Automated Skin Lesian Analysis with CNNs in Tensorflow And Keras

PROJECT-I REPORT

Submitted by

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Under the supervision of

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DECLARATION

I, **Ms. Bushra Mirza** a student of **Computer Science Engineering (BTCSE AI), Enrolment No: 2021-350-013** hereby declare that the

Project/Dissertation entitled **"Automated Skin Lesian Analysis with CNNs in Tensorflow And Keras"** which is being submitted by me to the Department of Computer Science, Jamia Hamdard, New Delhi in partial fulfillment of the requirement for the award of the degree of **Bachelor of Technology in Computer Science and Engineering with Specialization in Artificial Intelligence (BTCSE AI),** is my original work and has not been submitted anywhere else for the award of any Degree, Diploma, Associateship, Fellowship or other similar title or recognition.

Bushra Mirza

Date:26/04/2024

Place: New Delhi

ACKNOWLEDGEMENT

For the timely completion of the Project, I am thankful to all the individuals who contributed in the successful completion of the assignment from very beginning till its successful completion.

I am grateful to my supervisor ***Mr. Syed Sibtain Khalid***, for his support and guidance.

I am also indebted to all the Dept. staffs that helped me in the successful completion of this assignment.

"Successful passage and outcome of every work comes with dedication, determination and team work. All these turns futile in the absence of a visionary guidance"

Name: Bushra Mirza

Date: 26/04/2024

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ABSTRACT

Cancer is a disease characterized by the uncontrolled growth and spread of abnormal cells, forming tumors that can be either benign or malignant. Malignant tumors, known as cancerous, have the potential to invade other tissues and spread throughout the body. Skin cancer is one of the most common forms of cancer, with over 3 million Americans diagnosed annually. Early detection of skin cancer can significantly improve treatment outcomes, with potential interventions including topical medications, outpatient procedures, and surgery performed by dermatologists.

Melanoma, a particularly aggressive type of skin cancer, can quickly spread to other parts of the body and has a significant mortality rate. However, when diagnosed at an early stage, the survival rate is high, making early detection crucial. Visual examination by dermatologists, while helpful, has limitations in diagnostic accuracy, with rates around 60%. Dermoscopy, a method that improves diagnostic accuracy to approximately 89%, still faces challenges with certain types of lesions, particularly those lacking distinctive dermoscopic features.

The limitations of current diagnostic methods, coupled with the need for higher diagnostic accuracy, underscore the importance of developing computer-aided detection methods for skin cancers. This project aims to address these challenges by developing an automated classification system using image processing techniques and deep learning algorithms, specifically convolutional neural networks (CNNs), in TensorFlow and Keras. This system seeks to enhance the accuracy and efficiency of skin cancer diagnosis, ultimately improving patient outcomes and survival rates.

By leveraging advanced deep learning techniques, the project seeks to provide a practical tool for medical professionals to diagnose skin cancer more effectively and in a timely manner. The automated system can support dermatologists by classifying and identifying various types of skin lesions based on their visual characteristics, thereby streamlining the diagnostic process and contributing to better patient care.

1. INTRODUCTION

Skin cancer, particularly melanoma, is one of the most aggressive and potentially lethal forms of cancer. Early detection and diagnosis are crucial for successful treatment and improved patient outcomes. The traditional diagnostic process, involving clinical screening, dermoscopic analysis, and histopathological examination, can be time-consuming, costly, and prone to error. This project seeks to address these challenges by developing an automated classification system based on deep learning and image processing techniques to classify skin cancer using skin lesions images.

The proposed system utilizes convolutional neural networks (CNNs) in TensorFlow and Keras to analyze dermatological images and identify various types of skin lesions, such as benign and malignant. The model is designed to support medical professionals in diagnosing skin conditions more efficiently and accurately, ultimately leading to better patient outcomes and quicker medical assessments.

To achieve this, the project leverages data augmentation techniques to increase data variety and prevent overfitting. The model architecture includes convolutional, pooling, dropout, and dense layers to effectively extract features from images and classify them.

