AI BASED DIAGNOSIS OF THE FACE- SKIN DISEASE

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Abstract – Diseases not only manifest as internal structural and functional abnormalities, but also have facial characteristics and appearance deformities. Specific facial phenotypes are potential diagnostic markers, especially forendocrine and metabolic syndromes, genetic disorders, facial neuromuscular diseases, etc. Artificial-intelligence-based FR has been found to have superiorperformance in diagnosis of diseases.

Keywords: facial recognition, disease diagnosis, artificial intelligence.

I . INTRODUCTION

Skin diseases have a serious impact on people's life and health. It provides information in regard to age, sex, race, consciousness, emotion, and health status. As it is conveniently accessible and cost-effective, the face is widely accepted for reliable biometrics compared with the fingerprint and iris. Various diseases manifest not only as internal structural and functional abnormalities, but they also have facial characteristics and deformities. Diseases with facial manifestations are mainly endocrine and metabolic disorders, genetic syndromes, and neuromuscular diseases, some of which are complex and rare diseases. Early diagnosis and differentiation of these diseases areessential for timely therapy and better prognosis. To identify typical facialfeatures is a part of the traditional diagnosis path, and largely depends on expertise and experience.

In early 90's some of Automatic technology for facial recognition appeared in the 1960s, and mature approaches have been developed in real-world applications, covering areas of security surveillance, identity verification, forensic science, etc., In recent years, the emergence of artificial intelligence (AI) has changed human life and has also led to breakthroughs in healthcare.

II. OBJECTIVE

To address the issue of skin disease diagnosis and treatment, people used computer-aided diagnosis for automatic skin disease recognition based on the skin disease images earlier. With the rapid development of the artificial intelligence technology, deep learning has quickly developed a computer vision. The medical image processing of skin disease has become an essential component and received great attention in the cross-field of image processing, machine science, and intelligent medicine.

III. PROBLEM OF STATEMENT

Our aim is to find machine learning methods that can accurately classify the diseases type using HAAR algorithm.

IV. LITERATURE SURVEY

4.1. YAHYA ZENNAYI , FRANÇOIS BOURZEIX , AND ZOUHAIR GUENNOUN , "Analysing the Scientific Evolution of Face Recognition Research and Its Prominent Subfields" **(2022):**The analysis of the thematic evolution of face recognition research is done in this work using a science mapping approach. To determine the mostsignificant, fruitful, and highest-impact subfields, various bibliometric approaches (performance analysis, science mapping, and Co-word analysis) are integrated. Also, a graphical representation of the facerecognition field is displayed using various visualisation techniques to identify the thematic areas and their evolutionary behaviour. Ultimately, this study suggests the areas of study that are most pertinent tothe subject of face recognition. Results show that face recognition research has greatly increased since 2014. Comparing mixed approaches to local and global approaches, a significant interest was found. Deep learning algorithms are the newest thing in algorithms. On the other hand, the most significant and impactfuldifficulty facing the area of face recognition today is the effect that lighting variation has on algorithm performance.

4.2. Bannuru Ranjeeth , B. Srinivasa Reddy, Y. Manoj Kumar Reddy , S.Suchitra , B. Pavithra , "Smart Child Safety Wearable Device" (2020): The most prevalent global issue right now is child safety. There are many concerns regarding child safety, and this studyfocuses on protecting children from threats including missing persons and kidnappings. The technical aspect of this work is to establish a regular line of communication between the child andparent using a device that aids in locating the child and monitoring their temperature,pulse, and location using a deviceequipped with a GPS tracker, temperature sensor, and pulse sensor. Through the use of IoT and the WIFI module, this device facilitates parent-child communication.Via this device, the parent can sporadicallyaccess the child's data. Because to this, parents defend their children even when they are not present. The information is permanently kept on a cloud.To preserve the children's historical data for future use, the data is permanently kept on the cloud. When the sensors become susceptible to various activities, they immediately activate.

V. EXISTING SYSTEM

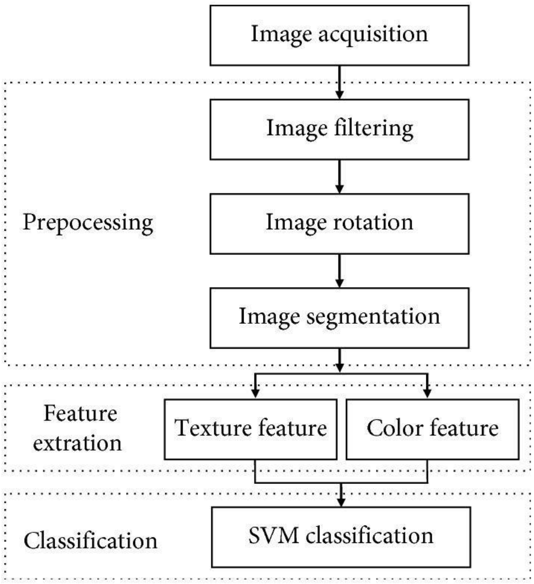
By using computer vision properties like LPB, HOG, and others, the current system describes face recognition. In comparison to other approaches, the characteristics that were recovered using a convolutional neural network (ConvNet) give us better facial expressions for face identification. Every single face photo belongs to a child, and the identification of children's faces is regarded as a problem with categorising photos.

