive framework for examining skin cancer images, integrating deep learning methodologies for preprocessing, segmentation, and classification tasks. We perform our methodology on skin lesion images as shown in Fig 1. The proposed framework considers the extensive spectrum of skin cancer types and their potential clinical outcomes in order to enhance the accuracy and efficacy of automated skin cancer detection. This will eventually improve patient outcomes and lessen the disease's global effect. Our methodology incorporates robust preprocessing steps to enhance the clarity and fidelity of images, precise segmentation algorithms to isolate lesions accurately, and sophisticated classification models trained on extensive datasets to achieve high diagnostic accuracy across various skin cancer types. Through rigorous evaluation and validation, we demonstrate the effectiveness of our framework in facilitating early and accurate diagnosis, thereby contributing to better patient care and public health

initiatives.

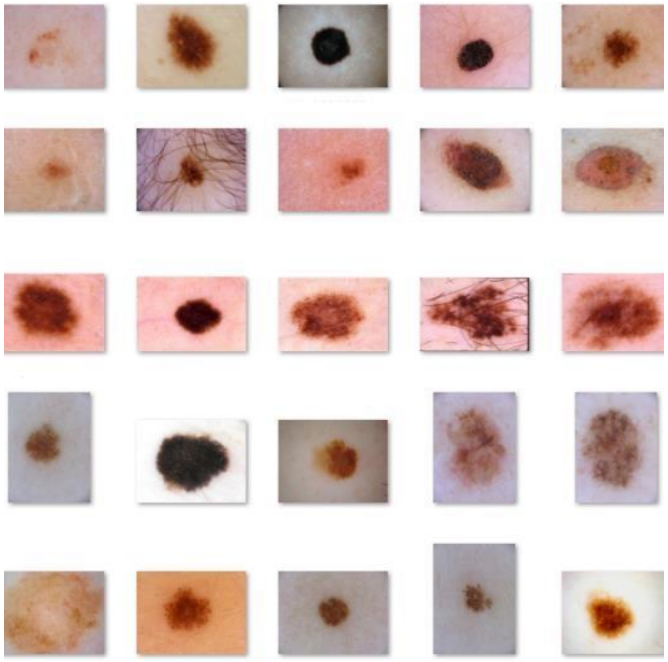

Fig. 1 Sample images from the dataset

2. METHODOLOGY

The machine learning discipline of deep learning, which is typified by multilayered neural networks, is the foundation for the classification technique for skin diseases. Large-scale datasets of dermatoscopic image analysis are analyzed by deep learning algorithms, which then autonomously learn discriminative characteristics linked to different forms of skin lesion. By training on diverse examples, these models discern subtle differences between lesion types, enabling accurate classification. Our investigation utilized inpainting algorithms to enhance image quality by addressing missing or damaged regions, followed by segmentation using the watershed algorithm to isolate lesion containing regions precisely. Subsequently, a custom convolutional neural network (CNN) model was developed and trained on pre-processed images, with performance evaluated on separate validation and test sets. The trained model produces predictions for new images, offering class labels, confidence scores, and accuracy metrics for precise classification. This methodology incorporates cutting-edge deep learning techniques to construct a sophisticated skin lesion classification system capable of precise diagnosis and categorization. Fig 2 illustrates the block diagram of the proposed skin lesion image analysis.

2.1 DATA ACQUISITION

The data acquisition phase involves gathering a comprehensive dataset comprising dermatoscopic images of skin lesions. As seen in Fig. 3, these images are accompanied by class designations that correlate to the type of lesion present. The dataset is obtained from International Skin Imaging Collaboration (ISIC) skin cancer images which are meticulously curated to ensure diversity and representativeness, encompassing various lesion types, sizes, and orientations [7]. High-resolution images obtained using dermatoscopes or similar imaging equipment are carefully chosen to enable precise analysis and classification.

