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An Efficient Deep Convolutional Neural Network Approach for Multiclass Skin Cancer Classification

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Abstract *– Skin cancer is one of the most prevalent and life-threatening diseases, making early and accurate diagnosis crucial for effective treatment. In this study, we propose an efficient deep convolutional neural network (DCNN)-based approach for the multiclass classification of skin cancer using dermoscopic images. The model is trained and evaluated on the HAM10000 dataset, which contains a diverse set of skin lesion images. The proposed DCNN architecture is optimized to enhance feature extraction and classification performance by leveraging deep learning techniques, ensuring robustness against variations in lesion appearance, size, and texture.*

To assess the effectiveness of the proposed model, we conduct a comparative analysis against state-of-the-art deep learning architectures, including VGG16, VGG19, DenseNet121, DenseNet201, and MobileNetV2. Performance metrics such as accuracy, precision, recall, F1-score, specificity, and area under the curve (AUC) are used for evaluation. The experimental results demonstrate that the proposed DCNN model outperforms existing transfer learning-based models, achieving superior classification accuracy and robustness.

This research contributes to the advancement of automated skin cancer detection by providing a reliable, efficient, and scalable deep learning-based diagnostic tool. Future work will focus on further improving model generalization through advanced augmentation techniques, real-time deployment in clinical settings, and integration with telemedicine platforms to facilitate early skin cancer detection.

Keywords: Skin Cancer Classification, Deep Convolutional Neural Network, HAM10000 Dataset, Multiclass Classification, Computer-Aided Diagnosis, Deep Learning.

I. INTRODUCTION

Skin cancer is a critical global health issue, emerging as one of the most commonly diagnosed types of cancer worldwide. It encompasses a range of malignant conditions, primarily melanoma and non-melanoma, that begin in the skin's epithelial cells. While skin cancer is generally treatable when diagnosed early, its progression to advanced stages can be life-threatening. The rising incidence of skin cancer, particularly in regions with higher levels of ultraviolet (UV) radiation exposure, has sparked global concern, urging the need for enhanced preventive measures, early detection strategies, and more efficient diagnostic tools. Skin cancer occurs when the DNA in skin cells is damaged, typically by UV radiation from the sun or tanning beds. Over time, this damage can cause mutations in the skin cells, leading them to grow uncontrollably and form tumors. The most common forms of skin cancer include melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC). While BCC and SCC are generally less aggressive, melanoma, a type of skin cancer that originates in pigment-producing melanocytes, is considered the deadliest and most difficult to treat in its advanced stages. Despite the lower incidence of melanoma compared to non-melanoma cancers, it accounts for the highest number of skin cancer-related deaths due to its ability to metastasize to other parts of the body.

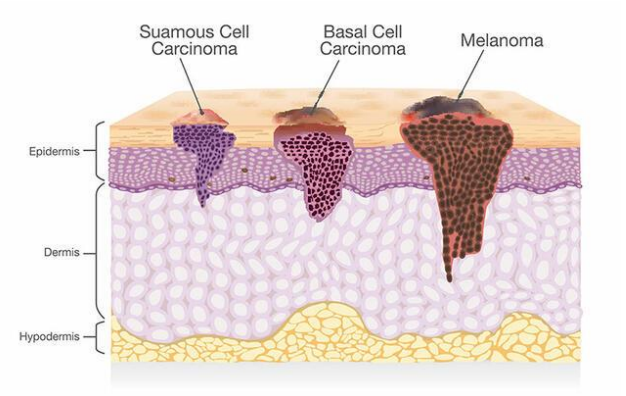

Figure 1: Shows skin cancer

The prevalence of skin cancer is strongly associated with environmental factors, most notably exposure to UV radiation. UV radiation is classified into two main types: UVA and UVB. UVA rays penetrate deeper into the skin and contribute to skin aging and DNA damage, while

