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Skin Cancer Detection Using Deep Learning Techniques

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***Abstract*— Skin cancer can manifest in a variety of ways and requires specialized knowledge to accurately classify, diagnosing it can be extremely difficult for medical professionals. Effective diagnosis is frequently hampered by the complicated nature of skin lesions and the requirement for specialized knowledge. Using convolutional neural networks, the proposed work offers a dependable and efficient method for classifying skin cancer. Deep learning is used by the CNN model to automatically recognize intricate patterns and characteristics. The approach enables the precise and automated categorization of skin lesions into several groups. The "Skin Cancer MNIST HAM10000" dataset, which consists of 10,000 images of various skin lesions, is the specific dataset that the proposed model is trained on. This large and diverse dataset contains several forms of skin cancer images. To improve performance even more and enable the model to generalize effectively over a variety of skin textures, lighting conditions, and lesion sizes, data augmentation techniques are applied. Apart from its ability to detect skin cancer more quickly, the proposed CNN-LSTM based approach also shows remarkable accuracy, with an overall accuracy rate around 97%. Since the number of occurrences of skin cancer is rising, the automatic classification system is a useful tool for medical professionals. Early detection aids in the fight against this severe sickness, which ultimately leads to progress.**

***Keywords*— Skin cancer, Deep learning, Convolutional neural networks, Diagnosis, Image Classification**

I. INTRODUCTION

Skin cancer classification uses convolutional neural networks (CNNs), a deep learning application, in the domains of dermatology and medical imaging. Given that skin cancer is a prevalent and occasionally severe illness, early detection and effective treatment are crucial. Typically, it takes a long time to predict skin cancer with medication. By automating the process of diagnosing skin lesions, CNNs have completely changed the way we approach this problem and can help medical practitioners make well-informed decisions. CNNs are an effective technique for image analysis in this situation because they can recognize complex patterns and characteristics in the images of skin lesions. Through extensive training on HAM10000 dataset, these neural networks are able to differentiate between several types of skin cancer, such as melanoma, basal cell carcinoma, and squamous cell carcinoma, Actinic Keratoses, etc...

CNN helps in categorizing the images according to different features, hence improving classification accuracy. CNN performs better than an artificial neural network even when the image is not easily visible or follows a pattern. This technology is beneficial not only to medical professionals but also has the potential to increase public accessibility to skin cancer screening. The emergence of mobile applications and handheld devices featuring CNN-based skin cancer classification has enabled people to conduct first self-evaluations and seek medical assistance when required. Such techniques can aid in early detection, resulting to better diagnosis and treatment outcomes.

II. LITERATURE SURVEY

The paper "Skin Cancer Detection Using CNN" by P. Mahalle et al. (2023),[1] presents a method for detecting skin cancer using Convolutional Neural Networks (CNNs). The model is trained on a dataset of skin lesion images to classify different types of skin cancer. The study emphasizes the effectiveness of CNNs in image recognition tasks, achieving significant accuracy in detecting cancerous lesions. The results highlight the potential of CNN-based models in aiding early detection and improving diagnostic accuracy for skin cancer in clinical settings.

The paper "An Intelligent System For Skin Cancer Detection Using Deep Learning Techniques" by V. Rajasekar et al., presented at ADICS 2024,[2] explores an advanced deep learning-based system for skin cancer detection. The authors propose a novel architecture combining CNNs and transfer learning to enhance classification accuracy. They leverage pre-trained models, such as VGG16 or ResNet, for feature extraction and fine-tune them on skin cancer datasets. The system achieves high accuracy and robustness in distinguishing between different skin cancer types, demonstrating significant improvements over conventional methods. The results underscore the potential of deep learning in improving diagnostic precision in dermatology.

