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A Comparative Study of Melanoma Images Using CNN And Resnet 50

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Abstract

Melanoma is a specific type of skin cancer that can be lethal if not diagnosed and treated early. This paper presents a deep-learning approach for the automatic identification of melanoma on dermoscopic images from the ISIC Archive dataset and non-dermoscopic images from the MED-NODE dataset. The method involves the development of Convolutional Neural Network (CNN) and ResNet50 models, along with various pre-processing techniques. The CNN and ResNet50 models detect melanoma from dermoscopic images with 98.07% and 99.83% accuracy respectively, using hair removal and augmentation techniques. For non-dermoscopic images, the CNN and ResNet50 models achieve an accuracy of 97.06% and 100% respectively, using the hair removal technique. Furthermore, combining age and gender as additional factors in identifying melanoma in dermoscopic images, leads to an accuracy of 96.40% using CNN. The results of this research suggest that the developed models when combined with various pre-processing techniques and the integration of age and gender as additional factors, can be an efficient tool in the early detection of melanoma.

Keywords: Melanoma Skin Cancer, Dermoscopic images, Non-dermoscopic images, Convolutional Neural Network (CNN), ResNet50

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1. Introduction

Skin cancer, or the unusual multiplication of skin cells, is most common on sun-exposed skin. Yet, it can grow gradually even in areas of the skin that are rarely exposed to sunlight [1].

Melanoma is a dangerous kind of skin cancer [3],[4]. Indeed melanoma is caught at an early stage, there is a potential that it may be treated with a more straightforward surgical procedure [5]. One of the most common imaging procedures used by dermatologists is known as dermoscopy [3]. It enlarges the surface of the skin lesion, expanding its structure so that the dermatologist can investigate it. Since the success of this method is entirely dependent on the visual acuity and expertise of the practitioner, it can only be utilized successfully by medical professionals who have received enough training [3]. Because of these limitations, the scientific community is motivated to find novel methods for visualizing and identifying melanoma. A computer-aided diagnostic system may help in making a more precise diagnosis of melanoma skin cancer [12]. The CAD program offers a comfortable and intuitive interface for dermatologists with little to no prior training. In the process of identifying melanoma cancer, evidence from a CAD diagnostic tool could serve as a second opinion.

Benign and malignant lesions are the two basic skin cancer classifications. It is typical to see melanin deposits in the epidermis of benign tumors (common nevi). Melanin is produced in highly abnormal ways by malignant tumors. Malignant lesions are not deadly as long as the melanocytes and the corresponding melanin are still present in the epidermal layer. However, the nature of the skin's color changes as they enter the dermis and leave deposits.

2. Related Works

B. Sreedhar et al., [3] in 2020 aimed to evaluate the efficiency of modern image processing techniques with traditional image processing techniques for melanoma skin cancer detection. Traditional methods are limited in detecting melanoma skin cancer, as they rely on manually selected features. In contrast, current image processing techniques, particularly deep-learning algorithms, have been shown to outperform traditional methods in terms of accuracy and efficiency. Recent research findings have shown that modern image-processing tools can detect melanoma skin cancer effectively.

In 2009, José Fernández Alcón et al., [4] conducted research on the automated skin cancer melanoma classification. Melanoma was classified into benign and malignant types with an accuracy rate of 86%. Segmentation, background correction, and threshold-based segmentation were used for image processing. The ABCD features such as asymmetry, border, color, and differential structures were extracted. A patient's risk was examined to their skin type, age, gender, and specific body part. Patients with lighter skin tones have higher chances of developing melanomas than those with brown or dark skin. Melanoma risk is higher in elderly patients. The incidence of melanoma varies depending on the patient's age and gender.

In 2017, Enakshi Jana et al., [5] proposed various image pre-processing techniques and skin classification algorithms. The median filter method was presented for hair removal and image noise reduction. A dull razor was used to remove hairs from an image. It finds hair and substitutes it with pixels nearby. Other pre-processing techniques, like sharpening filters, enhanced the definition of image edges. Image resizing was also required since all images must be the same size. Several deep learning and machine learning algorithms for classification have been described.

In 2019, Shetu Rani Guha et al., [6] developed an approach for categorizing seven different skin diseases using a CNN-based machine learning technique. To improve the classification accuracy, transfer learning along with CNN were utilized on the ISIC dataset. The training dataset consisted of 1137 images, and 197 were used for testing. The transfer learning model outperformed the CNN model, showing an 11.65% improvement in accuracy. Comparing both models, the transfer learning model had a higher accuracy than the CNN model.

