Dermatological Anomaly Detection via Machine Learning Frameworks

ANSHUK JIRLI[1], RISHAB MALALIKAR[2], ROHINI DESAI[3], SHRAVANI M. SAGARAM[4]

[1]Department of Computer Science Engineering, SGBIT, Belagavi 590001, India
[2]Department of Computer Science Engineering, SGBIT, Belagavi 590001, India
[3]Department of Computer Science Engineering, SGBIT, Belagavi 590001, India
[4]Department of Computer Science Engineering, SGBIT, Belagavi 590001, India

Email:anshuk.jirli2002@gmail.com, rishabmalalikar@gmail.com, rohinidesai206@gmail.com, smsagaram@gmail.com

1. ABSTRACT

Skin diseases are eminent health concern globally, emphasizing the urgent need for revamped diagnostic methods. Our research proposes a novel approach by utilizing advanced computer algorithms, specifically focusing on CNNs. In particular, we employ the VGG16 model, in image recognition tasks. These algorithms, inspired by the human brain's visual processing system, are adept at analyzing complex images, for anomaly detection. Our system works by examining images of skin abnormalities and categorizing them into different disease types, enabling early identification and intervention. This process involves preparing the data, training the computer model using specialized techniques, including the Adam optimizer with a standard learning rate over multiple epochs and integrating it into an easy-to-use web tool. With this, one can conveniently upload snapshots regarding skin issues for analysis. With the help of CNNs, particularly the VGG16 model our system demonstrates outputs in accurately identifying various skin diseases. The above method is an important tool for healthcare workers and also motivate people to examine their skin health proactively. Through continuous refinement and optimization, our system aims to further enhance its capabilities and broaden the influences over dermatological diagnostics. By providing efficient and reliable skin disease detection, this knowledge donates to improving healthcare outcomes and ultimately enhances life of people who affected by skin conditions.

2. INTRODUCTION

The research makes use of ML frameworks within dermatology, for the diagnosis and categorization of skin diseases. By harnessing convolutional neural networks and other ML algorithms, the study aims to enhance the accuracy in identifying skin ailments. Through extensive datasets comprising dermatological images, the research endeavors to create tools which can supplement dermatologists' diagnostic capabilities, thereby advancing patient outcomes and optimizing healthcare resources in the dermatological domain.

Skin diseases are increasingly prevalent due to lifestyle changes and environmental factors. In the United States, approximately one in five individuals is affected by some form of skin ailment. The conditions are activated by various factors such as genetic predisposition, dietary habits, and external influences, culminating in a spectrum of chronic and potentially malignant diseases. Early detection is key to managing these conditions effectively. Dermatology, focusing on hair, nails, and skin issues, traditionally relies on clinical examinations for diagnosis. Skin diseases not only impact physical health but also diminish quality of life, with symptoms including burning, redness, itching, and swelling. Some conditions, if not treated, may progress to malignancy.

Skin diseases encompass a wide spectrum of conditions, with unique characteristics plus entailments of patient health. Recognizing the significance of early detection and intervention, we developed a sophisticated system capable of detecting four distinct types of skin diseases: warts, vitiligo, ringworm, and melanoma. Such problems are chosen depending over the prevalence, severity, and potential impact on patient well-being.

1. Warts:

Warts are small, rough development on the epidermis because of human papillomavirus (HPV). They can appear on any part but are most common on the hands and feet. Warts are contagious and can infected by contact or by sharing items like towels or razors. Common types of warts include common warts, plantar warts (on the soles of the feet), and genital warts. Treatment options include over-the-counter medications, cryotherapy (freezing), laser therapy, and surgical removal.

Fig 1: Warts

Fig 2: Warts

2. Vitiligo:

It is a very common epidermis issue characterized with loosening of epidermal layer, resulting in white or depigmented areas. It is trusted, that involves autoimmune, genetic, and environmental factors. It affects major parts over human body including facial area, limbs, and feet. While vitiligo itself is not physically harmful, it can have significant psychosocial impacts due to changes in appearance. Treatment possibilities such as, phototherapy, and depigmentation therapy for widespread vitiligo.