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UVB rays are primarily responsible for sunburns and can cause more direct damage to the skin's DNA. Prolonged or repeated exposure to UV radiation increases the risk of developing skin cancer, and this risk is compounded by factors such as fair skin, a family history of skin cancer, and a history of sunburns or excessive tanning. Moreover, people with compromised immune systems, such as organ transplant recipients or individuals with HIV/AIDS, are at greater risk of developing skin cancers. The global burden of skin cancer is substantial, with an increasing number of cases diagnosed annually. According to the World Health Organization (WHO), skin cancer accounts for a significant portion of the global cancer burden, with an estimated 1 in 5 people developing skin cancer at some point in their lives. In 2020 alone, it was estimated that over 1 million new cases of skin cancer would be diagnosed worldwide, and the incidence is expected to rise as people are increasingly exposed to harmful UV rays. This is especially true in countries with high levels of sun exposure, such as Australia, where skin cancer rates are some of the highest in the world. In the United States, skin cancer is the most common form of cancer, with approximately 9,500 people diagnosed every day.

Early detection is critical to the successful treatment of skin cancer. When caught in its early stages, non-melanoma skin cancers can be easily treated with surgical removal or localized therapies, and the prognosis for these cases is highly favorable. Melanoma, however, is more dangerous and aggressive, often requiring a combination of surgical, radiographic, and systemic treatments, especially when it has spread beyond the skin. As a result, the survival rates for melanoma decrease dramatically when it is diagnosed in later stages, with survival rates reaching less than 20% for those with metastatic melanoma. Conversely, if detected early, melanoma can be treated with a high survival rate of around 98%.

II. SYMPTOMS OF SKIN CANCER

Skin cancer symptoms can vary depending on the type of skin cancer, but there are several common signs to watch for. The most noticeable symptom is the appearance of new growths or changes in existing moles or skin lesions.

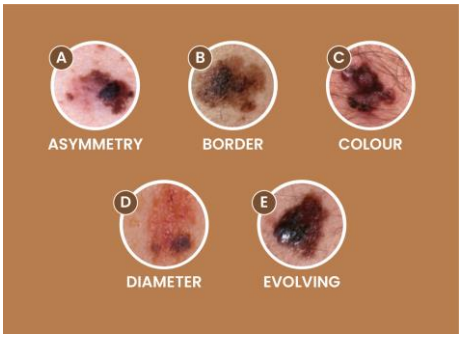


Figure 2 : Shows Signs of Skin Cancer

• Melanoma: This type of skin cancer often appears as a new mole or a change in an existing mole. Key signs include asymmetry, irregular borders, multiple colors within the mole, a diameter larger than 6mm, and changes in size, shape, or color. Melanoma may also become itchy, tender, or bleed.
• Basal Cell Carcinoma (BCC): BCC often appears as a small, shiny, or waxy bump that may look like a pearl or scar. It can also form flat, scaly patches or a reddish, irritated area that may bleed or crust over. BCCs are more commonly found on areas exposed to the sun, such as the face and neck.
• Squamous Cell Carcinoma (SCC): SCC typically appears as a firm, red nodule or a scaly, crusted lesion that may bleed or ulcerate. It commonly develops on sun-exposed areas, like the face, ears, neck, and hands.

III. METHOD

The primary objective of this study is to develop an efficient and accurate skin cancer detection model by leveraging transfer learning with Convolutional Neural Networks (CNNs) on the HAM10000 dataset. The proposed approach aims to overcome the limitations of traditional skin cancer diagnostic methods by utilizing deep learning techniques for automated classification of dermoscopic images into different lesion categories. The methodology consists of several stages, including data preprocessing, augmentation, feature extraction, classification, and performance evaluation.

