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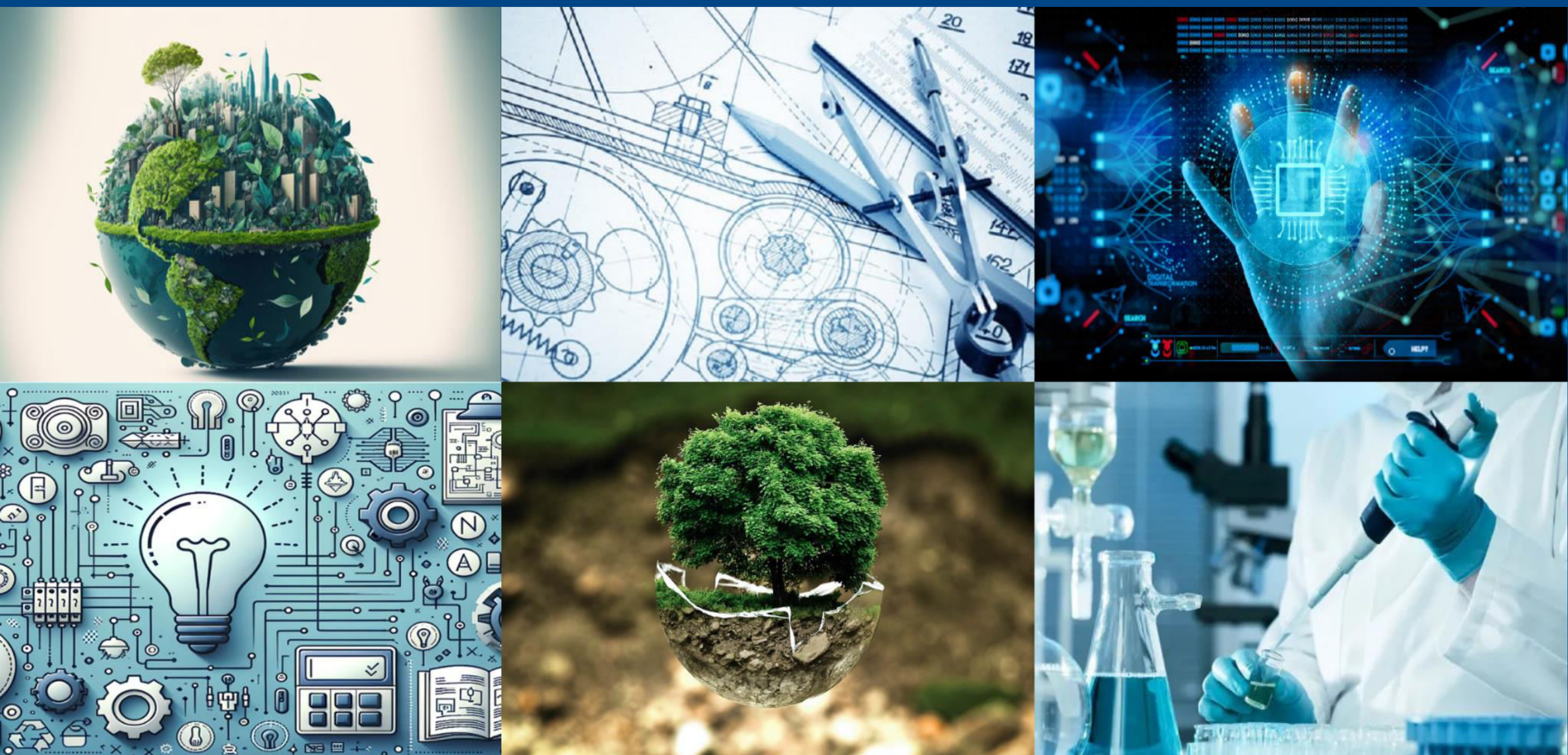

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Skin Disease Classification Using Convolutional Neural Network

Mr. B. Manikanth[1], L.Sai Adithya[2], M.Nitin Sundar[3], K.Mohan Krishna[4]

Assistant Professor, Department of ECE, Vasireddy Venkatadri Institute of Technology, Nambur, Guntur, A.P., India[1]

Undergraduate Students, Department of ECE, Vasireddy Venkatadri Institute of Technology, Nambur, Guntur, A.P., India[2-4]

