Skin Disease Detection System Using Convolution Neural Networks

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***Abstract*—The" Skin Disease Detection System Using Con- volutional Neural Network" is designed to accurately clas- sify 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.**

***Index Terms*—Skin Disease Dataset, Image Processing Tech- niques, Deep Learning Techniques, Convolution Neural Net- work, Classification, Accuracy.**

I. INTRODUCTION

With its rapid spread the increase of skin diseases has had an alarming outcome on people across the globe. It is imperative for these disorders to be diagnosed in an appropriate time span; however, a multitude of people face a challenge due to the broad similarities present amongst varying conditions. Sicknesses range from easily treatable to chronic disorders and can severely affect one's life. In most circumstances, specialized regions of medicine is complex to get a hold of, especially in rural areas. CNNs, or Convolutional Neural Networks, as a part of the deep learning phenomenon of Artificial Intelligence have transformed how medical prac- titioners carry out diagnosis. The rise of mushrooming AI systems is transforming health diagnosis at an unprecedented rate. AI systems and their intricate algorithms work towards detecting all sorts of patterns concealed within the harmful skin lesions. Such systems empower professionals within the field of medicine and make accurate diagnosis with the utmost precision. Furthermore, these systems provide accurate results in seconds, a feat that is vital to areas that suffer with scarce professionals in the medical field. The capability to auto- matically detect skin problems improves efficiency, mitigates treatment complexities, and enhances final results. The use of Artificial Intelligence in medicine, particularly dermatology,

can drastically change people's health for the better, offering prompt, easier and more effective ways to overcome ailments. Such strategies along with the application of CNNs smoothen the lack of skills and knowledge in dermatology as well as facilitate advanced disease chances. It boosts the confidence of professionals, promotes positive results for patients.

Skin diseases are clinical conditions that involve the skin, leading to inflammation, irritation, infections, or other ab- normal conditions. They can be mild, moderate, or severe and can also be temporary or chronic. Skin diseases may be caused by several factors, such as genetics, infection, immune system dysfunctions, allergies, and environmental stimuli.Skin conditions may lead to discomfort, itching, pain, and emotional distress. Effective management of these conditions can be achieved through proper diagnosis and treatment by derma- tologists or AI-based tools.

Advancements in medical technology, particularly in im- age processing and machine learning, are revolutionizing the approach to skin disease diagnosis. Automated systems lever- aging deep learning techniques, such as Convolutional Neural Networks (CNNs), are being developed to assist healthcare professionals by providing accurate, fast, and reliable diag- nostic tools.

II. LITERATURE SURVEY

[1] Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. Nature, 542(7639), 115-118.

Skin cancer, the most common malignancy, is mainly diag- nosed visually through clinical screening, dermoscopy, biopsy, and histopathology. Automated classification is challenging due to lesion variability. Deep convolutional neural networks (CNNs) offer potential for this task. We trained a CNN on 129,450 images covering 2,032 diseases and tested it against 21 dermatologists. It matched expert performance in distinguishing common and deadly skin cancers. With mobile integration, CNNs could expand dermatology access globally, leveraging billions of smartphones for affordable diagnostics.

[2] Haenssle, H. A., Fink, C., Schneiderbauer, R., To- berer, F., Buhl, T., Blum, A., ... & Enk, A. (2018). A deep learning CNN (Google's Inception v4) was trained and vali- dated using dermoscopic images for melanoma recognition. In a study, its performance was compared to 58 dermatologists

using a 100-image test set at two levels: dermoscopy only and dermoscopy with clinical data. Key metrics included sensitivity, specificity, and AUC for diagnostic accuracy. The CNN matched or outperformed dermatologists and was also compared to the top-five algorithms from the 2016 ISBI challenge.

[3] Tschandl, P., Rosendahl, C., & Kittler, H. (2017). The HAM10000 dataset addresses the challenge of limited and diverse dermatoscopic image datasets for training neural net- works in skin lesion diagnosis. It includes 10,015 images from various populations, acquired through different methods and processed using semi-automatic workflows. Over 50% of cases were confirmed by pathology, while others were validated through follow-up, expert consensus, or confocal microscopy. Publicly available via the ISIC archive, this dataset serves as a benchmark for machine learning and comparisons with human experts.