Through the use of callbacks such as ModelCheckpoint and EarlyStopping, the model is trained and validated using training and validation datasets. The model demonstrates promising performance, achieving high accuracy and generalization on unseen data. Additionally, the application of transfer learning enhances the model's accuracy and reliability.

The automated system has the potential to revolutionize the way skin cancer is diagnosed by providing real-time assistance to dermatologists and medical professionals. By using advanced deep learning algorithms, the system can quickly and accurately detect and classify skin lesions, offering a valuable tool for early detection and classification of skin cancers.

This project not only aims to improve the accuracy and efficiency of skin cancer diagnosis but also to reduce the burden on medical professionals and healthcare systems. Future work may focus on further refining the model, expanding the dataset to include more diverse skin types, and exploring hardware implementation for real-time deployment.

2. Specific Requirements

2.1 Functional Requirements:

- The system must automatically classify dermatological images into various types of skin lesions in real-time.
- The system must assist medical professionals in diagnosing skin conditions efficiently and accurately.

2.2 Performance Requirements:

- The model's classification accuracy must be above 75%.
- The response time for image classification should be low to facilitate real-time diagnosis.

2.3 Design Constraints:

- The system must integrate with existing medical diagnostic workflows and electronic health record systems.
- The model architecture must be scalable to accommodate different image sizes and types, as well as varying numbers of classes.

2.4 Hardware Requirement

- High-quality datasets that include clear and detailed dermatological images across various skin types and conditions should be used for training and evaluating the model.
- . The model requires substantial computational power and memory for training and inference due to its complexity.

2.5 Non-Functional Requirements

2.5.1 Reliability

- The system must accurately classify skin lesions across various lighting conditions and skin tones.
- The system should maintain consistent performance across different types of dermatological images.

2.5.2 Scalability

- The system must be adaptable and able to integrate with different dermatological imaging devices and medical information systems.

- The model should be scalable to accommodate varying dataset sizes and future expansion.

2.5.3Testing Requirements:

- The system must undergo rigorous testing to ensure accuracy, reliability, and robustness in classifying skin lesions.

- The model should be tested on diverse datasets, including images with different skin tones and conditions, to evaluate its generalizability.

3. METHODOLOGY

3.1Data Collection:

Obtain a dataset of dermatological images with both malignant and benign oncological diseases from the International Skin Imaging Collaboration (ISIC).

3.2Data Preprocessing:

Resize and normalize images to a consistent size (e.g., 180x180 pixels) and range (e.g., 0 to 1) for uniformity.

3.3Data Augmentation:

Apply data augmentation techniques such as rotation, flipping, and scaling to increase data variety and prevent overfitting.

3.4Data Splitting:

Divide the dataset into training, validation, and testing subsets while maintaining a representative distribution across different classes.

3.5CNN Design:

Create a convolutional neural network using the Sequential API in Keras.

Incorporate convolutional, pooling, dropout, and dense layers to form the network architecture.

3.6Model Compilation:

Compile the model using the Adam optimizer and categorical cross-entropy loss function.

Set accuracy as the evaluation metric for training and validation.

3.7Model Training:

A .Train the model on the training dataset while monitoring performance on the validation dataset. B. Utilize callbacks such as ModelCheckpoint and EarlyStopping to save the best model and avoid overfitting.

3.8Performance Evaluation:

A. Evaluate the model's performance using metrics such as accuracy, loss, precision, recall, and F1score.

B. Analyze training and validation loss and accuracy curves to assess convergence and stability.

3.9Model Testing:

Test the model's performance on the testing dataset to gauge its generalization ability on new, unseen data.

3.10Model Deployment:

A. Save the trained model for deployment.

B. Integrate the model into applications for medical professionals to use in assisting with the diagnosis of skin conditions.