Tasneem Alkarakatly et al. [7] presented a CNN model to categorize skin lesions. The PH2 dataset was used, which comprises 200 dermoscopic images divided into three classes: common nevus, atypical nevus, and melanoma. A five-layered CNN architecture was presented for categorizing skin lesions into three categories. Different image sizes were tested and the optimal size was selected for the neural network. The model's performance was evaluated using cross-validation and an accuracy of 95% was obtained.

Hari Kishan Kondaveeti and Prabhat Edupuganti [8] presented a study on applying transfer learning to detect skin cancer. The study's findings demonstrated the usefulness of transfer learning for skin cancer classification by highlighting that it performed better than conventional deep learning approaches in accuracy and efficiency. The study emphasized the utility of transfer learning in identifying skin cancer.

Shalu and Aman Kamboj [9] proposed a method for identifying melanoma skin cancer using digital photographs. The MED-NODE dataset was utilized, and pre-processing was applied to enhance the picture and remove artefacts. The effectiveness of the system was assessed using several classifiers, including Naive Bayes, Decision Trees, and KNN. With an accuracy of 82.35 percent, the Decision Tree classifier performed better than the others.

3. Proposed Work

3.1 Dataset

The dataset used is a dermoscopic image dataset from Kaggle ISIC [10]. The dataset used in the research and development of skin cancer diagnosis includes 1497 melanoma and 1800 benign images.

The dataset used is a non-dermoscopic image dataset from the Department of Dermatology's digital image library at the University Medical Center Groningen (UMCG) [11]. The dataset used in the research and development of skin cancer diagnosis from macroscopic photos includes 70 melanoma and 100 nevus images.

3.2 Pre-processing

An important stage in image analysis is image pre-processing, which significantly impacts the accuracy and efficiency of the research. Sharpening, normalization, hair removal, and augmentation are four critical pre-processing techniques applicable in various image analysis scenarios. The need for image pre-processing arises to enhance image quality, eliminate noise, correct inconsistencies, and highlight important features to enable accurate and efficient analysis [13].

Sharpening - Image sharpening is done to obtain clear images. Image sharpening can be accomplished through a variety of methods, such as unsharp masking, high-pass filtering, and image convolution. Convolution with a sharpening kernel is one of the more common methods for sharpening a picture. The image's high-frequency components are amplified, giving the appearance that the image is sharper.

Normalization - Image normalization is a technique that adjusts the range of pixel intensities in an image to produce a more consistent and visually pleasing result. It involves converting the intensity values to a specific range, such as [0, 1] or [-1, 1]. Normalization is important for creating high-quality images and improving the performance of models that use image data. Its goal is to eliminate inconsistencies in size, lighting, and contrast to enable precise comparison and analysis of image aspects.

Hair Removal - The pre-processing technique for hair removal involves resizing the image to 224x224 pixels and converting it to grayscale. The blackhat morphological operation is applied, and the image is thresholded to reduce noise. Lastly, the inpainting process restores the image's integrity by filling in the thresholded sections. This method is used to increase the precision of melanoma detection using deep learning.

Augmentation - Image augmentation artificially creates new training data samples from the existing ones by applying various random transformations such as rotations, translations, scaling, and flipping. Image augmentation aims to increase the training dataset's size, improving the model's generalization, and reducing overfitting. Rotation, vertical flip, and a combination of both are implemented on the dataset.

(1) (2) (3) (4) (5)

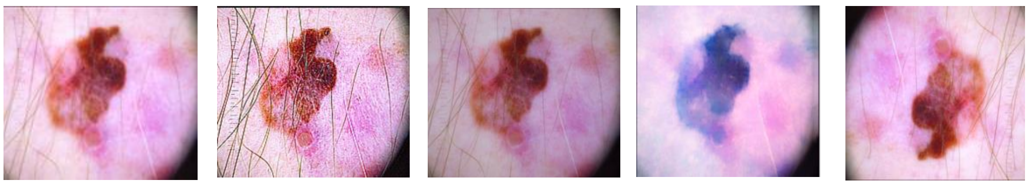

Figure 1. Sample images (1) actual image, (2) sharpened image, (3) normalized image, (4) hair removal image, (5) augmented image