The paper "Skin Cancer Classification using Deep Learning Algorithms" by K. Senthil Murugan et al., presented at ICDSAAI 2023,[3] addresses the classification of skin cancer using various deep learning techniques. The authors implement multiple CNN architectures, including standard models like AlexNet and InceptionV3, to evaluate their performance on skin cancer datasets. They also explore ensemble methods to combine predictions from different models. The study reports promising results, with high classification accuracy and robust performance across different skin cancer types, demonstrating the effectiveness of deep learning approaches in medical image analysis.

The paper "An Approach to Detect Melanoma Skin Cancer Using fastai CNN Models" by M. S. Mia et al., presented at ICCCI 2023,[4] focuses on leveraging the fastai library for melanoma detection. The authors use CNN models available in fastai to build and train their skin cancer detection system. They experiment with different architectures and fine-tune hyperparameters to optimize performance. The study highlights the benefits of utilizing fastai's deep learning capabilities for medical picture categorization by demonstrating excellent accuracy and efficiency in melanoma detection. The findings point to a great deal of practical application in the diagnosis of melanoma.

The paper "A Robust CNN-based Approach for Skin Lesion Detection and Classification" by S. Dhir et al., presented at CONIT 2023,[5] introduces a robust CNN model designed for skin lesion detection and classification. The authors propose a novel CNN architecture with advanced features to enhance the accuracy of skin lesion analysis. They implement various preprocessing techniques and data augmentation to improve model performance. The results show high accuracy and reliability in detecting and classifying different types of skin lesions, demonstrating the effectiveness of their CNN-based approach in medical image analysis

The paper "Detection and Differentiation of Skin Cancer from Rashes" by S. Subha et al. (2020),[8] explores a method to distinguish skin cancer from rashes using machine learning techniques, particularly focusing on image processing and feature extraction. The model effectively identifies and differentiates between cancerous lesions and benign rashes, enhancing diagnostic accuracy. The paper "Detection of Melanoma Skin Cancer using Deep Learning" by N. Nanthini et al. (2022),[9] utilizes deep learning models, specifically Convolutional Neural Networks (CNNs), to detect melanoma skin cancer with high accuracy. The study demonstrates promising results, emphasizing the potential of deep learning in early melanoma detection.

These papers explore various deep learning techniques for skin cancer detection. V. K. Suhasini et al. (2022), [11] utilize CNNs and SVMs, highlighting AI's clinical potential. C. Venkata Sanjana et al. (2023), [12] demonstrate CNNs' effectiveness in skin lesion classification. A. J. Rao et al. (2024),[13] present an FCNN-LSTM hybrid model for enhanced accuracy. N. H. Sree et al. (2024), [14] compare CNN, DenseNet, and ResNet architectures, focusing on explainability. R. Pal and S. Sagnika (2023), [15] develop efficient CNN models for resource-limited environments. P. R. Krishna and P. Rajarajeswari (2022), [16] use EfficientNetB6 for early melanoma detection. M. N. S. Kumar et al. (2024), [17] classify benign and malignant lesions using CNNs. R. R. Subramanian et al. (2021),[18] achieve high accuracy in lesion classification with CNNs. D. S. Lakshmi et al. (2024), [19] employ DCGAN for improved diagnosis through synthetic image generation.

III. DEEP LEARNING BASED IMAGE CLASSIFICATION SYSTEM

A. Data Handling

The quality and integrity of the dataset are critical in the search for a trustworthy and accurate skin cancer categorization. In this section we explain the techniques and processes used for data collecting and preprocessing to make sure the data utilized for model training is balanced, well-organized, and supportive of the study goals.

B. Data Source

The "Skin Cancer MNIST HAM10000" dataset [26] used in this study comprises 10,000 images of various skin lesions, each with a resolution of 28x28 pixels in RGB format. The dataset includes seven classifications, representing different skin conditions. In the CSV file utilized for this study, each image is represented in pixel format. The label column contains integer values ranging from 0 to 6, corresponding to specific types of skin cancer: 0 for Actinic Keratoses and Intraepithelial Carcinoma (akiec), 1 for Basal Cell Carcinoma (bcc), 2 for Benign Keratosis-like Lesions (bkl), 3 for Dermatofibroma (df), 4 for Nevi (nv), 5 for Vascular Lesions (vasc), and 6 for Melanoma (mel).