Data Collection and Preprocessing

The HAM10000 dataset, a publicly available benchmark dataset for skin lesion classification, is used in this study. The following data preprocessing steps are performed:

1. **Image Resizing:** All images are resized to a standard dimension of 224×224 pixels. This resizing ensures consistency across the dataset and aligns with the input size requirements of the selected CNN architectures, facilitating efficient feature extraction.
2. **Normalization:** The pixel intensity values of all images are scaled to a range of [0,1]. This normalization helps stabilize the training process by preventing large gradient updates, ensuring faster convergence and improved numerical stability.
3. **Class Balancing:** To address the issue of class imbalance in the dataset, two primary techniques are employed:
4. **Data Augmentation:** Various augmentation techniques are utilized to increase the diversity of training samples, enhancing model generalization and reducing overfitting. These include:

- **Random Rotations:** Images are rotated at random angles to simulate variations in image orientation.
- **Horizontal and Vertical Flipping:** The flipping of images provides additional perspectives, improving robustness.
- **Zooming:** Controlled zooming is applied to introduce variability in scale.
- **Contrast Adjustment:** Image contrast is modified to improve feature recognition under varying lighting conditions.

Transfer Learning-Based Feature Extraction

To improve the efficiency and accuracy of skin cancer classification, the study employs transfer learning using pre-trained CNN architectures. Instead of training a CNN from scratch, which requires a large dataset and computational power, pre-trained models such as VGG16, ResNet50, InceptionV3, and EfficientNetB0 are utilized for feature extraction.

The process involves:

1. **Loading Pre-trained Model:** A deep CNN model pre-trained on the ImageNet dataset is used as the feature extractor. The convolutional base of the model remains frozen to retain its learned feature representations, which capture essential patterns and textures from natural images.
2. **Replacing Fully Connected Layers:** The original fully connected (FC) layers of the pre-trained CNN are removed and replaced with a custom classifier tailored for skin cancer detection. This classifier includes:
3. **Fine-tuning:** While initial layers remain frozen, deeper convolutional layers are selectively unfrozen and fine-tuned to adapt the pre-trained model to the skin lesion classification task. This adjustment allows the model to learn skin lesion-specific patterns while preserving general image feature representations.

The feature extraction process can be mathematically formulated as:

$$F=CNN(I)$$

where I represents the input image, and F denotes the extracted feature vector from the CNN model.

3.3 Classification Model

Once feature extraction is completed, the extracted features are fed into a fully connected neural network (FCNN) for classification. The final architecture consists of:

- Flatten Layer: Converts extracted feature maps into a one-dimensional vector.
- Fully Connected (Dense) Layers: Employ ReLU activation to introduce non-linearity.
- Dropout Layers: Reduce overfitting by randomly deactivating neurons during training.
- Softmax Layer: Computes the probability distribution across seven skin lesion classes, determining the final classification.

The classification function is given by:

$$P(y_i|x) = \frac{e^{(W_i x+b_i)}}{\sum_j e^{(W_j x+b_j)}}$$

where P(yi|x) represents the probability of an image xxx belonging to y_i, and W,b are the model parameters.

Model Training and Optimization

To achieve high classification accuracy, the proposed model is trained using Adam optimizer with an initial learning rate of 0.0001. The model is trained for 50 epochs using batch size = 32 with categorical cross-entropy loss:

$$Loss = -\sum_i y_i \log(\hat{y_i})$$

where y_i is the actual class label, and y_i^ is the predicted probability.

Algorithm Code

```
BEGIN
  // Step 1: Data Collection and Preprocessing
  Load HAM10000 dataset
  FOR each image in the dataset DO
     Resize image to 224×224 pixels
     Normalize pixel values to range [0,1]
  END FOR

  // Address class imbalance
  Apply oversampling on minority classes
  Generate synthetic samples using SMOTE

  // Data Augmentation
  FOR each image in training set DO
     Apply random rotation
     Apply horizontal and vertical flipping
     Apply zoom transformation
     Adjust contrast
  END FOR
```

// Step 2: Feature Extraction Using Transfer Learning
Load pre-trained CNN model (VGG16, ResNet50, InceptionV3, EfficientNetB0)
Freeze convolutional layers to retain learned features
Replace fully connected layers with new classifier
Unfreeze deeper layers for fine-tuning