4. DATASET

In this project, the dataset used consists of 2,357 images of both malignant and benign oncological diseases. These images were sourced from the International Skin Imaging Collaboration (ISIC), a reputable organization dedicated to advancing the diagnosis and treatment of skin cancer. The dataset encompasses a variety of skin lesions, providing a comprehensive representation of different types of skin cancers.

To ensure balance across classes and avoid issues related to class imbalance, the dataset was augmented using a Python package called Augmentor. This process added more samples to each class, ensuring that none of the classes had very few samples and providing more robust data for model training.

The dataset includes the following classes and the corresponding number of images in each:

	Class	No. of Image
0	vascular lesion	139
1	seborrheic keratosis	77
2	squamous cell carcinoma	181
3	nevus	357
4	pigmented benign keratosis	462
5	melanoma	438
6	dermatofibroma	95
7	basal cell carcinoma	376
8	actinic keratosis	114

Fig 4.1 Class Distribution of Skin Lesion Images

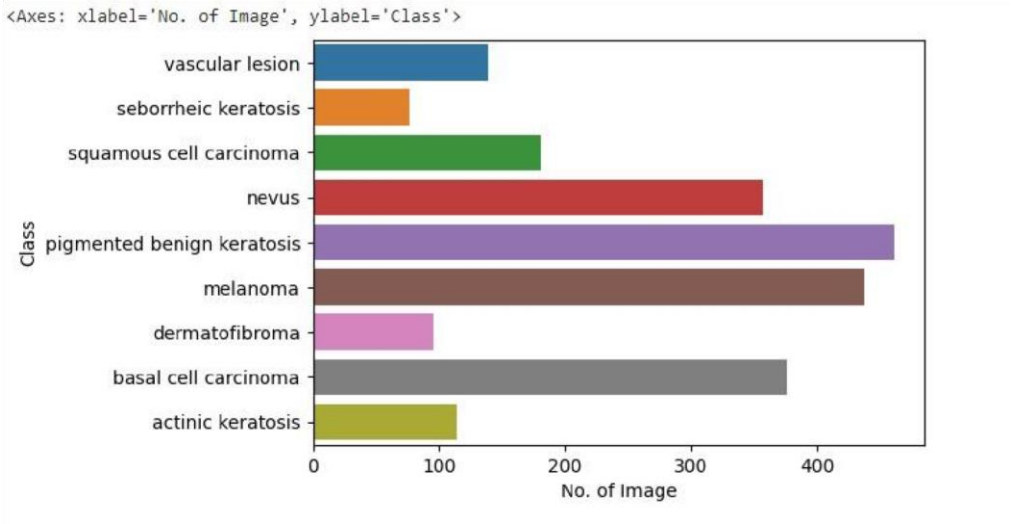

Fig4.2 Graph of Class Distribution

The diversity of the dataset provides a rich and varied training set, essential for training a robust model capable of accurately classifying different types of skin lesions. This variety in the data is crucial for the model's ability to generalize well and make accurate predictions on new, unseen data.