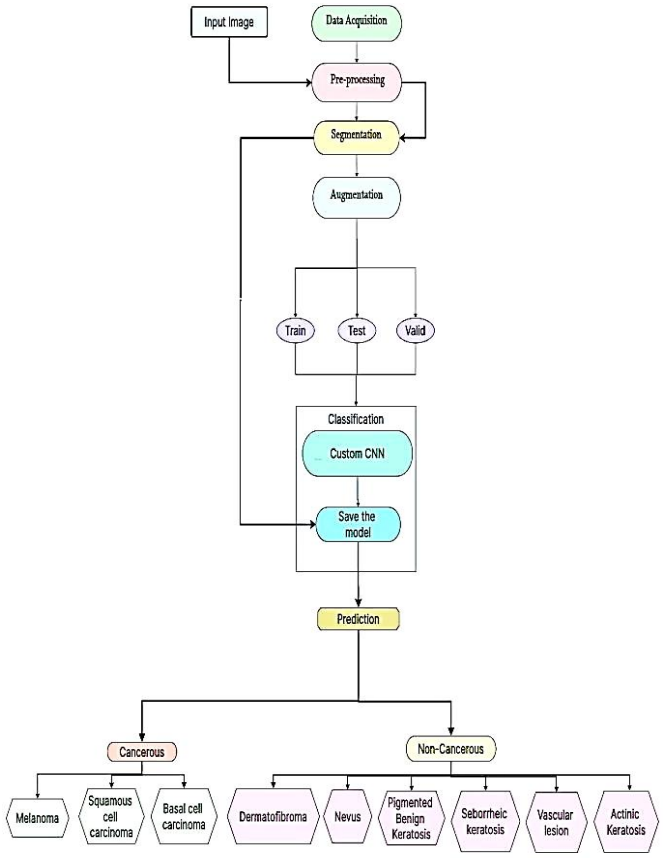

Fig. 2 Flowchart for the proposed image analysis system

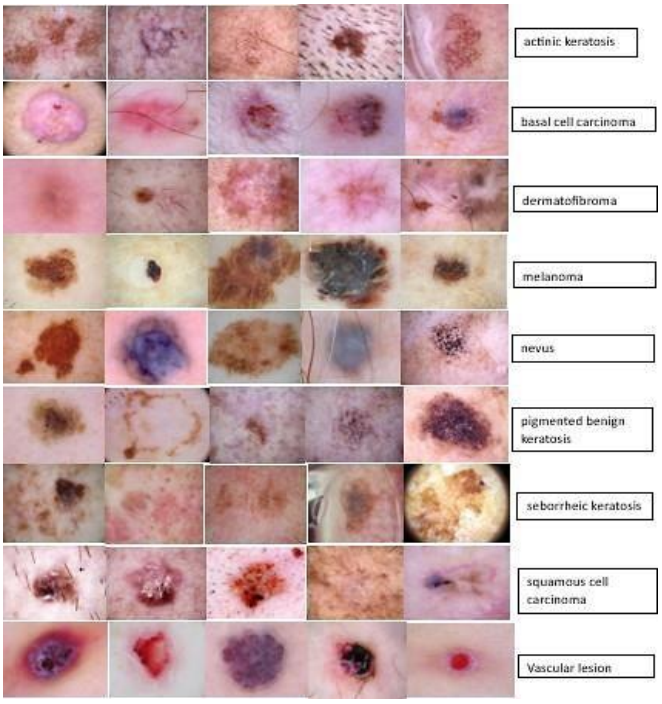

Fig. 3 Sample images per class

2.2 DATA PREPROCESSING

During the data preprocessing phase, inpainting algorithms significantly contribute to enhancing the quality of dermatoscopic images by rectifying any missing or damaged regions [8]. In order to make the images appropriate for further study, this crucial process entails filling in areas that might include artifacts or flaws. Inpainting techniques intelligently interpolate missing information based on surrounding pixel values, effectively restoring the integrity of the images without altering their overall appearance. By effectively addressing any irregularities, the inpainting process makes a substantial contribution to enhancing the accuracy of segmenting and classifying skin lesions in the subsequent stages of the analysis pipeline. The process unfolds in several sequential steps as shown in Fig 4. First, the original color dermatoscopic images are converted to grayscale from RGB. Grayscale images simplify subsequent processing by representing pixel intensities in a single channel, preserving essential structural information while reducing complexity. Subsequently, the grayscale images undergo a Black Hat transformation, which highlights regions darker than their surroundings, thereby enhancing subtle features and abnormalities present in the skin lesions [9]. Following this, a threshold mask is applied to the transformed images to segment the image into binary regions based on a predefined threshold value. This segmentation technique separates the foreground (lesions) from the background, making it easier to identify and isolate regions of interest. Lastly, inpainting algorithms are employed to fill in missing or damaged areas in the images, intelligently interpolating missing information based on surrounding pixel values. By restoring the integrity of the images, inpainting enhances the accuracy of subsequent segmentation and classification tasks [10],[11].