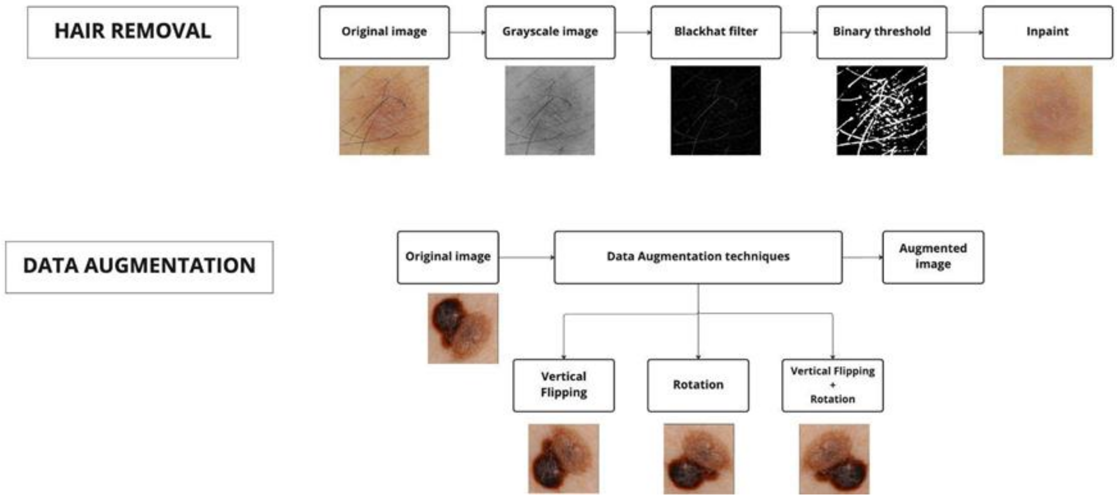

Figure 2. Hair Removal and Data Augmentation Process

3.3 Algorithms

3.3.1 Convolutional Neural Networks

The CNN is mostly used for computer vision. With an image as its input, this method gives features of varying image levels of significance to help differentiate between them [14].

Architecture for dermoscopic images with sharpening and normalization pre-processing techniques:

The sharpened and normalized pre-processed images were input into the CNN architecture to improve accuracy and efficiency. These pre-processing techniques help to enhance the pictures' quality and highlight essential features, which were then extracted by the convolutional layers of the model. The final classification was done using dense layers. A Conv2D layer with 32 filters and a kernel size makes up the model's initial layer (3, 3). This layer employs the ReLU activation function. The following layers are MaxPooling2D layers used to reduce the dimensions of the feature maps. The successive three Conv2D layers have a kernel size of 64 or 128 filters. The 3D feature maps are transformed into 1D vectors by the flatten layer and then fed into the dense layers. In the last dense layer, the binary classification is performed using the sigmoid activation function.

Architecture for dermoscopic and non-dermoscopic images using hair removal and augmentation pre-processing techniques:

In addition to the pre-processing techniques mentioned earlier, hair removal and augmentation were used on the images to further improve the accuracy of the CNN architecture for dermoscopic and non-dermoscopic images. These pre-processing steps also help to prevent overfitting by increasing the variation in the training data. The model begins with a Conv2D layer and employs the ReLU activation function. There are 32 filters total, each measuring 3x3. After the input layer, the next layer is a BatchNormalization layer, which subtracts the mean and divides it by the standard deviation to normalize the activations of the preceding layer. The BatchNormalization layer helps prevent overfitting and speeds up convergence. Next, the model uses a MaxPooling2D layer with a pool size of 2x2. The next layer used by the model has a dropout rate of 0.25. To minimize overfitting, the dropout layer arbitrarily sets certain input units to zero during training. To learn more complex features in the image, the model repeats the first three layers with additional filters (64 and 128). The last layer before the output layer is the flatten layer, which flattens the previous layer's output into a 1D array. The model then uses two dense layers with RELU activation functions. Finally, the model is applied using the binary cross-entropy loss function, which is adequate for binary classification.

The model architecture is modified to include techniques that help prevent overfittings, such as BatchNormalization, dropout, and MaxPooling2D layers. These modifications help to ensure that the model generalizes well to new, unseen data.

3.3.2 ResNet50

ResNet50 is a Convolutional Neural Network that accelerates and improves training using residual connections. ResNet50 comprises 50 layers, including convolutional and fully connected layers, and it is trained on massive datasets like ImageNet, which includes millions of pictures. The residual connections allow the network to bypass one or more layers, allowing the activations to flow directly from the earlier layers to the later ones. This enables the network to learn features at multiple levels of abstraction and improve the model's overall accuracy [15].