4.1SAMPLE IMAGE FROM DATASET

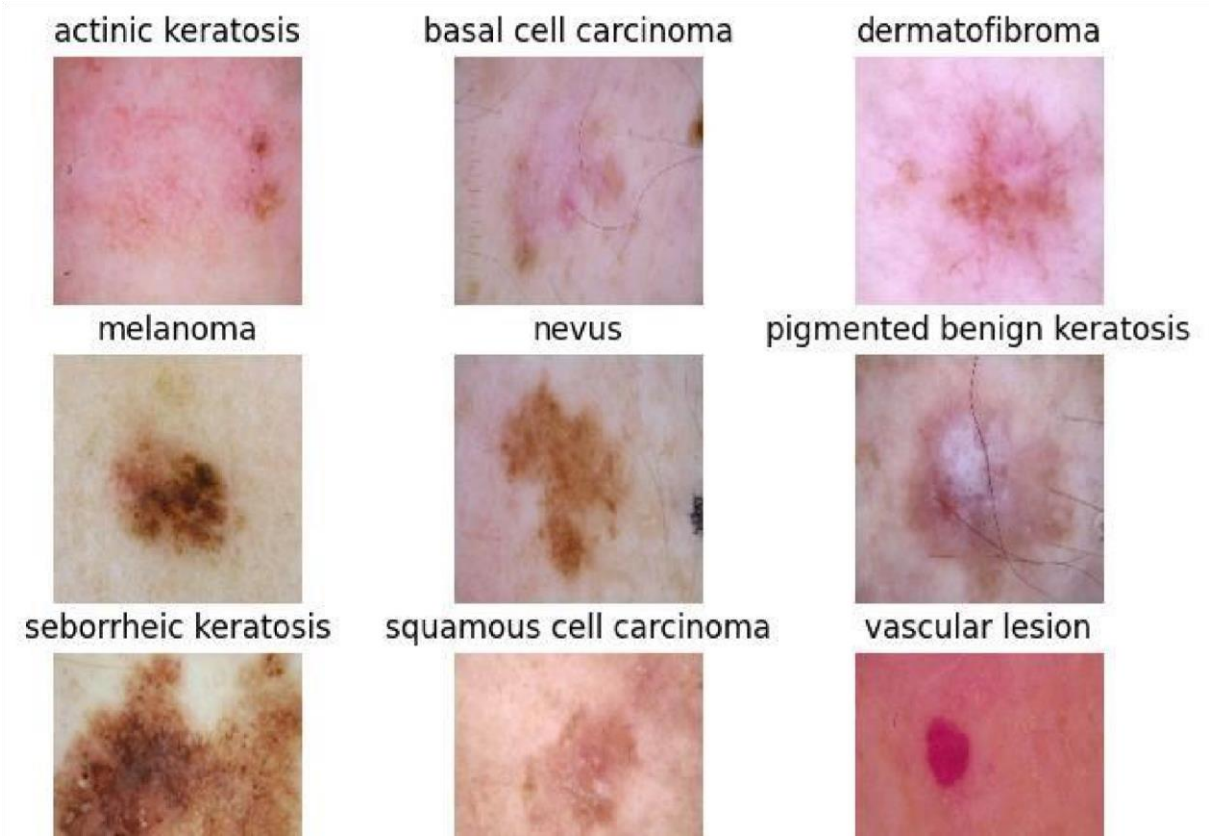

Fig4.3 Sample Image of Skin Lesian from Dataset

5.CNN ARCHITECTURE

Convolutional neural networks (CNNs) are a type of neural network architecture that excel in image recognition and classification tasks, making them well-suited for the automated detection of skin lesions in dermatological images. CNNs are trained using labeled data to learn the relationships between input images and their corresponding class labels.

The architecture of a CNN consists of several layers that each perform specific functions:

1. **Rescaling Layer:** Rescales input images from the range [0, 255] to [0, 1] for consistent data representation.
2. **Convolutional Layer:** Applies a convolution operation to the input, converting pixels within its receptive field into a single value. This process reduces image size and combines information from local regions into a single pixel.
3. **Pooling Layer:** Reduces the dimensions of feature maps, summarizing the features present in a region of the feature map generated by a convolutional layer. This reduces the number of parameters to learn and decreases computational complexity.
4. **Dropout Layer:** Randomly sets input units to zero during training, helping to prevent overfitting and improve model generalization
5. **Flatten Layer:** Converts data from multi-dimensional feature maps into a singledimensional array, preparing it for the next layer
6. **Dense Layer:** Also known as a fully connected layer, the dense layer connects each neuron in the layer to every neuron in the preceding layer. This layer performs the classification task based on the extracted features.
7. **Activation Function (ReLU):** The rectified linear activation function (ReLU) is used in the convolutional and dense layers. It outputs the input directly if it is positive; otherwise, it outputs zero. ReLU helps the model learn faster and perform better.
8. **Activation Function (Softmax):** The softmax function is used in the output layer to predict a multinomial probability distribution. The softmax function outputs probabilities ranging from 0 to 1, and the sum of the probabilities equals one.