ABSTRACT: The "Skin Disease Detection System Using Convolutional Neural Network" is designed to accurately classify various skin diseases through advanced image processing techniques. The process begins with the acquisition of input images, followed by several pre-processing steps to enhance image quality. Augmentation techniques such as rotation, flipping, and zooming are applied to increase the diversity of the training dataset and improve the model's robustness. The core of the system is a carefully designed Convolutional Neural Network (CNN) architecture, optimized for skin disease classification. The dataset is split into training, validation, and testing sets, with approximately 70-80% allocated for training and 10-15% for validation. This ensures a well-rounded model capable of generalizing to new data. The final classification step involves identifying specific skin diseases, including Actinic keratosis, Dermatofibroma, Melanoma, and Squamous cell carcinoma. This system aims to assist dermatologists in early and accurate diagnosis, ultimately improving patient outcomes through timely and precise treatment.

KEYWORDS: Skin Disease Dataset, Image Processing Techniques, Deep Learning Techniques, Convolution Neural Network, Classification, Accuracy.

I. INTRODUCTION

Skin diseases are prevalent conditions that can affect individuals of all ages, manifesting in various forms ranging from mild irritations to severe, life-threatening disorders. Common skin diseases include acne, eczema, psoriasis, and skin cancer, each with distinct symptoms and treatment protocols. These conditions can significantly impact a person's quality of life, causing physical discomfort, emotional distress, and social stigmatization. The complexity of skin diseases arises from their diverse etiologies, including genetic predisposition, environmental factors, and immune system dysfunctions. Early detection and accurate diagnosis are crucial for effective treatment and management. However, the visual similarities among different skin conditions can pose diagnostic challenges for dermatologists. Advancements in medical technology, particularly in image processing and machine learning, are revolutionizing the approach to skin disease diagnosis. Automated systems leveraging deep learning techniques, such as Convolutional Neural Networks (CNNs), are being developed to assist healthcare professionals by providing accurate, fast, and reliable diagnostic tools. These systems analyze high-resolution images of skin lesions, identify patterns indicative of specific diseases, and offer a diagnosis with high precision. The integration of such technologies in clinical practice promises to enhance diagnostic accuracy, streamline patient care, and improve treatment outcomes for individuals suffering from skin diseases.

II. MODEL IMPLEMENTATION

The system employs Convolutional Neural Networks (CNN) to classify images of skin diseases. The CNN architecture includes several convolutional layers for feature extraction, followed by fully connected layers for classification.

1. CNN Architecture:

The CNN model consists of the following layers:

- **Input Layer**: The model takes images of skin lesions as input. The images are preprocessed and resized to a consistent size (e.g., 224x224 pixels).

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- **Convolutional Layers**: Several convolutional layers are used to detect local patterns and features in the images, such as edges, textures, and shapes.
- **Pooling Layers**: Max-pooling layers are used to reduce the spatial dimensions of the image and extract the most important features.
- **Fully Connected Layers**: After feature extraction, the network connects to fully connected layers that perform the classification.
- **Output Layer**: The final layer outputs the probability distribution over different skin disease categories.

2. Preprocessing:

- **Data Augmentation**: To avoid overfitting and improve generalization, we use data augmentation techniques such as rotation, flipping, and scaling.
- **Normalization**: The pixel values of the images are normalized to a range between 0 and 1 to speed up the convergence during training.

3. Model Training:

The model is trained using a labeled dataset of skin disease images (e.g., the ISIC dataset). We use a categorical cross-entropy loss function for multi-class classification and the Adam optimizer for efficient training.

4. Evaluation:

We evaluate the model using accuracy, precision, recall, and F1-score to assess its performance in classifying various skin diseases. The confusion matrix is also used to visualize the model's performance across different categories.

5.Advantages:

Convolutional Neural Networks (CNNs) excel at image recognition and classification due to their ability to automatically learn features, minimize computation, and leverage spatial hierarchies, making them highly effective for tasks like object detection and image segmentation.

Here's a more detailed look at the advantages of CNNs:

Automatic Feature Extraction:

CNNs can automatically learn relevant features from raw input data, eliminating the need for manual feature engineering, which is a significant advantage.

Spatial Hierarchy Learning:

CNNs are designed to recognize and process spatial hierarchies in data, allowing them to learn complex patterns and relationships within images.

Weight Sharing:

CNNs use weight sharing, meaning that the same learned parameters (weights) are used across different regions of the input image, reducing the number of parameters and computational cost.