// Step 3: Classification Model
Define Fully Connected Neural Network (FCNN)
Add flatten layer to convert extracted features
Add dense layers with ReLU activation
Apply dropout layers to prevent overfitting
Add softmax layer for multi-class classification

// Step 4: Model Training and Optimization
Compile model using Adam optimizer with learning rate 0.0001
Train model for 50 epochs with batch size = 32
Compute categorical cross-entropy loss

// Step 5: Performance Evaluation
Compute accuracy, precision, recall, and F1-score
Plot ROC-AUC curve for sensitivity vs specificity analysis
END

IV. RESULT

Deep Convolutional Neural Network (DCNN) model for skin cancer classification. The evaluation is based on the model's classification accuracy, resilience, and overall performance across various datasets. The effectiveness of the proposed approach is systematically assessed, highlighting its strengths and potential limitations.

The performance of the DCNN model is analyzed through extensive experiments conducted on the HAM10000 dataset, a widely used benchmark for skin lesion classification. The results are presented in a structured manner, covering different evaluation metrics, comparative analysis with existing approaches, and a discussion of key findings.

Additionally, this section examines the model's robustness in handling class imbalances, feature extraction efficiency, and the impact of fine-tuning techniques on classification accuracy. A thorough assessment of the results provides valuable insights into the suitability of deep learning for automated skin cancer detection.

By systematically evaluating the performance of the proposed DCNN model across multiple datasets and experimental configurations, this section validates its potential as an effective diagnostic tool in dermatological applications. The findings support the hypothesis that