Overall, the CNN architecture combines these layers and functions to create a model capable of accurately classifying skin cancer using skin lesion images. The use of CNNs allows for efficient training and high performance, making the model a valuable tool for medical professionals in diagnosing skin conditions.

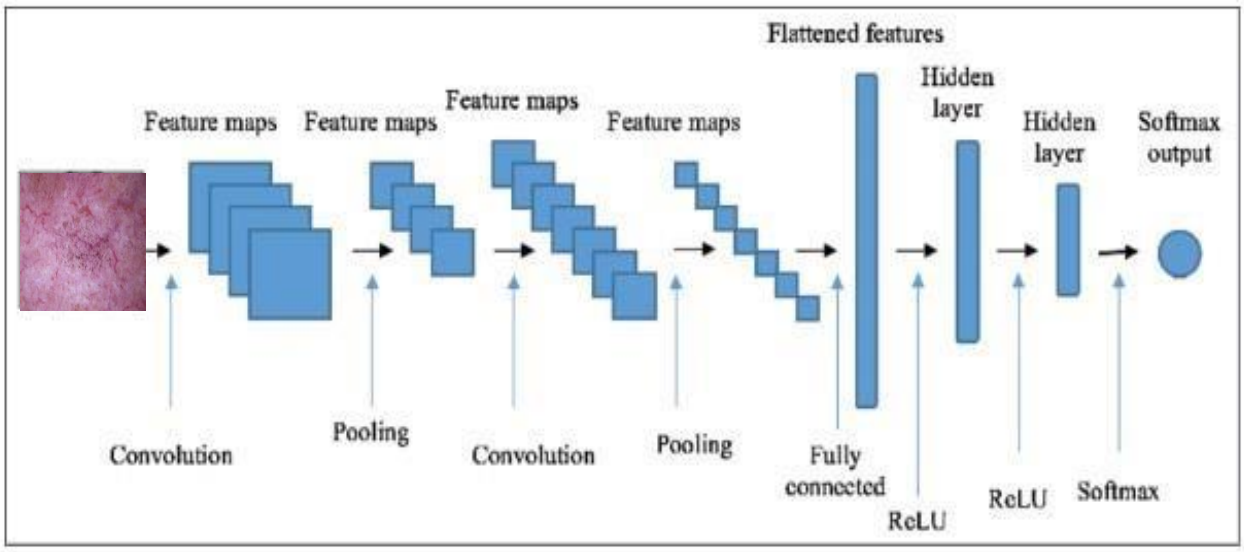

Fig5.1 CNN Architecture

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
rescaling (Rescaling)        (None, 180, 180, 3)       0
_________________________________________________________________
conv2d (Conv2D)              (None, 178, 178, 32)      896
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 89, 89, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 87, 87, 64)        18496
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 43, 43, 64)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 41, 41, 128)       73856
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 20, 20, 128)       0
_________________________________________________________________
dropout (Dropout)            (None, 20, 20, 128)       0
_________________________________________________________________
flatten (Flatten)            (None, 51200)             0
_________________________________________________________________
dense (Dense)                (None, 128)               6553728
_________________________________________________________________
dropout_1 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 9)                 1161
=================================================================
Total params: 6,648,137
Trainable params: 6,648,137
Non-trainable params: 0
```

Fig5.2 Model Architecture

6. MODEL EVALUATION

The evaluation of the CNN model for this project involves analyzing its performance across different epochs in terms of training and validation loss and accuracy. The goal is to monitor the model's progress over time and ensure that it is learning effectively from the data while avoiding overfitting. The following sections provide a detailed analysis of the model evaluation results.

6.1Training and Validation Metrics

The model's performance is assessed based on its loss and accuracy during the training and validation phases. Training loss and accuracy indicate how well the model is learning from the training data, while validation loss and accuracy provide insights into how well the model is generalizing to unseen data.