Minimizes Computation:

Weight sharing and the use of convolutional filters help minimize the computational complexity of CNNs, making them efficient for processing large images.

Generalization and Robustness:

CNNs are known for their strong generalization abilities, meaning they can perform well on unseen data, and are also robust to variations in image orientation, scale, and lighting conditions.

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III.SYSTEM ARCHITECTURE

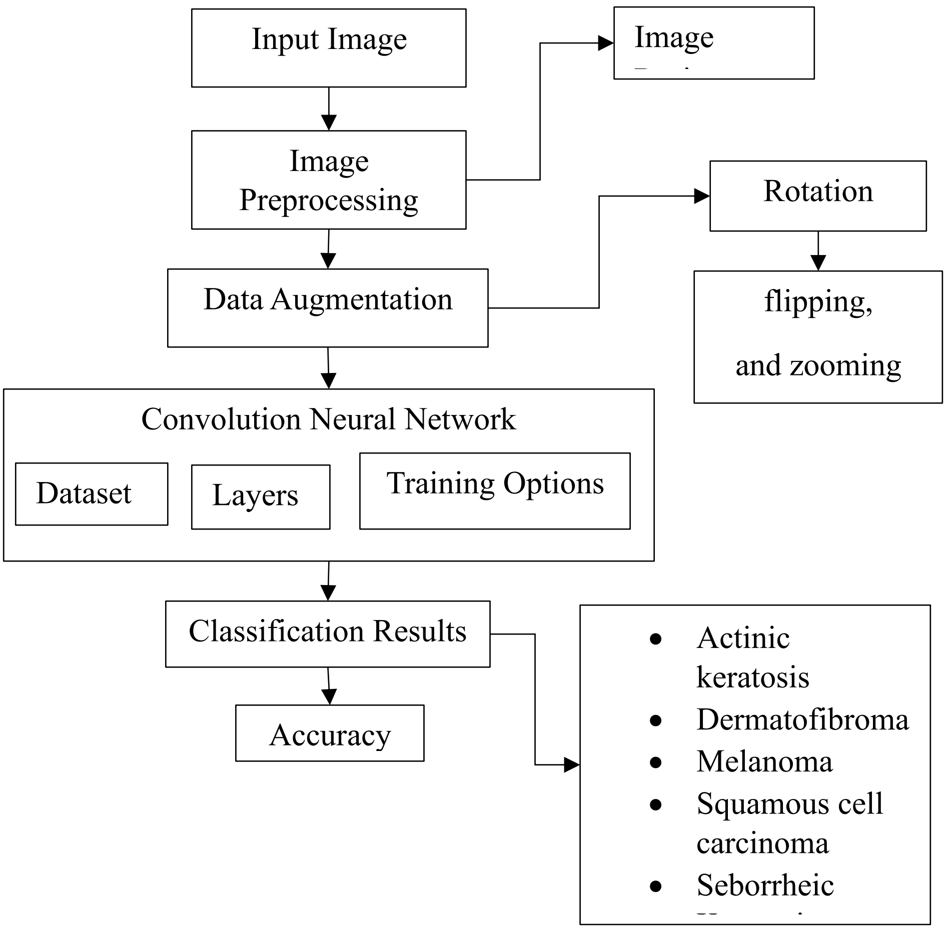

Fig 1.1 System architecture

The methodology of the "Skin Disease Detection System Using Convolutional Neural Network"involves a systematic approach to accurately classify various skin diseases. Initially, high-resolution input images of skin lesions are collected. These images undergo pre-processing steps to enhance their quality, including noise reduction, normalization, and resizing to a standard dimension suitable for the model. To improve the model's robustness and generalization, data augmentation techniques such as rotation, flipping, and zooming are applied, effectively increasing the diversity of the training dataset. The core of the system is the design of a specialized Convolutional Neural Network (CNN) architecture tailored for skin disease classification. This architecture includes multiple layers for feature extraction, pooling, and fully connected layers for final classification. The dataset is split into training, validation, and testing sets, typically with 70-80% of the data used for training and 10-15% for validation. This ensures that the model learns effectively while preventing overfitting. In the final step, the trained CNN classifies the images into specific categories: Actinic keratosis, Dermatofibroma, Melanoma, and Squamous cell carcinoma. This comprehensive methodology ensures the system's accuracy and reliability in assisting dermatologists with early and precise diagnosis of skin diseases.