Fig 3: Vitiligo

Fig 4: Vitiligo

3. Ringworm:

Ringworm, despite its name, is not caused by a worm but rather by various types of fungi. It presents as a red, circular rash with raised edges and may be accompanied by itching or scaling. Ringworm can affect the skin, scalp, groin area (jock itch), and feet (athlete's foot). It is highly contagious and spreads via physical contact of inoculate individuals, animals, or contaminated objects. Treatment typically involves antifungal medications, either topical or oral, depending on the severity and destination where the infection lies.

Fig 5: Ringworm

Fig 7: Ringworm

4. Melanoma:

It's one condition where the cells that produce pigment (melanin) in the skin. It often appears as a new mole or a change in an existing mole, with features such as asymmetry, irregular borders, varied color, and a diameter larger than a pencil eraser. Melanoma can occur anywhere on the body, including areas not exposed to the sun. There are various reasons which causes this rare contagious disease are excessive sun exposure, a history of sunburns, fair skin, etc., Early detection and treatment are crucial for favorable outcomes, as melanoma can spread over all the areas over the human-body if left untreated. Treatment may involve surgical removal, chemotherapy, immunotherapy, or targeted therapy, regarding which stage and extent of the disorder.

Fig 9: Melanoma

Fig 10: Melanoma

In recent years, technological advancements in artificial intelligence (AI) and ML have given new avenues for diagnosing skin diseases. This technology has found myriad applications in healthcare, including dermatology, where it offers the potential to enhance diagnostic accuracy and streamline patient care. Convolutional Neural Networks (CNNs) represent algorithms particularly well-suited for identification and classification tasks. Inspired by the organization of the animal visual cortex, CNNs excel at analyzing complex visual information, which is optimal as it interprets medical pictures which are used in dermatology. These networks have many layers, along with convolutional layers that fetch features from input images and pooling layers that reduce dimensionality, ultimately leading over categorization concerning input into different categories.

Among the various CNN architectures, the VGG16 model is more effective in image classification tasks. Developed by the Visual Geometry Group (VGG) at the IVY League Universities, VGG16 is categorized with its deep architecture, comprising 16 layers, and its use of small (3x3) convolutional filters. The above architecture is showed to achieve impressive results in various image recognition benchmarks, including those related to dermatological diagnostics. Our research aims to leverage the capabilities of machine learning, particularly CNNs and the VGG16 model, builds robust system for the detection of skin diseases. By teaching architecture over diverse dataset of images depicting various skin conditions, we seek and builds tools capable of accurately classifying and identifying these ailments. The above method provides a user-friendly interface, allowing individuals to conveniently upload images of their skin issues for analysis. With the unique process, the conclusion must enhance patient outcomes in dermatology and advance diagnostic methods for detecting skin diseases.

Through the improvement over the user-friendly system that allows individuals to upload images of their skin issues for analysis, which approaches and democratize access to advanced diagnostic capabilities and empower patients and suggests few treatments and manages the skin health. By bridging the gap between technology and healthcare, our knowledge contributes for the methodologies in skin disease detection, ultimately paving the way for a future where dermatological care is more accessible, efficient, and effective.

3 Methodology

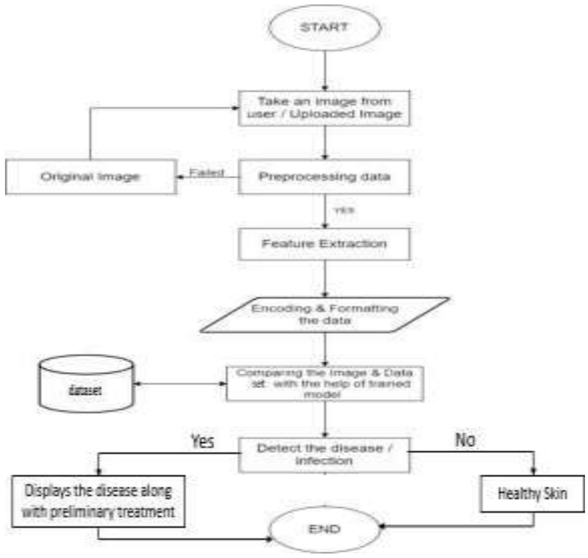

Fig 11: Flow Diagram

A. Data Collection:

The dataset used for our research is sourced from different reputable repositories, including Kaggle, Derment, Hamnet, and ISIC. These repositories host datasets pertinent to the research objectives and ensure a diverse range of data is available for analysis.