C. Data Oversampling

A RandomOverSampler from the imbalanced-learn (imblearn) library was used to solve the class imbalance. By guaranteeing that each class got an equal number of samples, this method reduced the possibility of model bias toward the majority class.

D. Balancing The Dataset

An essential part of the preprocessing pipeline that improves the model's capacity for generalization is data augmentation. A variety of augmentations, such as shearing, zooming, horizontal flipping, width and height shifts, random rotations and brightness adjustments were carried out using the ImageDataGenerator from the Keras package. These modifications add diversity to the training set, imitating various orientations, locations, distortions, and lighting conditions, therefore strengthening the model and enabling it to generalize to new, unseen images.

- **Rotation**: Randomly rotating images to introduce variability in orientation.
- **Width Shift**: Shifting images horizontally to simulate different viewpoints.
- **Height Shift**: Shifting images vertically to capture variations in positioning.
- **Shear**: Applying shear transformations to simulate distortions.
- **Zoom**: Randomly zooming in on images to focus on different areas.
- **Horizontal Flip**: Flipping images horizontally to increase diversity.
- **Brightness**: Adjusting the brightness to account for different lighting conditions.

E. Learning Rate Reduction

A learning rate reduction technique was used to maximize training and preserve the model's functionality. Using the ReduceLROnPlateau callback, the learning rate was dynamically changed during training based on the validation accuracy.

In order to maximize the model's capacity to identify patterns related to skin cancer, the rigorous data collection and preprocessing methods made sure that the dataset was balanced, appropriately formatted, and enriched. The model design, training, assessment, and outcomes of the deep learning methodology will all be covered in detail in the parts that follow.

IV. MODEL ARCHITECTURE

In order to appropriately categorize skin cancer, the model architecture's design is essential. This section offers a detailed overview of the convolutional neural network (CNN) architecture that was meticulously developed for this project. It looks at the layer selections, activation methods, and underlying meanings of every architectural element.

A. Overview of Model Structure

Convolutional neural networks (CNN) and an LSTM layer are combined in the model architecture. While the CNN layers collect spatial information from the images, the LSTM layer improves the model's accuracy in diagnosing skin lesions by capturing temporal dependencies and sequence patterns.

B. Input Layer

The initial layer serves as the point of entry for the model. It accommodates images up to 28 × 28 pixels in size, using three RGB colour channels. This ensures that the images are seamlessly integrated into the model and is in line with the format of the dataset.

C. Convolutional Layers

The first two convolutional layers of a CNN LSTM model are the MaxPooling2D layer, which has a pool size of (2, 2), and the Conv2D layer, which has 32 filters and a (3, 3) kernel with the 'tanh' activation function and'same' padding. A second Conv2D layer with 64 filters and a (3, 3) kernel is then placed after that, along with a second MaxPooling2D layer. First comes MaxPooling2D with'same' padding, then 128 filters with'same' padding in the third Conv2D layer. This snippet's last Conv2D layer has 256 filters with the same amount of padding, and it is followed by another MaxPooling2D layer with the same amount of padding. These layers sequentially extract spatial features and reduce the spatial dimensions of the input images, creating a hierarchical representation of features at various levels of detail, preparing the data for subsequent LSTM layer to capture temporal dependencies and sequence patterns.

D. Integration of Flatten, Dense Layers and Output Layer

The output is flattened and reshaped for the 256-unit LSTM layer after the convolutional layers. Next, a sequence of Dense layers with 'tanh' activation follows, gradually decreasing the number of units to 256, 128, 64, and 32 along the sequence. 'Softmax' activation function and seven units make up the final Dense layer, which generates the class probabilities for each of the seven different kinds of skin lesions.