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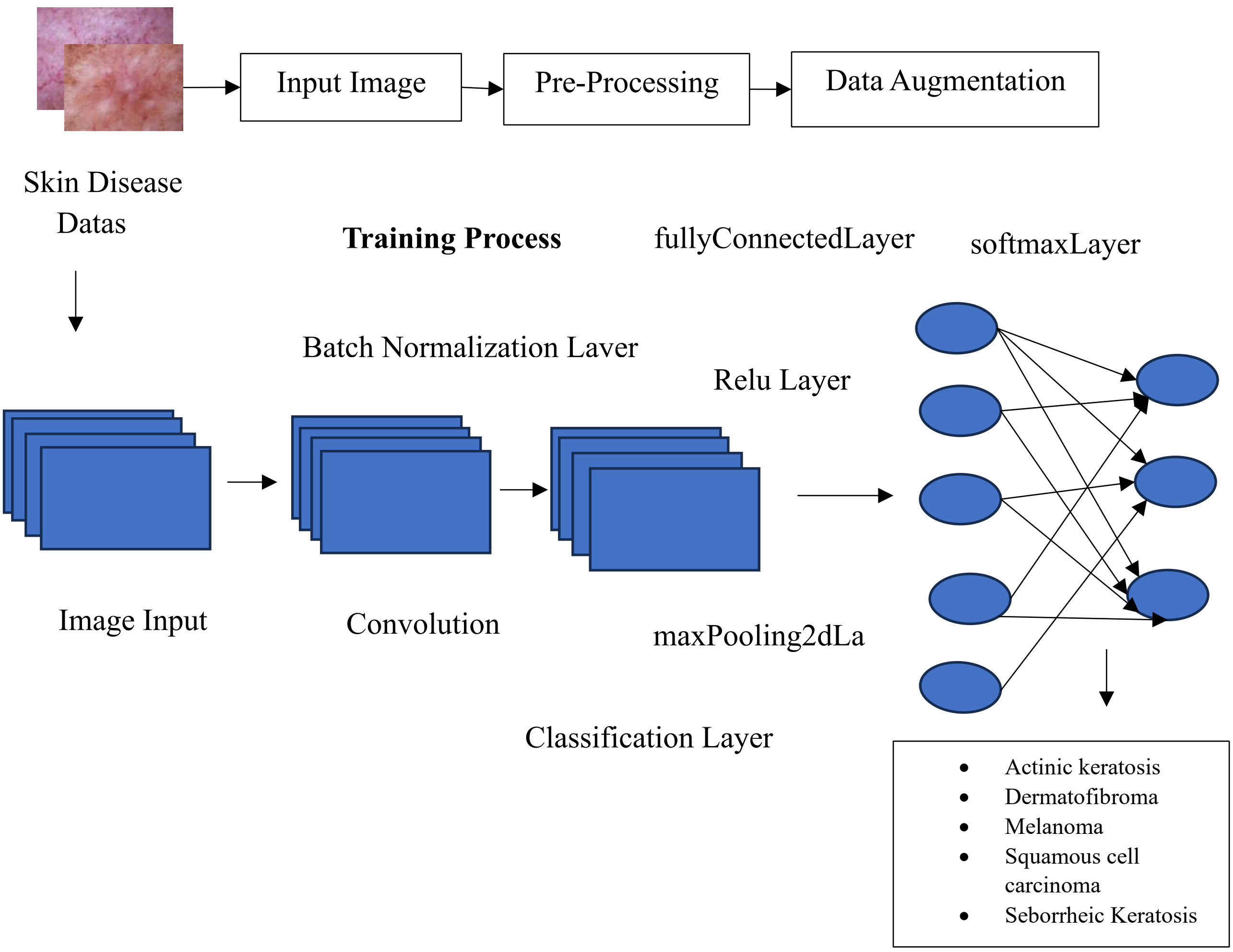
Image Processing Steps



A CNN can also be implemented as a U-Net architecture, which are essentially two almost mirrored CNNs resulting in a CNN whose architecture can be presented in a U shape. U-nets are used where the output needs to be of similar size to the input such as segmentation and image improvement. Each convolutional layer contains a series of filters known as convolutional kernels. The filter is a matrix of integers that are used on a subset of the input pixel values, the same size as the kernel. Each pixel is multiplied by the corresponding value in the kernel, then the result is summed up for a single value for simplicity representing a grid cell, like a pixel, in the output channel/feature map. These are linear transformations; each convolution is a type of affine function. In computer vision the input is often a 3 channel RGB image. For simplicity, if we take a greyscale image that has one channel (a two-dimensional matrix) and a 3x3 convolutional kernel (a two-dimensional matrix). The kernel strides over the input matrix of numbers moving horizontally column by column, sliding/scanning over the first rows in the matrix containing the images pixel values. Then the kernel strides down vertically to subsequent rows.