[4] Menegola, A., Tavares, J., & Fornaciali, M. (2017). Skin cancer accounts for 40% of global cancer cases, with 5.6 million diagnoses last year. Automated skin lesion classifica- tion is challenging due to variability in appearance, but deep learning shows promise. This study used a CNN (TensorFlow) with 81.24% accuracy and applied transfer learning (PyTorch) to improve accuracy, achieving up to 99.04% with VGG19. The model classifies seven skin cancer types and aims to make non- invasive screening more accessible and cost-effective.

Summary: Accurate, efficient, reliable, early diagnosis, improved treatment, enhanced care.

[5] Brinker, T. J., Hekler, A., Enk, A. H., Klode, J., Hauschild, A., Berking, C., ... & Schadendorf, D. (2019). Deep learning outperformed 136 of 157 dermatologists in a head-to-head dermoscopic melanoma image classification task. European Journal of Cancer, 113, 47-54.

For this comparative study, 4204 biopsy-proven images of melanoma and nevi (1:1) were used for the training of a convolutional neural network (CNN). New techniques of deep learning were integrated. For the experiment, an additional 804 biopsy-proven dermoscopic images of melanoma and nevi (1:1) were randomly presented to dermatologists of nine German university hospitals, who evaluated the quality of each image and stated their recommended treatment (19,296 recommendations in total). Three McNemar's tests comparing the results of the CNN's test runs in terms of sensitivity, specificity and overall correctness were predefined as the main outcomes.

Summary: Deep learning surpassed most dermatologists in melanoma classification.

[6] Zhou, B., Khosla, A., Lapedriza, A., Oliva, A., & Torralba, A. (2016). This work revisits the global average pooling layer, highlighting its role in enabling CNNs to localize discriminative image regions despite being trained only on image-level labels. It builds a generic localizable deep representation by exposing the implicit attention of CNNs. Without using bounding box annotations, the model achieves a 37.1% top-5 error in object localization on ILSVRC 2014,

demonstrating effective localization purely through classifica- tion training.

[7] Classification of skin cancer using CNN

analysis of Raman Spectra. This study compares convolutional neural networks (CNNs) and projection on latent structures with discriminant analysis for classifying carcinoma using Raman spectra stimulated by a 785 nm laser. Spectra from 617 skin neoplasm cases were recorded in vivo using a portable Raman setup. Classification models were developed for both approaches, with stability tested via 10-fold cross-validation. To prevent overfitting, the dataset was split into 80% training and 20% testing. Results show CNNs significantly outperform traditional methods in classification accuracy.

[8] Channel Attention based Convolutional Network for skin disease classification.

This research develops a CNN-based system for skin disease detection using a model called Eff2Net, built on Efficient- NetV2 with an Efficient Channel Attention (ECA) block. It replaces the Squeeze and Excitation (SE) block, reducing the total trainable parameters. The model learns around 16 million parameters, significantly fewer than existing deep learning approaches. Eff2Net classifies four skin diseases: acne, actinic keratosis (AK), melanoma, and psoriasis, improving efficiency while maintaining accuracy.

[9] The Automated skin lesion segmentation using at- tention based deep Convolutional Neural Network: This research proposes a deep learning-based end-to-end framework for automatic dermoscopic image segmentation using a modi- fied U-Net. It integrates Group Normalization (GN) instead of Batch Normalization (BN) in encoder and decoder layers for better feature extraction. Attention Gates (AG) enhance focus on crucial details, while Tversky Loss (TL) optimizes recall and precision balance. Atrous convolutions improve feature propagation in the network’s connecting bridge. The model is evaluated on the ISIC 2018 dataset, demonstrating improved segmentation performance.

[10] Deep learning approach to skin layer segmentation in inflammatory dermatoses

Manual skin analysis is time-consuming and lacks repeata- bility, while HFUS in dermatology lacks automated tools. To address this, an automatic segmentation method for epider- mis and SLEB layers was developed. It combines fuzzy c- means clustering for preprocessing with a U-Net-based CNN using batch normalization for robust segmentation. The model achieves Dice coefficients of 0.87 for the epidermis and 0.83 for SLEB, outperforming state-of-the-art methods and improving skin layer analysis efficiency.