i. **Kaggle:** The Kaggle repository provided a comprehensive range of labeled datasets of medical imaging, enabling access to images annotated with diagnostic information.
ii. **Derment:** This source has chipped-in into study by offering datasets focusing on dermatological conditions. The requirement of labeled images aided in creating a robust dataset for training and testing.
iii. **Hamnet:** Hamnet's repository contributed data specifically relevant to Aesculapian sanapshots analysis, offering high-quality, labeled images suitable for model training.
iv. **ISIC:** The International Skin Imaging Collaboration (ISIC) provided extensive datasets on dermatological conditions, including pictures of lesions. This source offered diverse, labeled data crucial for the model's development.

The datasets were downloaded and organized into directories based on their respective sources and classifications. Metadata accompanying the images gathered for further analysis and validation.

B. Data Preprocessing:

To prepare the datasets for model training, various data preprocessing methods were applied:

i. **Resizing:** All images were resized to a consistent dimension of 224x224 pixels, standard size to ensure uniformity. This step facilitated the compatibility regarding input with the chosen model architecture and improved computational efficiency.
ii. **Rotation and Augmentation:** Data augmentation like rotation, flipping, and zooming were employed to artificially increase the size including improvements in model's generalization ability. These techniques helped the model learn to recognize features from various perspectives.
iii. **Labeling and Encoding:** Images were labeled on the basis of their classification and annotated with the necessary metadata. Labels are transformed as digits to facilitate model training.
iv. **Quality Control:** Low-quality images, such as those that were blurry, underexposed, or otherwise unclear, were deleted through the archives. This process ensured that this architecture is instructed over high-quality, representative data.
v. **Normalization:** The pixel values of images were normalized from a radius of zero-one to standardize the data and improve the model's learning process.

Such pre-processing details play pivotal role for enhancing data quality and ensuring the model's optimal performance..

C. Model selection:

Several model architectures were considered during the research, focusing over the minute details of image classification tasks:

i. Evaluation of Models: The research team evaluated a lot of deep learning models, such as ResNet, Inception, and DenseNet, on the basis of their accuracy, efficiency, and adaptability.
ii. Selection of VGG16:

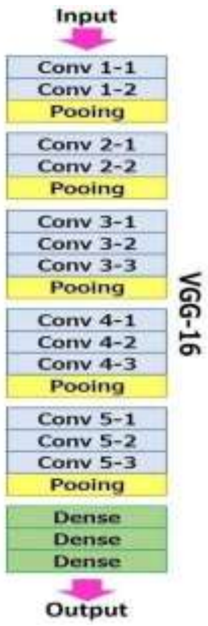

Fig 12: VGG 16

After careful evaluation, the VGG16 model was opted for its unique deep CNN architecture and proven success in image classification tasks. The model's pre-trained weights on ImageNet provided a strong starting point for fine-tuning on the specific dataset.

A CNN, also known as ConvNet, is a form of neural network widely used in vision tasks. VGG16 is a renowned CNN architecture recognized for its effectiveness in image classification and object detection. It comprises 16 layers, including 13 convolutional layers, five max-pooling layers, and three dense layers, totaling 21 layers. However, only 16 layers have trainable parameters. VGG16 is adept at classifying images of thousands of different categories with an accuracy of 92.7%. Notably, it utilizes 3x3 convolution filters with stride 1 and same padding, along with 2x2 max-pooling filters with stride 2, consistently across the architecture.

It has layers with varying numbers of filters, ranging from 64 to 512. Following the convolutional layers, there are 3 fully-connected layers, each with a different number of channels. The last layer performs 1000-way segregation for the ImageNet dataset. VGG16's simplicity in architecture and consistent design choices make it popular for image classification tasks and straightforward to implement, especially in transfer learning scenarios.

iii. Transfer Learning: Transfer learning was employed to leverage the model's pre-existing knowledge from ImageNet. The model's convolutional layers were retained, while the top layers were customized for the specific classification task.

iv. Fine-Tuning and Hyperparameter Tuning: The model's architecture was fine-tuned by adjusting the layers and units. Hyperparameter tuning was performed to optimize the model's learning rate, batch size, and other parameters.