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IV. RESULTS AND DISCUSSION

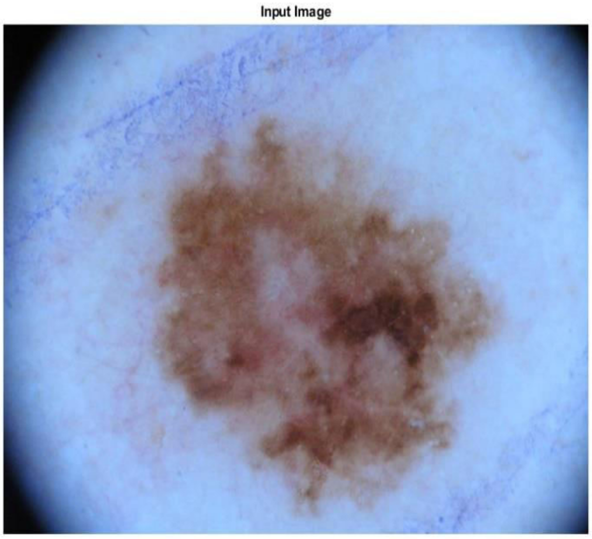

Fig: Input Image

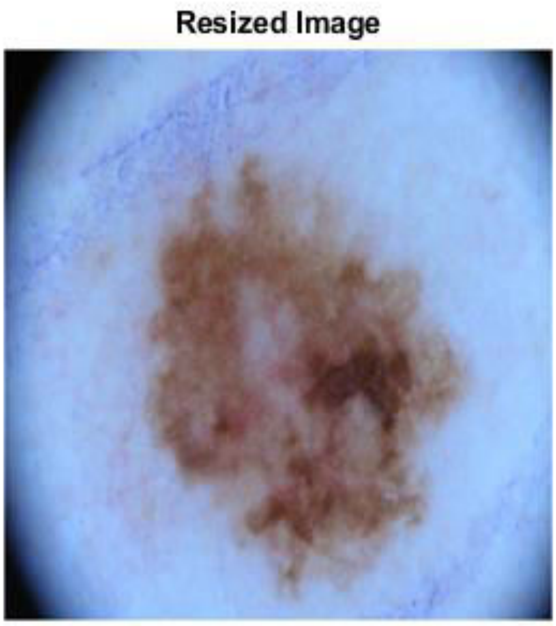

Fig: Resized Image

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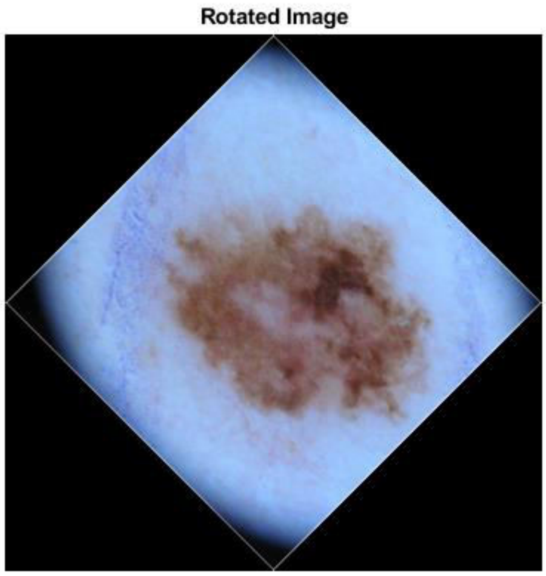