III. WORKING METHODOLOGY

The” Skin Disease Detection System Using Convolutional Neural Network” follows a structured approach to classify skin diseases accurately. High-resolution images undergo prepro- cessing, including noise reduction, normalization, and resiz- ing. Data augmentation techniques like rotation and flipping enhance model robustness. A specialized CNN architecture with feature extraction, pooling, and fully connected layers is

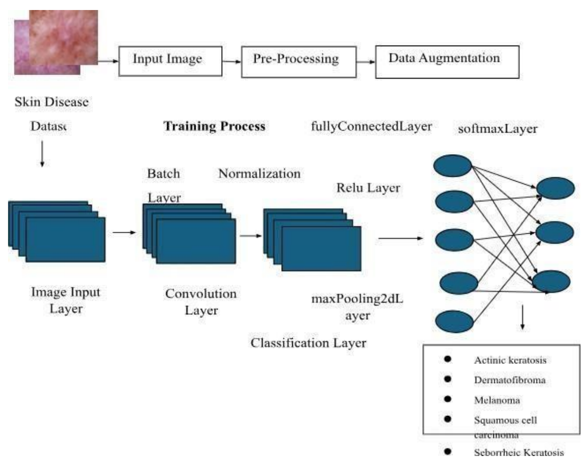

Fig. 1. Image Processing Steps

designed for classification. The dataset is split into training, validation, and testing sets to prevent overfitting. The trained model classifies diseases such as Actinic Keratosis, Melanoma, and Squamous Cell Carcinoma. This system ensures accuracy and aids dermatologists in early diagnosis.

Convolutional Neural Network:

Artificial Neural Networks excel in machine learning tasks like image, audio, and text classification. Recurrent Neu- ral Networks (RNNs) with LSTMs handle sequences, while Convolutional Neural Networks (CNNs) are used for image classification. CNNs consist of multiple convolutional layers, depending on data complexity. Understanding basic neural network concepts is essential before diving into CNNs.In a regular Neural Network, there are three types of layers:

1. Input Layers: The input layer has neurons equal to total features in data, such as pixels in an image.
2. Hidden Layer: The input layer feeds data into multiple hidden layers, each with varying neurons based on the model and data size. The output is computed through matrix multipli- cation with learnable weights, bias addition, and an activation function for non-linearity.
3. Output Layer: A Convolutional Neural Network (CNN) processes image data using convolutional layers to extract features for tasks like classification and segmentation. Filters (kernels) slide over the image, detecting patterns through linear transformations. The model undergoes feedforward computa- tion, error calculation, and backpropagation to minimize loss. U-Net, a CNN variant, is useful for segmentation tasks where input and output sizes are similar.

Padding:

To handle the edge pixels there are several approaches:

- Losing the edge pixels
- Padding with zero value pixels
- Reflection padding

Reflection padding copies edge pixels to the outside, ensuring convolutional kernels process boundary areas effectively. A 3x3 kernel requires one pixel of padding, while a 7x7 kernel

needs three. Ignoring edge pixels, as done in some research, leads to data loss, worsening with deeper networks. Padding helps maintain input dimensions when using a stride of one.

Strides:

Stride-2 convolutions reposition the kernel two pixels at a time, which results in the output being half the size when compared to stride-1. With padding, an input of size w×h×3w

\Times h \times 3 results in an output of \lceil w/2 \rceil

\times \lceil h/2 \rceil \times 1. For instance, stride-2 convo- lutions done on a 64×64 RGB image yields a 32×32 feature map. Choosing stride has an effect on the architecture of the network with regard to detail and complexity of the network.

Image Input Layer:

An image input layer inputs images to a network and applies data normalization. The input size is specified as height, width, and the number of channels (1 for grayscale, 3 for color).

Convolutional layer:

A 2-D convolutional layer applies sliding filters to the input, learning localized features. It consists of neurons that connect to sub-regions of images or previous layer outputs. The convolution2dLayer function allows specifying filter size and stride for feature extraction.