The chosen model provided a balance between performance and efficiency, making it suitable for the research objectives.

D. Model Training:

This procedure involved fine-tuning the VGG16 model using the preprocessed data. 70% of data-set is used in training purpose.

i. Dataset Splitting: The dataset was split into training set and test set to ensure proper model evaluation and avoid overfitting.

ii. Data Augmentation: Augmentation steps were applied during training to artificially increase the size and diversity of train set.

iii. Training Loop: The model was trained using a batch gradient descent algorithm, iterating over the training data in batches. Backpropagation was employed to update the model's weights based on calculated loss.

iv. Loss Function and Optimizer: The categorical cross-entropy loss function is employed to calculate the model's prediction accuracy. An appropriate optimizer, such as Adam, was selected to minimize the loss.

Adam optimizer:

The key components of the Adam optimizer include:

Learning Rate: A hyperparameter that establishes step size during optimization. In Adam, the rate of learning can be constant or decay over time.

First Moment (Mean) of Gradients: The first moment is calculated as an exponential moving average (EMA) of the gradients. It represents the average direction of the gradients.

Second Moment (Variance) of Gradients: The second moment is calculated as an EMA of the squared gradients.

Bias Correction: Since the moments are initialized to zero, they are skewed toward zero, specially in the early iterations. Adam applies bias correction to account for this.

Parameter Update: The parameters are updated using a combination of Lr and the moments.

A mathematical equation that describes the Adam optimizer, a stochastic optimization algorithm used in ML is given below. The Adam optimizer is designed to address shortcomings of other optimization algorithms, like the AdaGrad optimizer and the RMSprop optimizer. It's useful in variety of tasks, including training deep neural networks.

$$\nu_t = \beta_1 * \nu_{t-1} - (1 - \beta_1) * g_t$$

$$s_t = \beta_2 * s_{t-1} - (1 - \beta_2) * g_t^2$$

$$\Delta\omega_t = -\eta \frac{\nu_t}{\sqrt{s_t + \epsilon}} * g_t$$

$$\omega_{t+1} = \omega_t + \Delta\omega_t$$

η: Initial learning rate

g_t: Gradient at time t along wi

ν_t: Exponential average of gradients along wj

s_t: Exponential average of squares of gradients along wj

β_1, β_2: Hyperparameter

Here's a breakdown of the equation:

- The first three equations define how the Adam optimizer updates the estimate of the first moment (v_t)along with the second moment (s_t) of the gradients, along with the update for the weight ($\Delta\omega_t$).
- The final equation shows how the weight is updated at each time step.

v. Early Stopping: Early stopping was utilized to prevent overfitting. The procedure for training was halted and validation loss stopped improving for a specified number of epochs.

vi. Model Evaluation: The model's performance was evaluated on the test set after each epoch, using metrics such as accuracy, precision, recall, and F1- score.

vii. Training process was iterative, with adjustments made according to the evaluation results to improve performance.

E. Model Testing:

After training, the model was rigorously tested on a test sub-dataset which was 30% of the whole dataset.

1. Performance Metrics: The performance was evaluated using measurements such as accuracy, precision, recall, and F1-score. These calculations provide information into the model's classification accuracy and its ability to distinguish between different classes.

2. Model Interpretation: Visual inspection of the model's predictions was conducted to understand its decision-making process and identify potential sources of error.

4. IMPLEMENTATION

The execution of our project was a comprehensive process that involved meticulous planning and execution across multiple stages. We began by carefully selecting the VGG16 architecture as the base of our machine learning model. This decision was driven by the architecture's proven track record in image recognition tasks, particularly its ability to extract intricate features from complex visual data, making it well-suited for our objective of detecting dermatological anomalies. With the model architecture decided, we turned our attention on building the frontend interface, which works as the primary point of interaction for users. Leveraging various front-end technologies , we crafted a efficient and attractive interface that enables users to effortlessly upload images of skin anomalies for analytics. The next crucial component of our implementation was the fusion of Flask, a lightweight Python web framework, to enable data-exchange between the frontend interface and the ML model . Through Flask's RESTful API capabilities, we established a seamless connection that enables data transmission from the frontend to the backend for analysis. The dataflow is as follows:

- Image Upload and Preprocessing:
    1. When an image is uploaded through the Flask API, it undergoes preprocessing.
    2. This step standardizes the image format and enhances clarity for improved comparison with dataset images.