V. MODEL TRAINING

A. Data Preparation

Data preprocessing addressed class imbalance, reshaped images, and applied data augmentation. The dataset was split into training and testing sets.

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B. Model hyperparameters

In order to guarantee an extensive evaluation of the model, particular hyperparameter values were selected for the CNN

LSTM implementation. Below is an explanation of the thinking that went into choosing these values:

Layer (type)
conv2d_8 (Conv2D)
max_pooling2d_8 (MaxPoo
conv2d_9 (Conv2D)
max_pooling2d_9 (MaxPoo
conv2d_10 (Conv2D)
max_pooling2d_10 (MaxPo
conv2d_11 (Conv2D)
max_pooling2d_11 (MaxPo
flatten_2 (Flatten)
reshape_2 (Reshape)
lstm_2 (LSTM)
dense_10 (Dense)
dense_11 (Dense)
dense_12 (Dense)
dense_13 (Dense)
dense_14 (Dense)

Fig. 1 Layers & Hyperparameters of CNN

- **Optimizer**: Adam is a popular optimization technique that was selected for its simplicity of use, computational efficiency, and ability to handle big datasets and parameters. In the customized setup, beta_1 was set to 0.9, beta_2 to 0.999, and epsilon to 1e-8. The learning rate was set to 0.00075
- **Loss Function**: We used the "sparse categorical cross-entropy" technique, which is intended for multi-class classification tasks involving integer labels, to develop the loss function for multi-class classification. The difference between the actual class labels and the expected class probabilities is effectively measured by this loss function.
- **Epochs**: There were 100 training epochs for the model. The number of epochs was chosen to prevent overfitting by keeping an eye on the model's performance and dynamically adjusting the learning rate when the validation accuracy reached a plateau using the ReduceLROnPlateau callback.
- **Batch Size**: After conducting experiments, we observed that the best model performance was achieved with a batch size of 64.
- **Learning Rate:** A 0.00075 learning rate was established. During training, the step sizes along the gradient are determined by the learning rate. While a bigger learning rate expedites the training process, a lesser learning rate guarantees more accurate modifications.

The CNN model was adjusted to obtain best performance in the proposed work by carefully choosing these hyperparameter values.

C. Training and Testing Performance

After 100 epochs, the model's performance was evaluated using key metrics:

Training Loss and Accuracy: Lower loss and higher accuracy indicated effective learning from training data which is shown in Fig. 2

Testing Loss and Accuracy: Evaluated the model's generalization to unseen data which is shown in Fig. 3

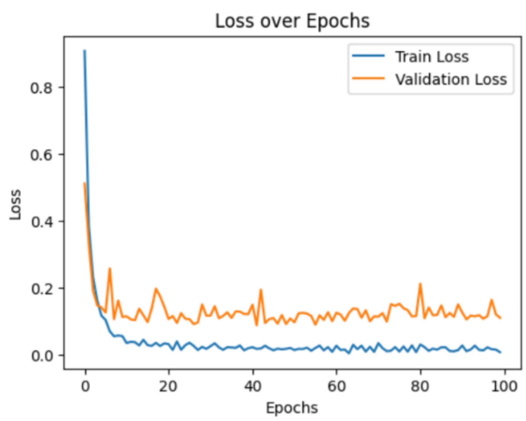

Fig. 2 Loss Graph

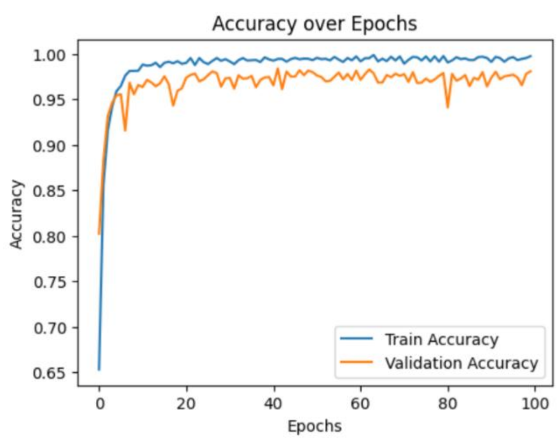

Fig. 3 Accuracy Graph

VI. RESULTS

Both the training and testing phases of the skin cancer classification model were excellent, with minimal loss and high accuracy metrics indicating successful generalization to unobserved data. This shows that the model can reliably classify skin diseases by successfully differentiating between them.