Architecture for dermoscopic images with sharpening and normalization pre-processing techniques:

The ResNet50 model is trained on sharpened and normalized pre-processed images, which enhances the model's ability to classify images accurately. This pre-processing step helps to improve the contrast and clarity of the images, making it easier for the model to detect and differentiate between different features in the images. The model's first layer is a pre-trained ResNet50 trained on ImageNet, with fully-connected layers excluded. The weights and pooling arguments are set to 'imagenet' and 'max', respectively. The second layer is dense, with a single output node and sigmoid activation. The input image is mapped to a value between 0 and 1, indicating the chance that it belongs to a specific class. The binary cross-entropy loss function, accuracy, and the Adam optimization technique are used to build the model. The Adam optimization approach improves the model's predictions over time by updating the model parameters depending on the gradients of the loss function. The combination of the ResNet50 model, the Adam optimization technique, the binary cross-entropy loss function, and the accuracy metric yields a deep learning model that correctly classifies images in binary classification problems.

Architecture of dermoscopic and non-dermoscopic with hair removal and augmentation pre-processing techniques:

To improve the accuracy of the ResNet50 model, the images are pre-processed with hair removal and augmentation methods. The two main components of the model are the ResNet50 convolutional base and a fully connected layer with a sigmoid activation function. The ImageNet dataset is used to train the ResNet50 architecture. To fine-tune the model for a specific task, most of the layers in the ResNet50 base are froze and only the last eight layers are allowed to be trained. This allows to utilize the pre-trained network's learned features while allowing the model to adjust to the specific task. The model uses a flatten layer to convert the feature maps into a one-dimensional vector after starting with a ResNet50 base. A 0.5-rate dropout layer is added before the final output layer, which comprises a single unit with a sigmoid activation function, to prevent overfitting. The model architecture is modified to enhance generalizability and avoid overfitting specific image attributes.

The proposed flow diagram for melanoma skin disease classification using dermoscopic images includes several steps. Dermoscopic pictures [10] are used to detect the disease. The dataset is divided into two sections: training and testing dataset. Pre-processing techniques like resizing, sharpening, normalization, hair removal, and augmentation are implemented to increase image quality and clarity.

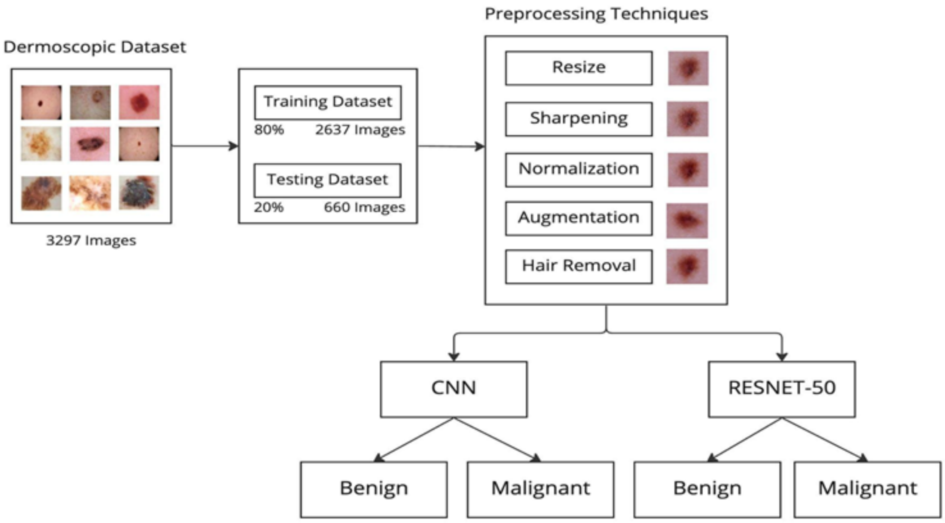

Figure 3. Flow diagram for Dermoscopic Images

The pre-processed and raw images are fed into the CNN and ResNet50 models, which identify the images as benign or malignant. In addition, the patient's age and gender are also provided to one of the CNN and ResNet50 models.