- VGG16 Model Analysis:
    1. Once preprocessing is complete, the image is analyzed using the VGG16 model.
    2. The model compares the image with those in the dataset to identify any dermatological anomalies.
    3. It uses learned features to make accurate predictions about the skin condition.

- Prediction and Feedback:
    1. The model's predictions are shared with the user through the Flask API.
    2. Preliminary treatments are recommended according to the detected anomalies, are also provided.
    3. Users receive prompt, actionable information to help them manage their skin health.

- User Empowerment:
    1. This system empowers users with timely insights and treatment recommendations.

Users can step towards managing their dermatological health effectively. The implementation of our project involved a cohesive integration of machine learning and web development infrastructure to deliver a robust and user-friendly solution for dermatological anomaly detection and preliminary treatment guidance. Through meticulous planning and execution, we have created a tool that has high potential to significantly enhance healthcare efficiency in the areas of dermatology.

A. Module diagram

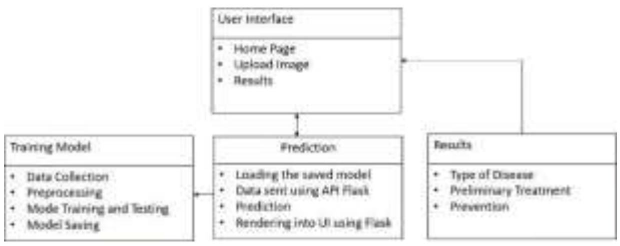

Fig 13: Module diagram

The user interface section points out various methods users utilize and make use of the system. It includes a home page, a section for uploading images, and a results section where predictions are displayed.

Data collection: This is the primary process in the training process. It involves gathering the images that will be utilized to train the model.

Preprocessing: Once the images are gathered ,they are supposed to be preprocessed. This may involve resizing the images, trans-mutating them to a specific format, or normalizing the pixel values.

Model training and testing: This is the core of the ML process. Our prototype is trained on subset of the data and then tested on a separate subset to evaluate its performance.

Model saving: Once the model has been trained, it is saved to a file so that it can be used later for prediction

Prediction shows how the trained model is used to make predictions on new images.

Loading the saved model: When the user uploads a new image, primary step is to load the saved model from disk.

Data sent using API Flask: This likely refers to a web framework that is used to send the image to the prototype for prediction.

Prediction: The model makes a prediction about the image, such as what disease it is likely to show.

After predicting the disease , the resultant predicted disease is displayed on the UI along with the preliminary treatment to treat that disease. As well as some common measures to prevent that disease

B. Architecture:

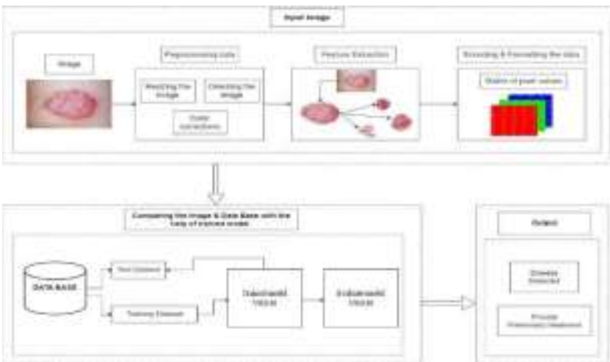

Fig 14: Architecture diagram

The diagram depicts the sequential process of disease detection from an input image using a trained model. Beginning with preprocessing steps like image resizing, orientation adjustment, and color correction, the image undergoes feature extraction to identify critical diagnostic characteristics. The features are extracted and then encoded and formatted into a pixel value matrix representing red, green, and blue colors. Following this, the trained VGG16 model compares the data with its knowledge-base containing test and training datasets for diagnosis. The resultant either indicates the detection of a disease, providing preliminary treatment

RESULT

The model was trained to classify four classes of skin diseases: Melanoma, Ringworm, Vitiligo and Warts.