6.2Initial Epochs

In the initial epochs, the model demonstrates improvement in both training and validation accuracy. For example, in the first epoch, validation accuracy improved from 0.3170 to 0.4402, while training accuracy increased from 0.1730 to 0.3559. This suggests that the model is effectively learning from the data and beginning to generalize well to the validation set.

6.3Subsequent Epochs

As the training process continues, consistent improvements in both training and validation accuracy and loss are observed. Notable milestones include a rise in validation accuracy from 0.4402 to 0.5813 and a decrease in validation loss from 1.5014 to 1.0961. These improvements indicate that the model is becoming more effective at classifying skin lesions.

6.4Optimal Epochs

Around epochs 17 and 18, the model achieves its highest validation accuracy of approximately 0.8018. Concurrently, training loss reduces to 0.3705, and validation loss decreases to 0.6817. These results suggest that the model is approaching its optimal state and achieving high performance on both training and validation data.

6.5Model Checkpointing

To ensure that the best model is saved, checkpoints are set during the training process to save the model whenever validation accuracy improves. This practice allows for the selection of the most effective model for deployment.

6.6Convergence and Stability

The model exhibits stability and convergence around the later epochs, with minor fluctuations in accuracy and loss. This consistency is a positive indicator that the model is performing reliably and is suitable for real-world deployment.

6.7Prevention of Overfitting

The model uses techniques such as dropout layers and careful monitoring of loss and accuracy to prevent overfitting. These methods help maintain the model's robustness and ensure that it performs well on new, unseen data.

In summary, the evaluation of the CNN model reveals that it achieves high accuracy and low loss in both training and validation phases. The model demonstrates consistent improvements over the epochs, indicating effective learning and generalization. This makes the model a valuable tool for diagnosing skin lesions based on dermatological images and suggests its potential for real-world applications.

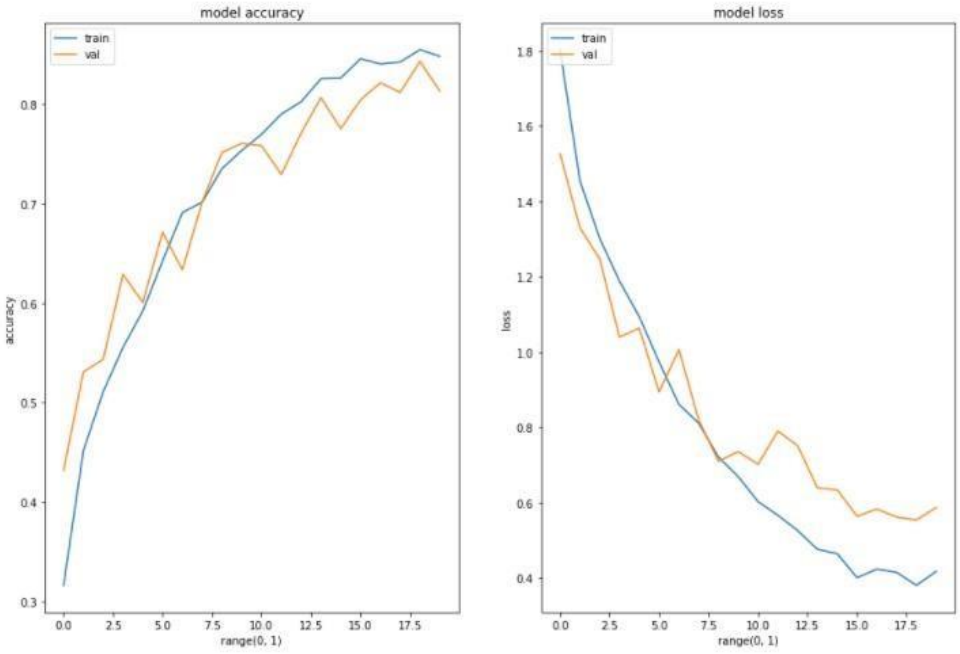

Fig6.1 Model Accuracy & Model Loss Graph

7.RESULT