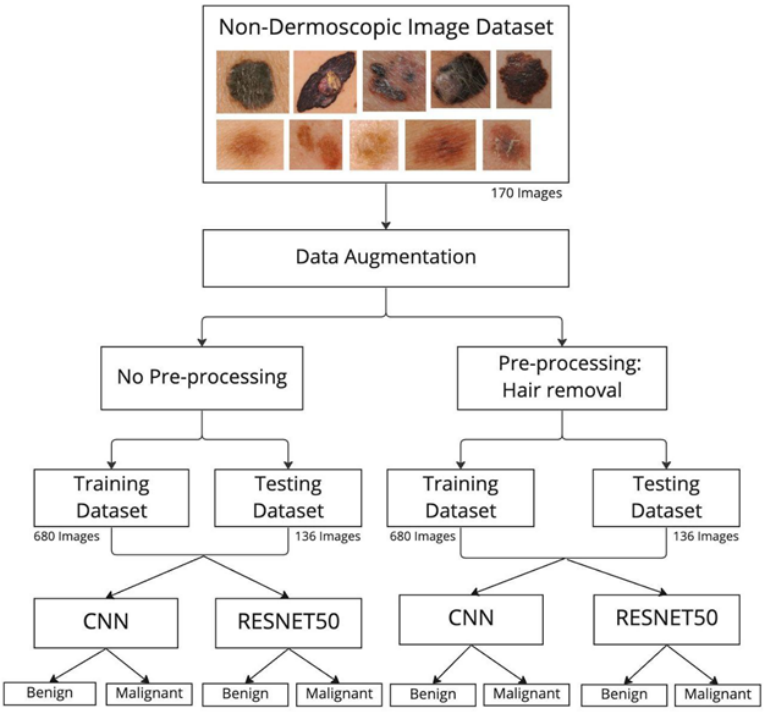

Figure 4. Flow diagram for Non-Dermoscopic Images

The proposed flow diagram for melanoma skin disease classification using non-dermoscopic images includes multiple steps. Non-dermoscopic images [11] are used to predict the disease. Since the dataset contains fewer images, data augmentation techniques have been used. Hairs are eliminated from the image through the pre-processing method of hair removal. Training and testing datasets are created from both raw and pre-processed images. The CNN and ResNet50 models categorize the images as benign or malignant after being trained on the dataset.

3.4 Software/Platform used

For this research study, Google Colab is used as the platform for data pre-processing, training, and testing of the deep learning models. The free Jupyter notebook environment with GPU resources provided by Colab allows for efficient data pre-processing using Python libraries and faster model training times, enabling quicker experimentation and iteration. The models are implemented using the TensorFlow software framework on the Google Colab platform.

4. Results and Discussion

Table 1. Performance evaluation of dermoscopic images

Models	**Pre-processing**	**Train Accuracy**	**Test Accuracy**
CNN	No pre-processing	82.71	82.73
CNN	Sharpening	83.45	80.00
CNN	Normalization	89.09	89.08
CNN	Augmentation	91.48	97.98
CNN	Hair Removal	90.61	**98.07**
CNN (age, gender)	No pre-processing	98.50	96.40
ResNet50	No pre-processing	74.02	77.73

ResNet50	Sharpening	88.84	88.72
ResNet50	Normalization	75.18	58.89
ResNet50	Augmentation	94.31	**99.83**
ResNet50	Hair Removal	94.04	99.74
ResNet50 (age, gender)	No pre-processing	68.20	68.20

The table presents the evaluation results of different models trained on the dermoscopic images dataset. The evaluation metrics used are train accuracy and test accuracy. The models evaluated in the study include CNN and ResNet50, with different pre-processing techniques. Additionally, the model's performances are evaluated with and without considering age and gender. The table demonstrates that the CNN model had a test accuracy of 98.07% when trained using the hair removal pre-processing method. In contrast, the ResNet50 model, trained using the augmentation pre-processing method, had the test accuracy of 99.83%. The CNN model trained on the age and gender data achieved a high train accuracy of 98.50%, but the test accuracy was comparatively lower at 96.40%. The findings imply that employing the proper pre-processing methods can considerably enhance the models' classification of dermoscopic images.

Table 2. Results of CNN and ResNet50 for dermoscopic images dataset

Models	**Pre-processing**	**Train Accuracy**	**Test Accuracy**
CNN	Hair Removal	90.61	98.07
ResNet50	Augmentation	94.31	99.83

The results suggest that the ResNet50 model achieved higher accuracy in both train and test datasets compared to the CNN model. The use of different pre-processing techniques resulted in different levels of performance, with hair removal pre-processing for the CNN model and augmentation pre-processing for the ResNet50 model yielding the best test accuracy.