	Precision	Recall	F1-score	Support
Melanoma	0.95	0.96	0.95	238
Ringworm	0.90	0.87	0.88	104
Vitiligo	0.96	0.91	0.93	196
Warts	0.94	0.97	0.96	212
Accuracy			0.95	1258
Macro avg	0.94	0.94	0.94	1258
Weighted avg	0.95	0.95	0.95	1258

Table 1:

Precision, recall, and F1-score are measurements that are utilized to assess performance of image classification models. They are computed for each class and provide information into the working of model which classified each skin disease. Support refers to the quantity of images in each class. In our situation, there are from 104 to 311 images in each class.

i. Melanoma: The model achieved a precision of 95%, recall of 96%, and F1-score of 95%. This means that out of all the images the model classified as Melanoma, 95% were actually Melanoma, the model correctly identified 96% of all the Melanoma images, and the overall performance for this class was 95%.
ii. Ringworm: The model achieved a precision of 90%, recall of 87%, and F1-score of 88%.
iii. Vitiligo: The model achieved a precision of 96%, recall of 91%, and F1-score of 93%.
iv. Warts: The model achieved a precision of 94%, recall of 97%, and F1-score of 96%.

The accuracy is a metric that represents the overall performance of the model across all classes In this scenario, the model obtained an accuracy of 94%. This means that out of all the 1258 images, the model classified 94% correctly

CONCLUSION

In conclusion, the inception of a robust model for the detection of skin diseases marks a significant advancement in dermatological diagnostics. By utilizing ML frameworks, specifically convolutional neural networks, our research has demonstrated a high prospect that enhances the precision and coherence of identifying skin ailments. Through the incorporation of diverse datasets comprising dermatological images, our system aims to augment dermatologists' diagnostic capabilities, ultimately advancing as well as optimizing healthcare resources in the dermatological domain. The targeted focus on four common skin diseases—warts, vitiligo, ringworm, and melanoma— underscores the significance of early detection and intervention in mitigating the adverse effects of these conditions. Moving forward, continued research and refinement of our system hold promise for further improvements in dermatological diagnostics, making way for a future where timely and accurate diagnosis is accessible to all, thereby enhancing overall patient care and well-being in dermatological field

References

[1] Hongfeng Li, Yini Pan, Jie Zhao, Li Zhang, Skin disease diagnosis with deep learning,2021

[2] Venkatesh R Pai Soujanya G Pai, P M Suhasi, P M Rekha, Identification and Classification of Skin Diseases using Deep Learning Techniques, 2023

[3] Ismail Oztel, Gozde Yolcu Oztel, and Veysel Harun Sahin, Deep Learning-Based Skin Diseases Classification using Smartphones , 2020

[4] Puneet Thapar, Manik Rakhra, Gerardo Cazzato and Md Shamim A Novel Hybrid Deep Learning Approach for Skin Lesion Segmentation and Classification , Journal of Healthcare Engineering Volume ,2022

[5] Tri-Cong Pham Antoine Doucet Chi-Mai Luong, Cong-Thanh Tran and Van-Dung Hoang, Improving Skin-Disease Classification Based on Customized Loss Function Combined With Balanced Mini-Batch Logic and Real-Time Image Augmentation 2020

[6] Mohamed A. Kassem, Khalid M. Hosny, Robertas Damaševičius and Mohamed Meselhy Eltoukhy , Machine Learning and Deep Learning Methods for Skin Lesion Classification and Diagnosis ,2021

[7] Karl Thurnhofer-Hemsi, Ezequiel López-Rubio Enrique and David A. Elizondo , Skin lesion classification by ensembles of deep convolutional networks and regularly spaced shifting ,2019

[8] Ahmed E. Elngar, Rishabh Kumar, Amber Hayat, Prathmesh Churi , Intelligent System for Skin Disease Prediction using Machine Learning ,2021