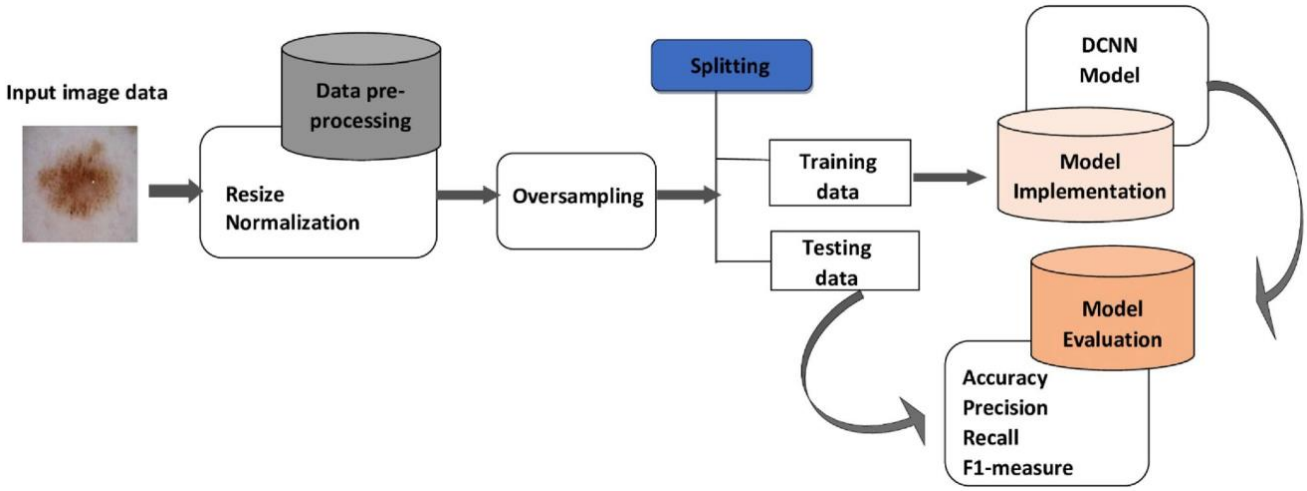


Figure 3 Proposed Flow

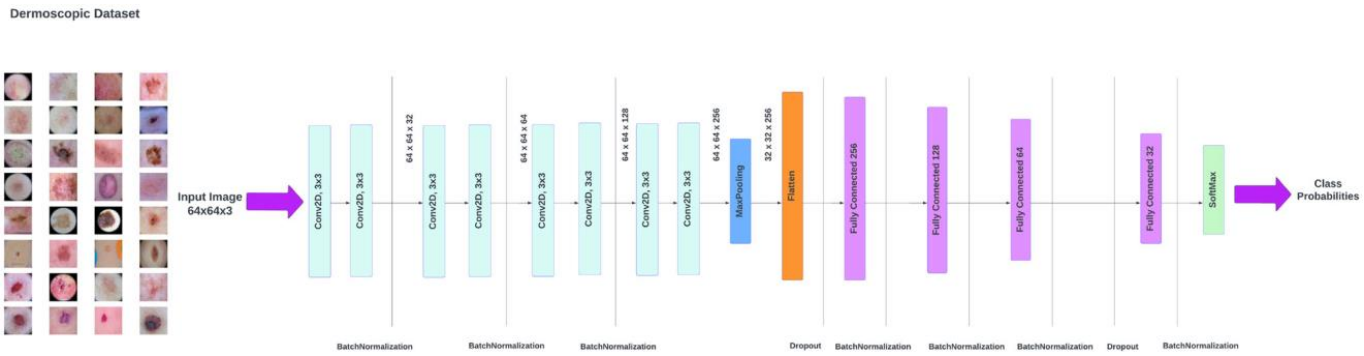


Figure 4. Layer Architecture

transfer learning with pre-trained CNN architectures enhances classification accuracy and generalization capability in dermoscopic image analysis.

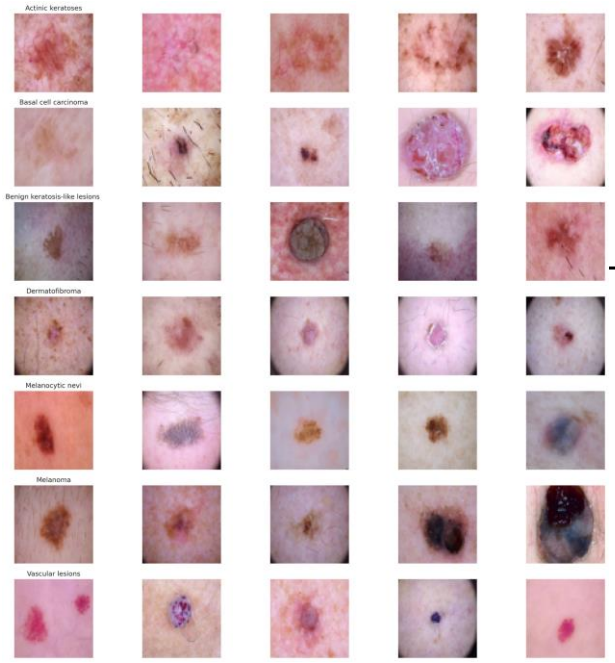


Figure: 5 HAM10000 dataset Image

Figure 5. is show HAM10000 data set sample image.