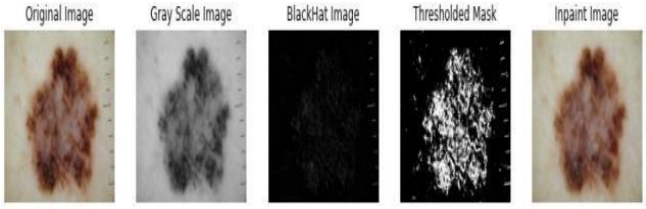

Fig. 4 Inpaint algorithm-based pre-processed image analysis

2.3 DATA SEGMENTATION

The data segmentation phase incorporates the Watershed algorithm into a comprehensive procedure for precisely outlining areas of interest within dermatoscopic images [12]. This algorithm utilizes intensity gradients to efficiently detect boundaries between various regions, thus distinguishing skin lesions from surrounding tissue, as depicted in Fig 5.

The procedure initiates with gradient computation, during which the algorithm calculates the gradient magnitude of the dermatoscopic image, identifying edges and changes in intensity through methods such as Sobel or Scharr filters [13]. Subsequently, initial markers are strategically positioned on the image to denote areas of interest such as suspected lesions. These markersguide the algorithm's segmentation journey and can be manually specified or automatically generated based on criteria like local maxima in the gradient magnitude [14].

Subsequently, the Flood-Filling step commences from the markers, with the Watershed algorithm simulating a flooding process where water fills the basins of the gradient landscape. As the water rises, watershed lines emerge along the boundaries where different regions intersect, effectively segmenting the image. By using segmentation, the dermatoscopic picture is divided into separate sections, each of which represents a different item or area of interest. Finally, post-processing steps refine the results, eliminating small or extraneous regions and merging adjacent areas with similar attributes [15].

Through meticulous segmentation of the images, the Watershed algorithm significantly enhances the accuracy of subsequent analysis and classification tasks [16]. This pivotal step is essential for isolating regions containing lesions and extracting relevant features for classification. Ultimately, the Watershed algorithm is instrumental in enhancing the robustness and efficacy of the skin lesion classification system by enabling accurate segmentation of dermatoscopic images.