```
from glob import glob
Test_image_path = os.path.join(data_dir_test, class_names[3], '*')
Test_image = glob(Test_image_path)
Test_image = load_img(Test_image[7],target_size=(180,180,3))
plt.imshow(Test_image)
plt.grid(False)

img = np.expand_dims(Test_image,axis=0)
pred = model.predict(img)
pred = np.argmax(pred)
pred_class = class_names[pred]
print("Actual Class "+ class_names[3] +'\n'+ "Predictive Class "+pred_class )
```

```
1/1 [==============================] - 0s 37ms/step
Actual Class melanoma
Predictive Class melanoma
```

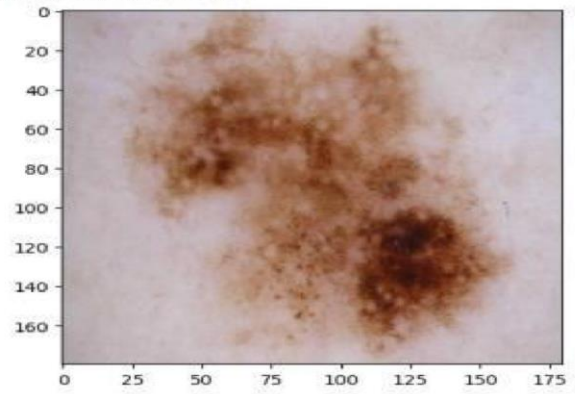

Fig7.1 Melanoma Prediction

```
from glob import glob
Test_image_path = os.path.join(data_dir_test, class_names[1], '*')
Test_image = glob(Test_image_path)
Test_image = load_img(Test_image[10],target_size=(180,180,3))
plt.imshow(Test_image)
plt.grid(False)

img = np.expand_dims(Test_image,axis=0)
pred = model.predict(img)
pred = np.argmax(pred)
pred_class = class_names[pred]
print("Actual Class "+ class_names[1] +'\n'+ "Predictive Class "+pred_class )
```

```
1/1 [==============================] - 0s 62ms/step
Actual Class basal cell carcinoma
Predictive Class nevus
```

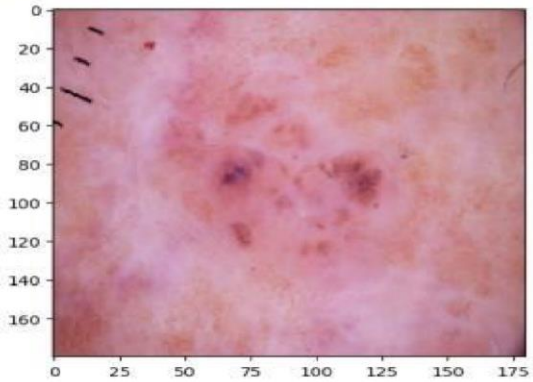

Fig7.2 Nevus Prediction

```
from glob import glob
Test_image_path = os.path.join(data_dir_test, class_names[5], '*')
Test_image = glob(Test_image_path)
Test_image = load_img(Test_image[14],target_size=(180,180,3))
plt.imshow(Test_image)
plt.grid(False)

img = np.expand_dims(Test_image,axis=0)
pred = model.predict(img)
pred = np.argmax(pred)
pred_class = class_names[pred]
print("Actual Class "+ class_names[5] +'\n'+ "Predictive Class "+pred_class )
```

```
1/1 [==============================] - 0s 42ms/step
Actual Class pigmented benign keratosis
Predictive Class pigmented benign keratosis
```

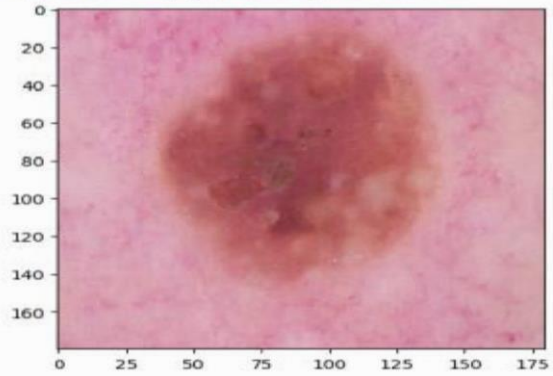

Fig 7.3 Pigmented Benign Keratosis