Table 3. Performance evaluation of non-dermoscopic images

Models	Pre-processing	Train Accuracy	Test Accuracy
CNN	Augmentation	87.65	93.43
CNN	Hair Removal	96.77	**97.06**
ResNet50	Augmentation	96.95	100
ResNet50	Hair Removal	99.85	**100**

The CNN model was augmented to increase diversity, resulting in 87.65% training accuracy and 93.43% test accuracy. Hair removal pre-processing improved the CNN's performance to 96.77% training accuracy and 97.06% test accuracy. The ResNet50 model was also evaluated with a training accuracy of 96.95% and a test accuracy of 100% which was obtained using the augmented dataset. However, the hair removal pre-processing technique resulted in even higher performance, with a training accuracy of 99.85% and an ideal test accuracy of 100%

Table 4. Result of CNN and ResNet50 for non-dermoscopic images

Models	Pre-processing	Train Accuracy	Test Accuracy
CNN	Hair Removal	96.77	97.06
ResNet50	Hair Removal	99.85	100

The ResNet50 model showed training and test accuracy of 99.85% and 100%, compared to 96.77% and 97.06%, respectively, for the CNN model. The models' high accuracy implies that the hair removal pre-processing step effectively improved the models' ability to classify images. The ResNet50 model outperformed the CNN model on the test set, showing that it may be a better alternative for this particular task.

5. Conclusion

The results presented in this research paper show that deep learning models, specifically CNN and ResNet50, can achieve high accuracy in classifying melanoma on dermoscopic and non-dermoscopic images with appropriate pre-processing techniques. The hair removal pre-processing technique was found to be particularly effective in improving model performance, resulting in a significant increase in the accuracy for both CNN and ResNet50 models. Augmentation also proves to be a helpful technique for improving model performance, particularly for ResNet50. The ResNet50 model consistently outperforms the CNN model, achieving near-perfect accuracy on both the train and test sets. However, the CNN model achieves relatively high accuracy, particularly when combined with appropriate pre-processing techniques. These findings suggest that careful selection of pre-processing techniques and model architecture is crucial for achieving high accuracy in image classification tasks.

6. Future Scope

This system could be developed for many skin diseases to aid in early detection. The study examined the effectiveness of CNN and ResNet50, two popular deep-learning models. Future studies may examine the performance of several deep-learning models like VGG or Inception to determine which architecture is best suited for image classification tasks. A larger dataset can be utilized to assess performance.

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Author's biography

Niharika Harihar Wamane is a final-year IT student at Datta Meghe College of Engineering with a passion for technology and deep learning. She has completed several projects, including a Chatbot, a Full-stack E-commerce website, and an Age Prediction Project. Niharika enjoys reading and music and recently worked on an Early Detection Melanoma Skin Cancer project. She aspires to pursue research opportunities in artificial intelligence and deep learning.

Aishwarya Bhalchandra Yadav is a final-year IT engineering student at Datta Meghe College of Engineering and is passionate about computer science and engineering. Her impressive projects include a web-scraping chatbot and an e-commerce website that analyzes user sentiment. Her current research project focuses on the early detection of melanoma skin cancer, with the potential to contribute significantly to cancer detection. Aishwarya enjoys dancing, and swimming, and has participated in various cultural events and competitions.

Jidnyasa Sunil Bhoir is a final-year IT engineering student at Datta Meghe College of Engineering, with a passion for deep learning and AI. She has completed various projects, including Travel Management System, Placement Management System, and Welnox - Hospital System using Disease prediction. Alongside her academic pursuits, Jidnyasa enjoys dancing, and art and craft. Her current research focuses on Melanoma skin cancer detection, where she applies her skills in deep learning and AI to develop innovative solutions.

Deep Santosh Shelke is a final-year IT engineering student at Datta Meghe College of Engineering with a keen interest in AI and deep learning. He has completed noteworthy projects, including developing a chatbot, creating a sentiment analysis e-commerce website, and working on an AI-based melanoma skin cancer detection project. Deep is also a passionate cricket player and music enthusiast. With his programming proficiency and dedication to the field, he aspires to pursue a career in AI and contribute to its advancements.

Deepali Prakash Kadam is a computer engineer with a B.Tech degree from VJTI, Mumbai, and an M.E. in Computer Engineering. She is pursuing a Ph.D. in the field of AIDS, specifically in the domain of Natural Language Processing. Throughout her academic journey, she has demonstrated a strong passion for using her technical skills to impact society positively. Her research interests include machine learning, natural language processing, and data analysis.