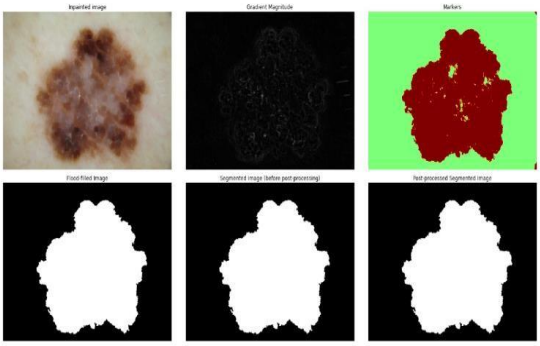

Fig. 5 Region-based segmentation of the lesion

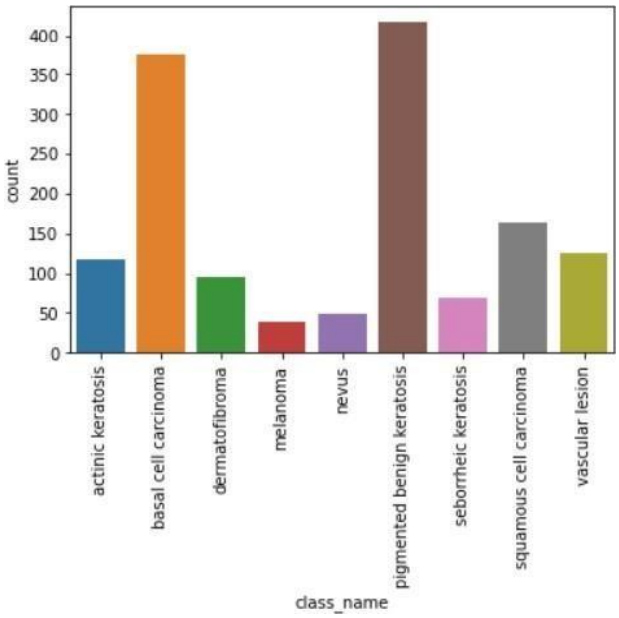

Fig. 6 Number of images per class from the dataset

2.4 DATA AUGMENTATION

Data augmentation involves various techniques aimed at increasing the diversity and size of the dataset. Common methods include rotation, flipping, scaling, and translation, which generate new training samples from existing images. By introducing variability into the dataset, data augmentation enhances the robustness of the classification model. This variability enables the model to learn from a broader range of image variations, improving its generalization performance on unseen data [17],[18]. Data augmentation often improves deep learning models' ability to diagnose skin lesions effectively by expanding the dataset and strengthening the model's resistance to various picture circumstances.

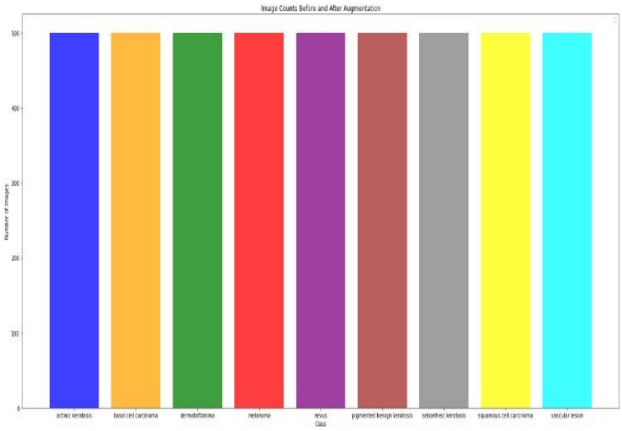

Fig. 7 Augmented image distribution per class

2.5 TRAIN-TEST-VALIDATION SPLIT

To facilitate efficient model training, hyperparameter tuning, and evaluation, the dataset was split into training, validation, and test sets. The training set facilitated learning intricate patterns crucial for accurate predictions, while the validation set aided in preventing overfitting and ensuring robust generalization [19]. The test set served as the ultimate benchmark for evaluating the model's performance on unseen data. This all-encompassing strategy ensured our classification model's resilience and dependability. The dataset was divided into around 64 percent training, 16 percent validation, and 20 percent testing portions, in that order.

The model's classification accuracy throughout consecutive epochs on the training and validation sets is displayed on the accuracy curve in Fig 8. It aids in determining how effectively the model generalizes to new data and learns from the training set. Ideally, both training and validation accuracies should increase steadily during training, indicating that the model is learning effectively without overfitting.