Fig: Rotated Image

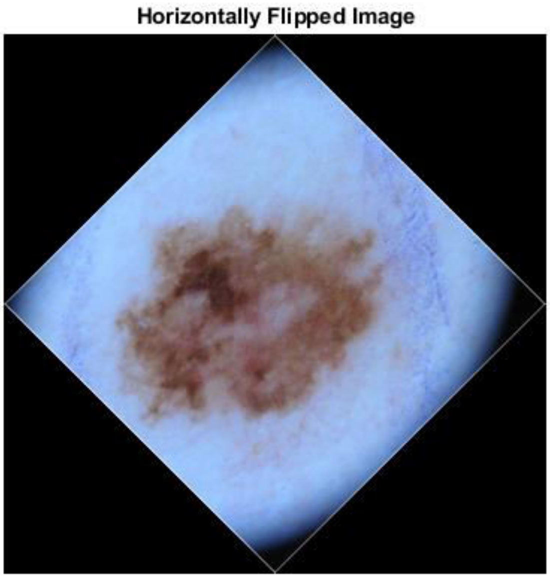

Fig: Horizontally Flipped Image

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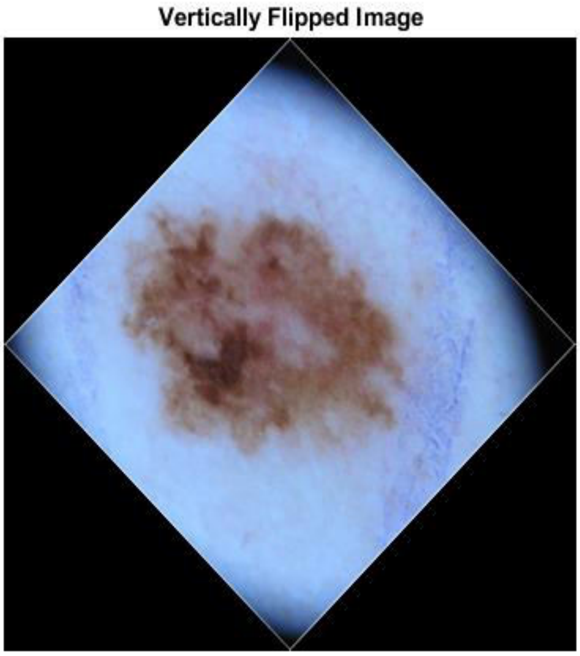