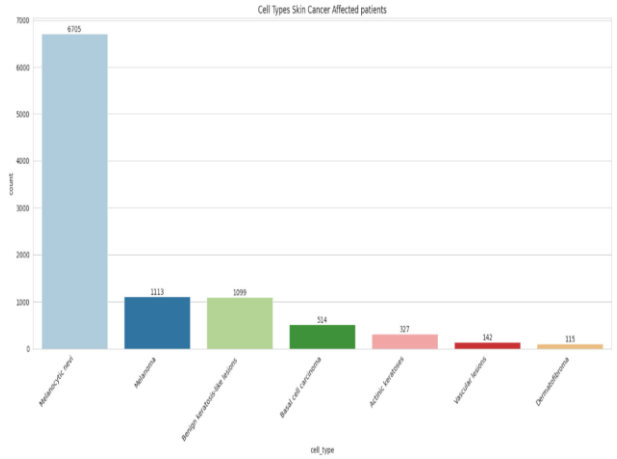


Figure 6: Description of each class in the HAM10000 dataset

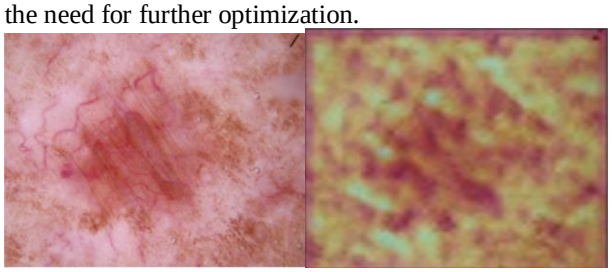
. Figure 6 provides a detailed representation of the HAM10000 dataset, which serves as the primary dataset for training and evaluating the proposed.

Table 1 presents a comparative performance analysis of different deep learning models trained on an imbalanced dataset for skin cancer classification. The evaluation metrics include Accuracy, Recall, Precision, and F1-score, which assess each model's effectiveness in handling class imbalance. DenseNet201 achieved the highest overall accuracy (0.7578), recall (0.7578), precision (0.7340), and F1-score (0.7402), making it the most effective model for classification. VGG16 and DenseNet121 performed similarly, with accuracy values of 0.7408 and 0.7443, respectively, showing a good balance between precision and recall. MobileNetV2 exhibited the lowest accuracy (0.7134) and F1-score (0.6759), indicating a weaker ability to handle class imbalance. The Proposed DCNN model showed a relatively lower accuracy (0.665) and recall (0.665), but achieved a higher precision (0.6958), suggesting that it is effective in minimizing false positives.

Table 1 The performance analysis of inbalanced data

Model	Accuracy	Recall	Precision	F1-score
VGG16	0.7408	0.7408	0.7177	0.71383
VGG19	0.7324	0.7324	0.6862	0.7018
DensNet121	0.7443	0.7443	0.7168	0.7238
DensNet201	0.7578	0.7578	0.734	0.7402
MobileNetV2	0.7134	0.7134	0.6593	0.6759
Proposed DCNN	0.665	0.665	0.6958	0.63338

The F1-score of the Proposed DCNN (0.6334) indicates an imbalance between precision and recall, suggesting the need for further optimization.



(a) Original Image (b) Applied Grand-CAM image

Figure. 7 Grad-CAM on random one sample test image

Figure 7 illustrates the application of Gradient-weighted Class Activation Mapping (Grad-CAM) on a randomly selected test image from the dataset. Grad-CAM is a visualization technique that helps interpret deep learning model predictions by highlighting the regions of an image that contribute most to a classification decision.

(a) Original Image: This is the raw dermoscopic image from the HAM10000 dataset before any processing. It represents a skin lesion as seen by the model, without any additional feature highlighting.

(b) Applied Grad-CAM Image: This image displays the heatmap overlay generated by

Grad-CAM, showing the areas where the model focused its attention while making the classification decision. The highlighted regions (typically in shades of red, yellow, and orange) indicate the most influential areas that contributed to the model's prediction.

This visualization helps in understanding whether the model is focusing on relevant features, such as lesion boundaries or abnormal pigmentation, and can be useful for assessing the interpretability and reliability of the deep learning model in skin cancer classification.