The model's error over epochs on the training and validation sets is shown by the loss curve in Fig 8. The loss function calculates the deviation between the actual labels and the model's predictions. A decreasing loss indicates that the model is improving its predictions over time. However, if the training loss continues to decrease while the validation loss starts to increase, it suggests overfitting, indicating that the model is becoming too specialized for the training data.

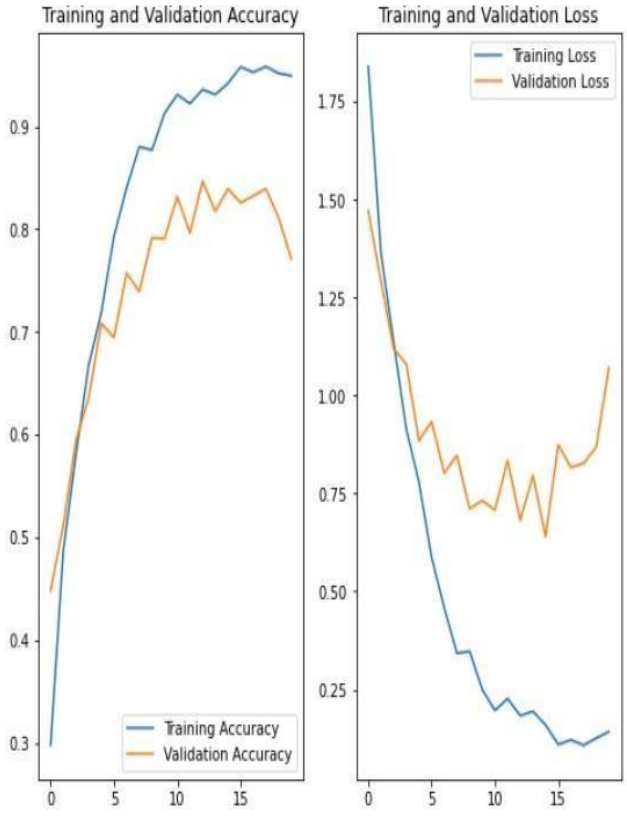

Fig. 8 Training and testing accuracy/loss curve

2.6 IMPLEMENTATION OF CNN

The implementation of the CNN model for skin lesion classification utilized a custom CNN architecture, integrating segmented image datasets to enhance performance. Convolutional, pooling, and fully linked layers were used in this architecture to effectively extract features from segmented input pictures. Overfitting was addressed using dropout layers, while ReLU activation functions were employed to introduce non-linearity. Utilizing TensorFlow's Keras API, the model incorporated a preprocessing layer for input image rescaling, followed by convolutional and max-pooling layers for feature extraction [20]-[23]. The model underwent training on segmented image data, with performance evaluation conducted on the validation set, employing optimization through the Adam optimizer and utilizing the Sparse Categorical Cross entropy loss function. Rigorous scrutiny of validation and test datasets ensured precise classification of skin lesions.

2.7 BUILDING UP CNN AND TRAINING PROCESS

As illustrated in Fig. 9, our suggested approach uses the TensorFlow Keras API to create a customized convolutional neural network (CNN) model for image classification tasks. Here's a breakdown of the implementation

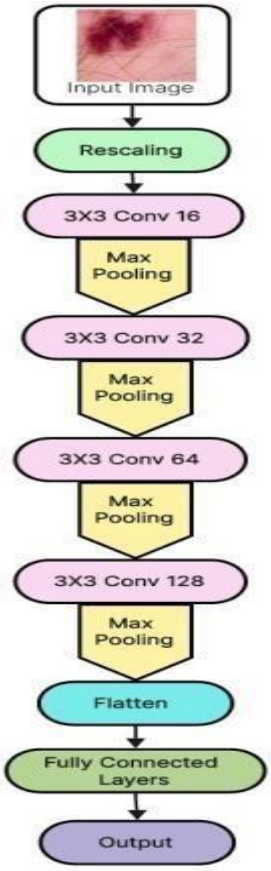

Fig. 9 Layers of proposed CNN

The model is built using the Sequential API, which permits the orderly stacking of layers [24],[25].