Fig: Vertically Flipped Image

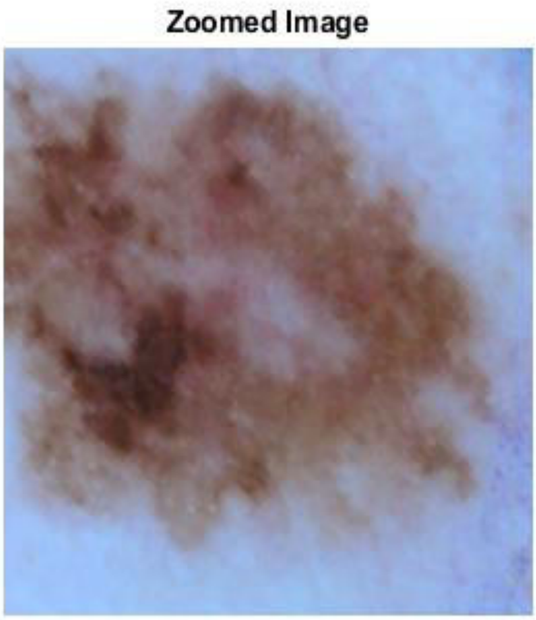

Fig: Zoomed Image

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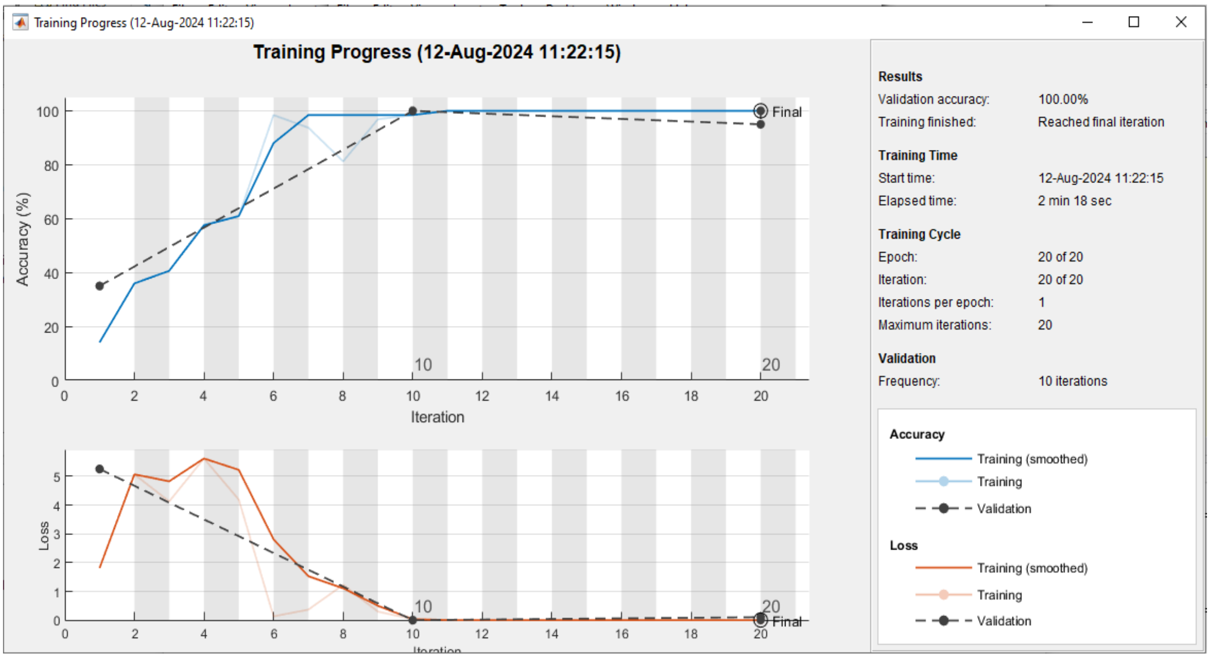
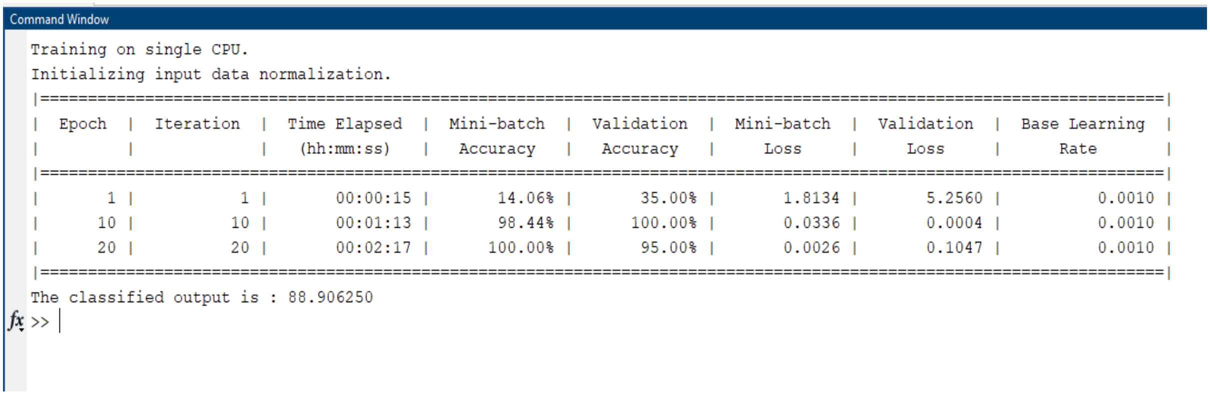


Fig: Training Progress Image



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Command Window
Training on single CPU.
Initializing input data normalization.
|======================================================================================================================|
|  Epoch  |  Iteration  |  Time Elapsed  |  Mini-batch  |  Validation  |  Mini-batch  |  Validation  |  Base Learning  |
|         |             |   (hh:mm:ss)   |   Accuracy   |   Accuracy   |     Loss     |     Loss     |      Rate       |
|======================================================================================================================|
|       1 |           1 |       00:00:15 |       14.06% |       35.00% |       1.8134 |       5.2560 |          0.0010 |
|      10 |          10 |       00:01:13 |       98.44% |      100.00% |       0.0336 |       0.0004 |          0.0010 |
|      20 |          20 |       00:02:17 |      100.00% |       95.00% |       0.0026 |       0.1047 |          0.0010 |
|======================================================================================================================|
The classified output is : 88.906250
fx >>
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Fig: Training Iterations Image