Dilated Convolution:

A dilated convolution expands filters by inserting spaces be- tween elements, increasing the receptive field without adding parameters or computation. The dilation factor determines the step size for sampling the input, effectively up-sampling the filter. This allows larger coverage while maintaining efficiency. For example, a 3×3 filter with a dilation factor of [2,2] behaves like a 5×5 filter with inserted zeros.

Rectified Linear Unit (ReLU):

A Rectified Linear Unit is used as a non-linear activation function. A ReLU says if the value is less than zero, round it up to zero. Create a ReLU layer using reluLayer. A ReLU layer performs a threshold operation to each element of the input, where any value less than zero is set to zero. Convolutional and batch normalization layers are usually followed by a nonlinear activation function such as a rectified linear unit (ReLU), specified by a ReLU layer. A ReLU layer performs a threshold operation to each element, where any input value less than zero is set to zero, that is, The ReLU layer does not change the size of its input.

Batch normalization layer:

Batch normalization stabilizes network predictions, mini- mizes overfitting, and speeds up training. Batch normalization normalizes activations across a mini-batch by subtracting the mean and dividing by the standard deviation, then scales and shifts via learnable parameters and. Optimisation is enhanced by this, enabling larger learning rates and less regularization. Batch normalization layers are inserted in between convolu- tional and activation layers to optimize training efficiency. Maximize benefits by shuffling training data prior to each epoch through the use of the 'Shuffle' option.

Max and Average Pooling Layers: Max pooling takes the maximum, and average pooling calculates the mean across

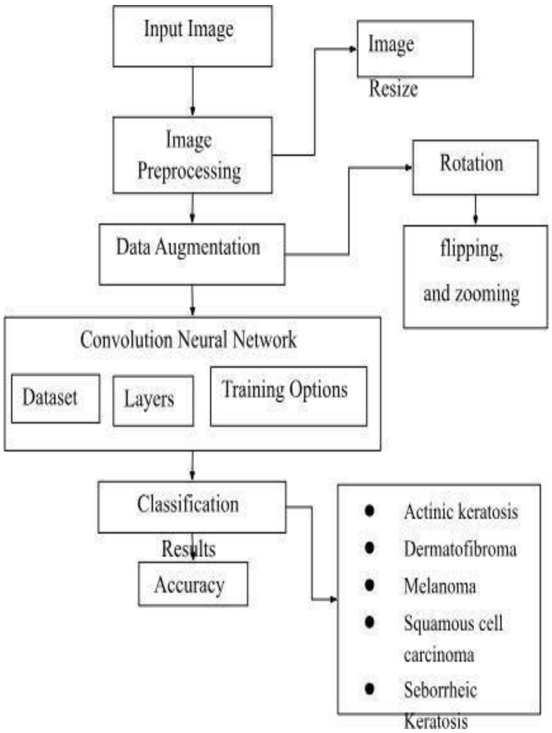

Fig. 2. Software Implementation

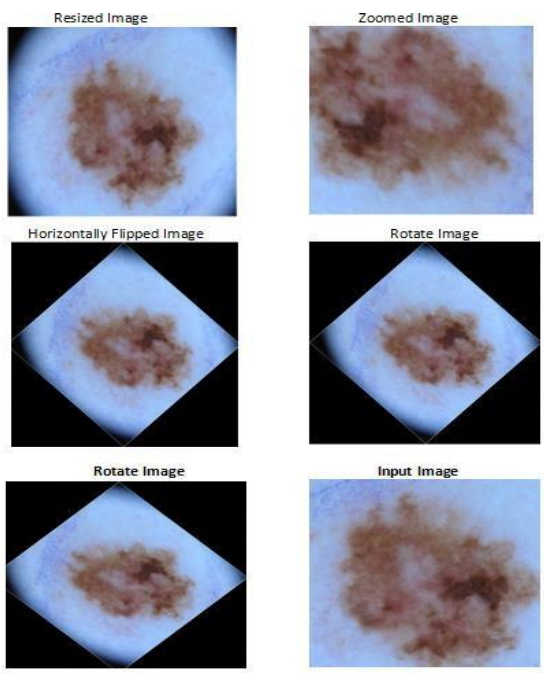

Fig. 3. Phases of Image Processing

pooling regions, minimizing parameters and overfitting. Fertil- izer suggestions from AI boost plant resistance to disease by compensating for nutritional deficiencies, maximizing yield, and enhancing sustainability.