The Rescaling layer is used to normalize pixel values of input images to the range [0, 1]. This normalization helps in stabilizing and accelerating the training process.

The model includes multiple convolutional layers (Conv2D) with progressively increasing numbers of filters (32, 64, 128, 256, 512) and kernel sizes of 3x3 pixels. Through convolutions, these layers are responsible for extracting information from the input images.

A MaxPooling2D layer is inserted after each convolutional layer to carry out spatial downsampling. This aids in lowering the feature maps' spatial dimensions while keeping the most crucial data.

After the convolutional and pooling layers, a flatten layer is added to prepare the data for input into the fully connected layers. The 2D feature maps are flattened into a 1D vector as a result.

Two dense layers with 1024 and "no-classes" units (number of output classes) added, respectively, are dense (completely connected) layers. For these deep layers, non-linearity is added to the model using the ReLU activation function.

A softmax activation function is used in the last dense layer to provide a probability distribution across the classes. In light of the input image, it forecasts the likelihood of each class.

The model is constructed utilizing the Adam optimizer with a learning rate set to 0.001. The selected loss function, Sparse Categorical Cross Entropy, demonstrates effectiveness in multi-class classification tasks where the labels are integers. Additionally, accuracy is employed as a metric to evaluate the model's performance [26], [27].

Finally, the summary () approach provides a brief overview of the model architecture, including what is included in and how large of each layer as well as the total number of parameters, as shown in Fig. 10.

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 sequential_1 (Sequential)   (None, 180, 180, 3)       0

 rescaling_2 (Rescaling)     (None, 180, 180, 3)       0

 conv2d_6 (Conv2D)           (None, 180, 180, 16)      448

 max_pooling2d_6 (MaxPoolin  (None, 90, 90, 16)        0
 g2D)

 conv2d_7 (Conv2D)           (None, 90, 90, 32)        4640

 max_pooling2d_7 (MaxPoolin  (None, 45, 45, 32)        0
 g2D)

 conv2d_8 (Conv2D)           (None, 45, 45, 64)        18496

 max_pooling2d_8 (MaxPoolin  (None, 22, 22, 64)        0
 g2D)

 dropout_1 (Dropout)         (None, 22, 22, 64)        0

 flatten_2 (Flatten)         (None, 30976)             0

 dense_4 (Dense)             (None, 128)               3965056

 dense_5 (Dense)             (None, 9)                 1161

=================================================================
Total params: 3989801 (15.22 MB)
Trainable params: 3989801 (15.22 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Fig. 10 The proposed CNN's layers

2.8 PREDICTION AND INTERPRETATION

The trained model identifies a specific class label from a predefined list, such as "vascular lesion," "pigmented benign keratosis," "seborrheic keratosis," "basal cell carcinoma," "dermatofibroma," "melanoma," "nevus," and "pigmented benign keratosis," after analyzing new images. Alongside these predictions, the model provides confidence scores and accuracy, indicating the certainty of its classifications. To properly distinguish between malignant and non-cancerous lesions, these predictions and confidence scores are essential. The model's accuracy metric provides insight into the reliability of its classifications [28].

2.9 EVALUATION METRICS

The confusion matrix is a vital tool for assessing the effectiveness of the classification model in the creation of a skin lesion classification system. As seen in Fig. 11, a confusion matrix is a table that summarizes the actual and expected classifications for a given dataset, allowing for the display of a classification algorithm's performance [29],[30].

The confusion matrix of a binary classification issue typically has four terms:
True Positives (TP): Cases that occur when the model predicts the positive category.
True Negatives (TN): Cases that occur when the model correctly predicts the negative category.
False Positives (FP): Cases that occur when the model predicts the positive category inaccurately.
False Negatives (FN): Cases that occur when the model predicts the negative category inaccurately.