[9] Parvathaneni Naga Srinivasu, Jalluri Gnana SivaSai, Muhammad Fazal Ijaz, Akash Kumar Bhoi, Wonjoon Kim, James Jin Kang , Classification of Skin Disease Using Deep Learning Neural Networks with MobileNet V2 and LSTM , 2021

[10] Amina Bibi, Muhamamd Attique Khan, Muhammad Younus Javed, Usman Tariq, Byeong-Gwon Kang, Yunyoung Nam, Reham R. Mostafa, Rasha H. Sakr , Skin Lesion Segmentation and Classification Using Conventional and Deep Learning Based Framework ,2021

[11] Vinay Gautam, Naresh Kumar Trivedi, Abhineet Anand, Rajeev Tiwari, Atef Zaguia, Deepika Koundal, Sachin Jain Early Skin Disease Identification Using Deep Neural Network , 2022

[12] Hai Qin, Zhanjin Deng, Liye Shul, Yi Yin, Jintao Li, Li Zhou, Hui Zeng, Qiaokang Liang Portable Skin Lesion Segmentation Systemwith Accurate Lesion Localization Based on Weakly Supervised Learning ,2023

[13] Saja Salim Mohammed, Jamal Mustafa Al-Tuwaijari , Skin Disease Classification System Based on Machine Learning Technique , 2021

[14] Singla, Jimmy & Prashar, Deepak & Jha, Sudan & Joshi, Gyanendra Prasad Medical Diagnostic Systems Using Artificial Intelligence (AI) Algorithms (2020). Medical diagnostic systems using AI algorithms. IEEE Access.

[15] Jufeng Yang, Xiaoping Wu, Jie Liang, Xiaoxiao Sun, Ming-Ming Cheng, Paul L. Rosin, and Liang Wang, Self-Paced Balance Learning for Clinical Skin Disease Recognition , 2020

[16] Janoria, H., Minj, J., Patre, P, Classification of skin disease from skin images using transfer learning technique ,2020

[17] Shanthi, T., Sabeenian, R.S., Anand, R. Automatic diagnosis of skin diseases using convolution neural network ,2020

[18] Shankar, V., Kumar, V., Devagade, U., Karanth, V., Rohitaksha, K.Heart disease prediction using CNN algorithm ,2020

[19] Prottasha, M.S.I., Hossain, A.B.M., Rahman, M.Z., Reza, S.M.S., Hossain, D.A.Identification of various rice plant diseases using optimized convolutional neural network ,2021

[20] M. A. Khan, M. Sharif, T. Akram, R. Dama sevicius, and R. Maskeliunas, Skin lesion segmentation and multiclass classification using deep learning features and improved moth flame optimization ,2021

[21] Megha D. Tijare, Dr. V. T. Gaikwad at el. Detecting skin disease by accurate skin segmentation using various color spaces ,2018

[22] Nawal Soliman ALKolifi ALEnezi, A method of skin disease detection using image processing and machine learning ,2019

[23] Pravin S. Ambed, A S Shirsat, A image analysis system to detect skin diseases ,2013

[24] Li-Sheng Wei, Quan Gan and Tao ji Skin Disease Recognition Method Based on Image Color and texture features ,2018

[25] R. Sumithra, M. Suhilb, and D. S. Guruc, , Segmentation and classification of skin lesions for disease diagnosis , 2015.

[26] Rahat Yasir, Md Ashiqur rehman and Nova Ahmed, Dermatological Disease Detection using image processing and Artificial Neural Network ,2014

[27] R. Yasir, M. S. I. Nibir, and N. Ahmed, A skin disease detection system for financially unstable people in developing countries ,2015.

[28] Kumar, V., Kumar, S., & Saboo, V. Dermatological Disease Detection Using Image Processing and Machine Learning. ,2016

[29] S. Kumar and A. Singh, Image processing for recognition of skin diseases, ,2016

[30] Dawid Połap,* Alicja Winnicka, Kalina Serwata, Karolina Kęsik, and Marcin Woźniak et al. An Intelligent System for Monitoring Skin diseases , 2018

[31] Nidhal K. Al Abbadi, Nizar Saadi Dahir, Muhsin A. AL-Dhalimi and Hind Restom, "Psoriasis Detection Using Skin Colour and Texture Features", 2010