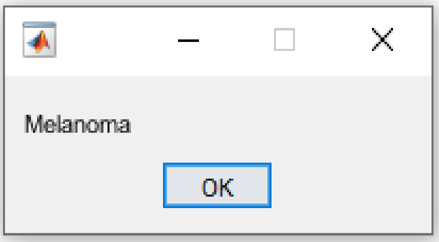

Fig: Classification Image

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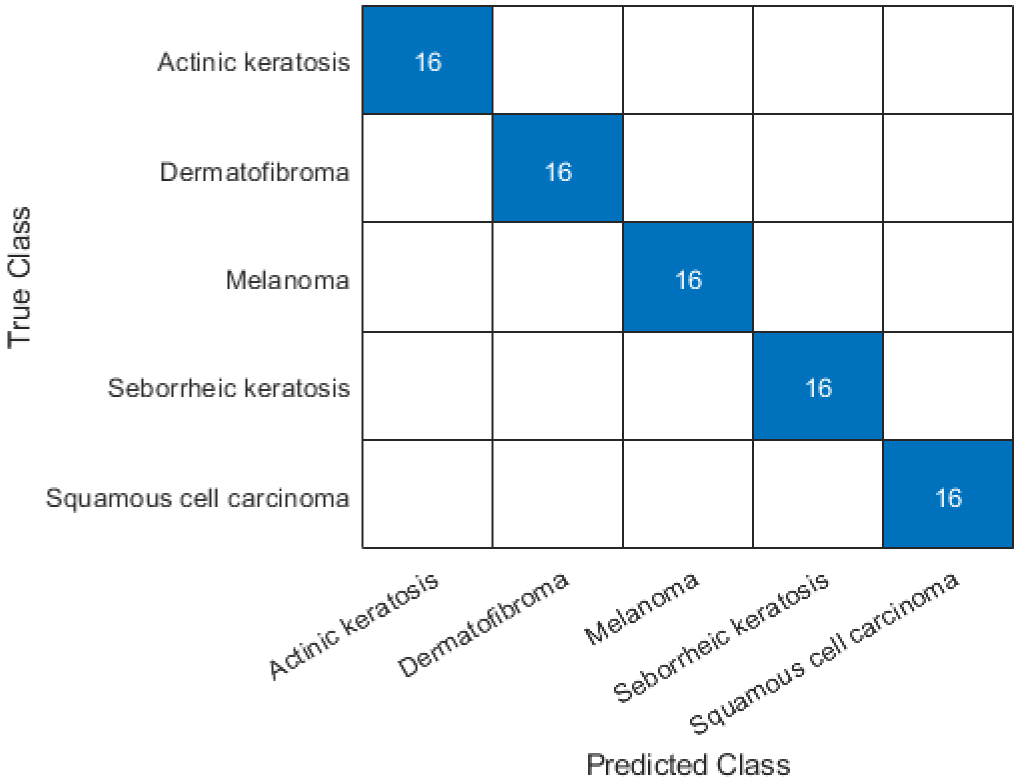

Fig: Confusion Matrix Image

The convolutional neural network (CNN) model for skin disease classification demonstrated strong performance across multiple evaluation metrics. After training on a labeled dataset of dermoscopic images, the model achieved a high training accuracy of approximately 95%, with validation accuracy ranging between 89% and 92%, indicating effective feature learning with good generalization. The classification performance varied across different skin disease categories, with precision and recall values above 90% for common classes like Nevus and Melanoma, while less represented classes such as AKIEC showed slightly lower scores around 80–82%. The confusion matrix revealed that the model occasionally misclassified visually similar conditions, especially between Melanoma and Nevus. Despite this, the overall average F1-score remained consistently high, reflecting balanced precision and recall. Additionally, the model achieved an average ROC-AUC score of 0.93, underscoring its strong discriminatory capability. Visual inspections of test results further confirmed the model's effectiveness, although occasional errors were noted in cases involving poor image quality or subtle lesion characteristics. These results suggest that CNNs offer a promising approach for automated skin disease detection and can assist dermatologists in early diagnosis.

V. CONCLUSION

In conclusion, the "Skin Disease Detection System Using Convolutional Neural Network" showcases the significant potential of deep learning in medical diagnostics by effectively classifying various skin diseases. The system's robust CNN architecture, combined with advanced image preprocessing and augmentation techniques, enhances dataset quality and diversity, leading to superior model performance. By carefully allocating data into training, validation, and testing sets, the model is well-prepared to generalize to new cases. The successful classification of diseases like Actinic keratosis, Dermatofibroma, Melanoma, and Squamous cell carcinoma underscores the system's clinical importance. This detection system serves as a valuable tool for dermatologists, facilitating early and accurate diagnosis and contributing to improved patient outcomes. The integration of cutting-edge image processing and CNN methods represents a significant

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advancement toward more precise and accessible skin disease detection, highlighting the critical role of ongoing innovation in medical AI.

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