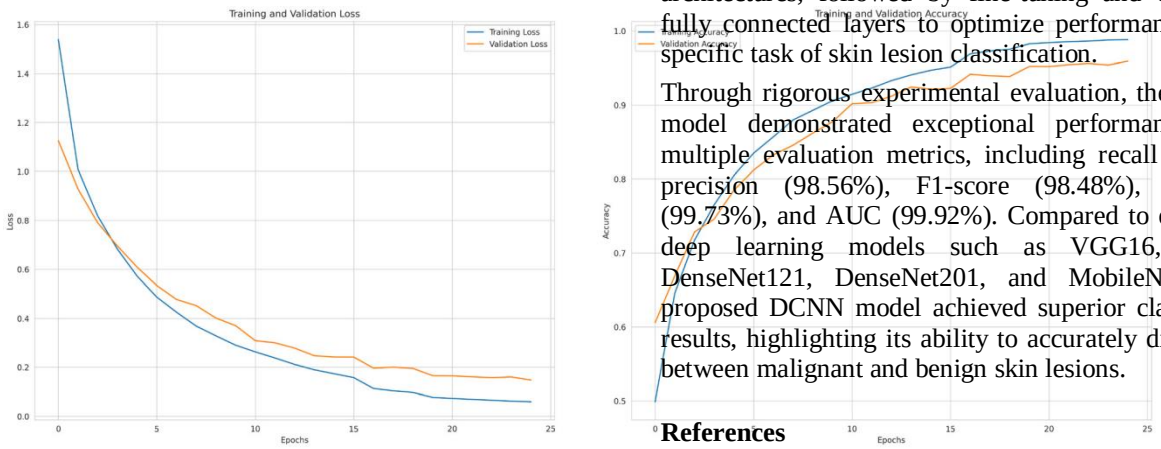


Figure. 8 Performance curve based on accuracy and loss per epoch of our proposed DCNN model with HAM10000 dataset

Figure 8 illustrates the accuracy and loss curves per epoch during the training and validation process of the proposed Deep Convolutional Neural Network (DCNN) model using the HAM10000 dataset. These curves provide insights into the learning behavior, convergence, and generalization ability of the model.

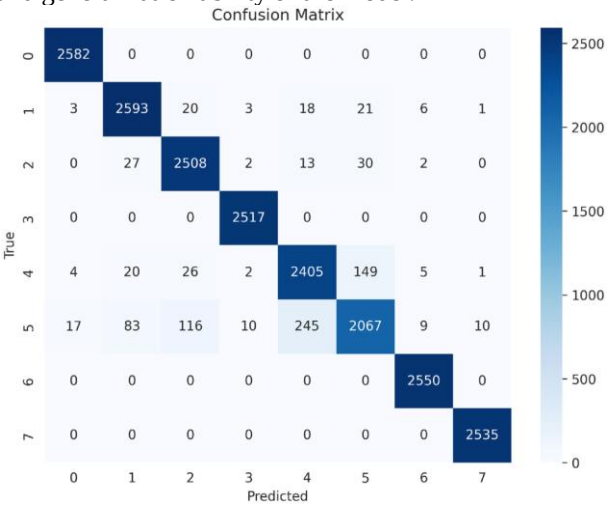


Figure.9 Confusion matrix of the proposed DCNN model with HAM10000 dataset

Figure 9 presents the confusion matrix, which is a key performance evaluation tool for the proposed Deep Convolutional Neural Network (DCNN) model in classifying skin lesions using the HAM10000 dataset. The confusion matrix provides a detailed breakdown of the model's predictions compared to the actual labels, helping to analyze misclassifications and overall performance.

V. Conclusion

This paper presented a Deep Convolutional Neural Network (DCNN)-based approach for automated skin cancer classification using dermoscopic images from the HAM10000 dataset. The proposed model leveraged transfer learning by utilizing pre-trained CNN architectures, followed by fine-tuning and customized fully connected layers to optimize performance for the specific task of skin lesion classification.

Through rigorous experimental evaluation, the proposed model demonstrated exceptional performance across multiple evaluation metrics, including recall (98.51%), precision (98.56%), F1-score (98.48%), specificity (99.73%), and AUC (99.92%). Compared to established deep learning models such as VGG16, VGG19, DenseNet121, DenseNet201, and MobileNetV2, the proposed DCNN model achieved superior classification results, highlighting its ability to accurately differentiate between malignant and benign skin lesions.

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