A. Software Implementation

Image Resize:

In MATLAB, image resizing adjusts dimensions using the imresize function with interpolation methods like nearest neighbor, bilinear, and bicubic, ensuring consistency while maintaining the aspect ratio.

Rotation:

Image rotation in MATLAB uses the imrotate function to rotate images by a specified angle, supporting interpolation methods to minimize distortion for alignment and object recognition.

flipping, and zooming:

The flip function in MATLAB creates a mirror image horizontally or vertically, useful for data augmentation and preprocessing. Image zooming in MATLAB, done using im- resize, scales images up or down to focus on details, though excessive zooming may cause pixelation.

IV. RESULTS AND DISCUSSION

This section elaborates the working and efficiency of the Skin Disease Detection System Using Convolutional Neural Network. In terms of time, reliability of data, efficiency and total or overall perfomance

A. Phases of image processing

This figure displays the original input image alongside a resized version, rotated variations, a horizontally flipped version, and a zoomed-in example. These transformations, including resizing, rotation, flipping, and zooming, were uti- lized to enhance the training dataset and improve the model's performance, leading to more robust results.

Fig. 4. stage classification of disease

*B. Classification Resul***t**

stage classification of disease

The system was tested in different conditions to validate the accuracy and response time of the sensors. The moisture sensor had a high accuracy with minimum response time to give timely alerts if the diaper wetness exceeded the threshold. The temperature sensor maintained a steady accuracy, while the TDS and pH sensors were able to detect chemical residues and waste contamination. Overall, the system performance was consistent and ensured reliable and real-time monitoring of the diaper environment.

Fig. 5. classification of Disease

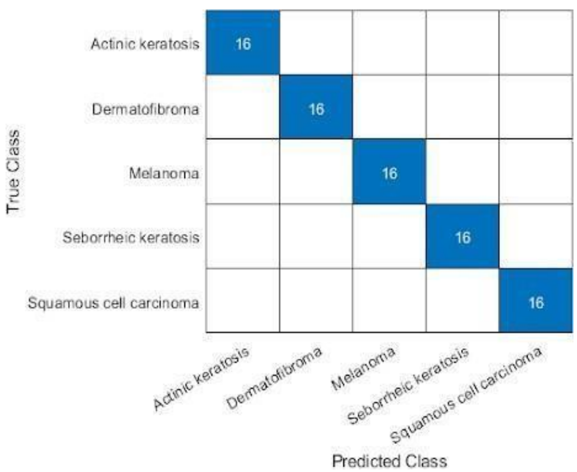

Fig. 6. Confusion matrix

C. Confusion Matrix

This confusion matrix shows the ideal scenario for a classifi- cation model. The model has achieved perfect accuracy on this dataset. All data points were correctly classified, as evidenced by the non-zero values only appearing along the diagonal and the absence of values in the off-diagonal cells.

D. Comparison with Alternative Solutions

Compared to the usual methods The Proposed Method demonstrates a higher value than the Existing Method. Specif- ically:

Trial 1: Existing Method scored 88.2, Proposed Method scored 98.66.

Trial 2: Existing Method scored 88.9, Proposed Method scored 98.05.

Trial 3: Existing Method scored 88.91, Proposed Method scored 99.01.

Trial 4: Existing Method scored 88.06, Proposed Method scored 98.6.

Trial 5: Existing Method scored 88.1, Proposed Method scored 98.01.

Improvement In every trial, the proposed method outper- forms

the existing method. This is a strong indication that the proposed method offers a real improvement.

Magnitude of improvement the improvement ranges from approximately 9.46 (98.05 - 88.9) to 10.95 (99.01 - 88.06). The improvements are substantial and consistent across all trials. This suggests that the proposed method isn’t just marginally better, but significantly so.

V. CONCLUSION

In conclusion, the” Skin Disease Detection System Us- ing Convolutional Neural Network” showcases the signifi- can’t 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 advancement toward more precise and accessible skin disease detection, highlighting the critical role of ongoing innovation in medical AI.

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