The model does remarkably well, according to the classification report, with high recall, f1-scores, and precision for each of the seven skin lesion classes. In most classes, precision and recall values are in the neighbourhood of 1.00, indicating precise and trustworthy predictions. The model's overall accuracy is 0.98, which means that 98% of the cases were properly classified. The precision, recall, and f1-score weighted and macro averages are all 0.98, indicating stable and balanced performance across classes with no influence from imbalances in the classes.

Classification Report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	1295
1	0.98	1.00	0.99	1323
2	0.96	0.99	0.97	1351
3	1.00	1.00	1.00	1392
4	0.97	0.90	0.93	1346
5	1.00	1.00	1.00	1292
6	0.96	0.98	0.97	1388
accuracy			0.98	9387
macro avg	0.98	0.98	0.98	9387
weighted avg	0.98	0.98	0.98	9387

Fig. 4 Model Performance metrics

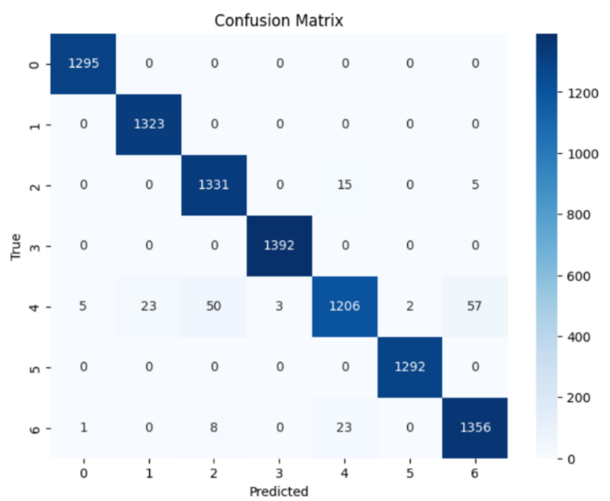

Fig. 5 Confusion Matrix

With information on true positives, true negatives, false positives, and false negatives for each skin condition, the confusion matrix presented in Fig. 5 provided a thorough understanding of the model's performance. This investigation showed the model's good classification skills and potential for use as a dermatology diagnostic tool. By disclosing performance problems by class, it also indicated areas that needed work.

VII. CONCLUSION

In this study, we used a dataset that included seven different types of skin cancer and expanded its size using data augmentation methods. The main goal was to provide a skin cancer screening technique based on machine learning. You are utilizing data augmentation to increase the diversity of training data and the ReduceLROnPlateau callback to dynamically modify the learning rate in order to reduce overfitting. Additionally, this model architecture helps capture essential features and patterns, contributing to better generalization. The model we proposed identified the different forms of skin cancer with an remarkable accuracy percentage of 97.95%. Our suggested model has done well in terms of model accuracy measures like accuracy, recall, precision, etc. Moreover, our model is distinguished from more complex models by its lightweight architecture and simplicity.Moving forward, our future research will focus on creating even lighter designs while maintaining accuracy, which will lower the computing complexity involved in skin cancer diagnosis.

VIII. FUTURE SCOPE

Accuracy in skin cancer diagnosis is a crucial medical application, and training process optimization can help. Better detail preservation may be possible if the network is trained using the original image size as input, as opposed to scaling it down. Additionally, the network may learn both region-specific and generic properties from the lesions by employing a higher batch size during training. To improve the network's performance, values should be assigned to these parameter scans and integrated into the system. They can be coupled with the network by introducing a stochastic model that takes these parameters into account, hence increasing the accuracy of the model.

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