```
from glob import glob
Test_image_path = os.path.join(data_dir_test, class_names[2], '*')
Test_image = glob(Test_image_path)
Test_image = load_img(Test_image[4],target_size=(180,180,3))
plt.imshow(Test_image)
plt.grid(False)

img = np.expand_dims(Test_image,axis=0)
pred = model.predict(img)
pred = np.argmax(pred)
pred_class = class_names[pred]
print("Actual Class "+ class_names[2] +'\n'+ "Predictive Class "+pred_class )
```

```
1/1 [==============================] - 0s 41ms/step
Actual Class dermatofibroma
Predictive Class dermatofibroma
```

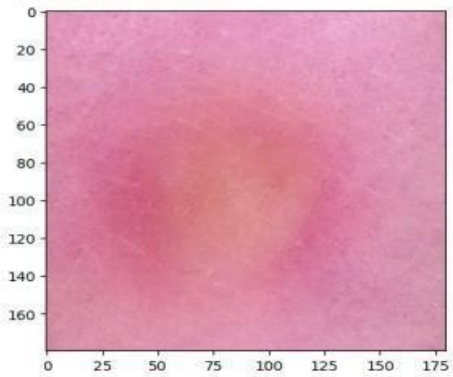

Fig7.4 Dermatofibroma Prediction

8. CONCLUSION

The project aimed to develop an automated system for the detection and classification of skin lesions using convolutional neural networks (CNNs) in TensorFlow and Keras. By leveraging deep learning techniques and advanced image processing, the model effectively classified dermatological images into various types of skin lesions, including benign and malignant cases.

Key takeaways from the project include:

1. **High Performance:** The model achieved a high level of accuracy and performance in classifying skin lesions, providing medical professionals with a reliable tool for diagnosis.
2. **Improved Efficiency:** The automated system streamlines the diagnostic process, reducing the time and effort required for manual examination of skin lesions.
3. **Support for Medical Professionals:** The model offers valuable assistance to dermatologists and other medical practitioners, enhancing their ability to make informed decisions and improving patient outcomes.
4. **Potential for Real-Time Diagnosis:** The system's efficiency and speed suggest its potential for real-time application in clinical settings, enabling prompt diagnosis and treatment.
5. **Need for Further Improvement**: While the model demonstrates promising results, its efficiency is not yet highly accurate, suggesting that more accurate datasets and advanced training and fine-tuning may be necessary to improve the model's performance.
6. **Future Research:** Additional research can explore avenues such as integrating more diverse datasets, enhancing training methods, and addressing challenges related to different skin types and colors.

In summary, the project successfully demonstrated the feasibility and potential of using deep learning-based CNN models for the automated detection and classification of skin lesions. This technology represents a significant advancement in the field of dermatology and opens the door for further innovation and development in the diagnosis and treatment of skin conditions.

9. LIMITATIONS

1. **Dataset Diversity:** The dataset may not represent the full range of skin types and tones, potentially affecting the model's generalizability.

2. **Class Imbalance:** The dataset may have imbalanced classes, leading to biases in the model's predictions for less prevalent skin conditions.

3. **Data Quality:** Variability in image quality, such as resolution and lighting, may impact the model's performance and consistency.

4. **Generalization Issues:** The model may struggle to generalize to new, unseen data or different clinical settings, especially if the data distribution differs from the training set.

5. **Complexity and Resource Demands:** The model's complexity may require significant computational resources, which could limit real-time performance and accessibility in some clinical environments.

6. **Potential for Bias:** Training data biases may propagate to the model's predictions, leading to skewed results for certain skin conditions.

7. **Lack of Interpretability:** CNN models can be difficult to interpret, making it challenging to understand how the model arrives at specific predictions.

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