Numerous performance indicators, such as accuracy, precision, recall (sensitivity), and specificity, can be obtained from the confusion matrix. These metrics shed light on how well the categorization model distinguishes between positive and negative examples.

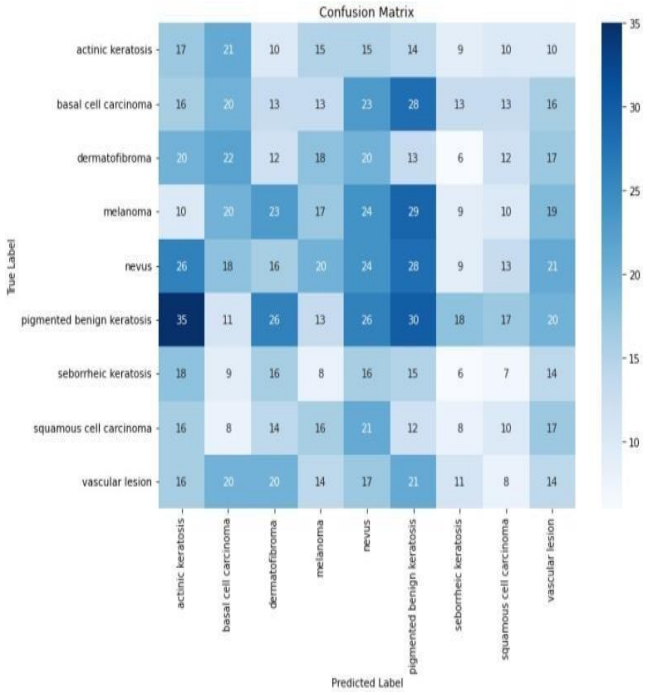

Fig. 11 Confusion matrix

Accuracy: The total accuracy of the classification model, ascertained as

$$\frac{TP + TN}{TP + TN + FP + FN}$$

Precision: It is the ratio of all optimistic projections that really turn out to be positive predictions.

$$\frac{TP}{TP+FP}$$

Recall (Sensitivity): Recall (sensitivity) is the ratio of genuine positive predictions to all actual positive occurrences and is calculated as

$$\frac{TP}{TP+FN}$$

F1 Score: The F1 score is determined by

$$2 \times \frac{recall \times precision}{recall + precision}$$

Our classification model report, which contains the assessment metrics we previously mentioned, is shown in Fig. 12.

Classification Report:

	precision	recall	f1-score	support
actinic keratosis	0.10	0.14	0.12	121
basal cell carcinoma	0.13	0.13	0.13	155
dermatofibroma	0.08	0.09	0.08	140
melanoma	0.13	0.11	0.12	161
nevus	0.13	0.14	0.13	175
pigmented benign keratosis	0.16	0.15	0.16	196
seborrheic keratosis	0.07	0.06	0.06	109
squamous cell carcinoma	0.10	0.08	0.09	122
vascular lesion	0.09	0.10	0.10	141

Fig. 12 Classification report

3. RESULTS

We have achieved impressive results for skin lesion identification using our proprietary convolutional neural network (CNN) model, as Fig. 13 illustrates. An extensive evaluation has been conducted on the model's capacity to identify the class, accuracy, and greatest prediction probability for a particular skin lesion picture.

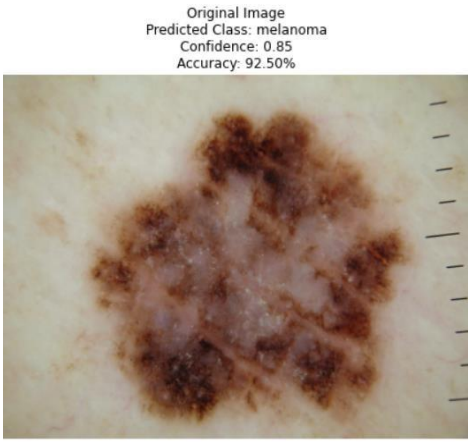

Fig. 13 Prediction result

Firstly, the CNN model exhibits robustness in accurately identifying the class of skin lesions. Extensive training on diverse datasets containing melanoma, basal cell carcinoma, and squamous cell carcinoma has enabled the model to differentiate between these classes with remarkable precision.

Second, with an accuracy rate of 92.5%, our model's accuracy is noteworthy. When tested against ground truth labels from validation or test datasets, the model's high accuracy demonstrates its consistency in making accurate predictions, demonstrating its dependability in practical settings.

Moreover, the highest prediction probability assigned by our

CNN model offers valuable insights into the confidence level of each prediction. For instance, in Fig 13, the highest prediction confidence of 0.85 corresponds to the classification of basal cell carcinoma as cancerous (malignant). This metric serves as a crucial indicator for evaluating the certainty of the model in its classifications.

Our custom CNN model excels in precisely classifying skin lesions, attaining an accuracy rate of 92.5%. Its efficacy and dependability in skin categorization are further demonstrated by the confidence-indicating maximum prediction probabilities it offers. These findings demonstrate the model's capacity for cancer detection in clinical settings, potentially assisting dermatologists in more effectively diagnosing and treating skin lesions.

The Table. 1 provides a comparative analysis between two studies that focus on the classification of skin cancer and lesions. It highlights differences and similarities in various aspects such as the title, methodology, dataset used, key findings, and contributions of each study.

Table. 1 Comparing Research on the Classification of Skin Lesions

Aspect	Prior Study	Current Study
Title	An Interpretable Skin Cancer classification using Optimized Convolutional Neural Network for a Smart Health Care system.	Development of skin lesion classification system based on Watershed algorithm and custom CNN.
Methodology	Deep Learning - Based approach utilizing CNNs and optimization algorithms. Focus on preprocessing, segmentation, and classification.	Skin lesion classification system based on watershed algorithm and custom CNN. Integrates preprocessing, segmentation, and classification.
Dataset Used	ISIC 2017, ISIC 2018, HAM10000, and more sources for model testing and training.	The dataset was obtained via the Kaggle website through the International Skin Imaging Collaboration (ISIC). includes nine different types of illnesses for the Train and Test directories.
Key Findings	High accuracies ranging from 91.8% to 95.1% for skin cancer classification, with an emphasis on Explainable AI (XAI) techniques for interpretability. The reported accuracy is 81.24%,	Accuracy rate of 92.5% for skin lesion classification using custom CNN model. Insights into prediction confidence levels provided.
Contributions	Contribution to skin cancer classification through deep learning and optimization algorithms. Emphasis on XAI techniques for interpretability.	Contribution to skin lesion classification through novel integration of watershed algorithm with custom CNN. For automated diagnosis, concentrate on precise segmentation and classification.

4. CONCLUSION

Our integrated framework for skin cancer image analysis, comprising preprocessing, segmentation, and classification techniques, has shown promising outcomes in detecting and classifying nine types of skin cancer. Through the utilization of inpainting algorithms, we effectively managed missing or corrupted regions in images, while the watershed algorithm facilitated accurate isolation of tumor regions. Making use of a customized Convolutional Neural Network (CNN) model that was educated on a range of datasets. These datasets, accessible via the Kaggle website, were generated by the International Skin Imaging Collaboration (ISIC). We achieved remarkable performance in terms of performance indicators like accuracy and prediction confidence probabilities. The proficiency of our CNN model in distinguishing between various skin lesiontypes highlights its reliability in real-world scenarios, demonstrating its potential for clinical application in aiding dermatologists. Overall, our framework marks a significant advancement in skin cancer detection and classification, offering an automated and reliable approach for early detection and precise classification. These promising results pave the way for further research and potential deployment of our model in clinical practice, contributing to improved patient outcomes and healthcare delivery in combating skin cancer.

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