5.1 Disadvantages

- This is one of the main drawbacks in the existing system for identifying missing children. Every day, there are around 100+ children in the area who are reported missing; some of these children are found, while others aren't.
- There is no system available to detect children's facial expressions in a variety of environments, such as noises, lightning conditions, with different facial attitudes, and with different children.

VI. PROPOSED SYSTEM

The proposed approach for identifying skin disease recognition 1) processing of the original image; (2) feature extraction; and (3) classification based on SVM. The first stage is image processing. Because image may contain some unwanted noise, it becomes necessary to filter the image to remove the noise. Then, by using image rotation and segmentation, the representation of an image into something that is more meaningful and easier to analyze. The specific areas of skin lesions are precisely divided, and the identification accuracy is improved through vertical image segmentation. The second stage is feature extraction, in which the image texture features and color features of the skin lesions are further extracted. In texture feature extraction, GLCM is used to find the mathematical parameters of like contrast, correlation, entropy, uniformity, and energy. The third stage is to identify the three various types of skin diseases according to obtained features based on SVM.



Block Diagram of Proposed for diagnosing skin related System.

VII. SYSTEM DESIGN

Programming configuration is used at the specialised stage of the product development process without regard for the advancement worldview or zone of usage. The initial stage of any intended item or framework's advancement is called arrangement. The designer is likely to deliver a representation or model of a material that will subsequently be put together. The first of three specialised exercises—plan, code, and test—needed to create and validate programming begins after the necessity ofthe framework has been identified and deconstructed.

VIII. MODULES

- Image preprocessing
- Upload missing children photo.
- Missing children search
- Convolutional Neural Networks (CNN)

8.1. Description of Modules

8.1.1. IMAGE ACQUISTION

In the context of face identification, Preprocessing input raw photos entails collecting the face region and standardising images in a format compatible.

ALGORITHM STEPS UNDER PREPROCESSING

1. **IMAGE FILTERING**

Resizing is often done to ensure that all images are the same size, which is necessary for many machine learning algorithms**.**

Reasons to resize the Image data includes

- **Reduce the memory** and processing requirements of the subsequent processing steps.
- A **consistent** size can help ensure that all the images in the dataset have the same dimensions andavoid issues such as dimension mismatches or invalid input sizes.
- Improves the generalization performance of the model by reducing the complexity of theinput data and avoiding overfitting.

2. IMAGE ROTATION

ROTATION is the removal of an image's elements that are unimportant to the analysis. This can aid in lowering data noise and enhancing the precision of machine learning models.

Cropping is advantageous for a number of reasons:

- Eliminating obtrusive areas from the image: Often, the image dataset may include obtrusive areas or artefacts that are irrelevant to the work at hand. By cropping the image, we may eliminate these areas and concentrate exclusivelyon the important areas of the picture.

NORMALIZATION

The contrast and details in the image can be improved by normalizing the pixel values, which makes it simpler to extract important features and patterns.

3. IMAGE SEGMENTATION

Through the use of various transformations, such as rotation, flipping, and brightness or contrast adjustments, new images can be created by means of image augmentation. Increasing the dataset size and strengthening the robustness of machine learning models are frequent goals of this practice.

4. FEATURE EXTRACTION

The process of extracting importantaspects from an image, such as edges, corners, shapes, colors, and textures, is known as feature extraction. Both feature detection and feature description are involved in feature extraction. Local features in the image, such as edges, corners, and blobs, are identified in this feature detection step. These characteristics were chosen for their distinctiveness and capacity to record significant visual data. This stage of the feature description Using a collection of numerical descriptors that represent their geographic distribution, orientation, and other pertinent aspects, local features are described after being found. These descriptors can be used to match and compare features across several images because they are often invariant to transformations like rotation, scaling, and translation.

8.1.2. CONVOLUTIONAL NEURAL NETWORKS

Convolutional neural networks (CNNs), which are better suited for handling visual input, are heavily used in deep learning approaches. The **collection of interconnected layers** that make up CNNs or ConvNets includes **ReLU (rectified linear units), pooling layers, fully connected layers, and repeating convolutional block layers**. In order to produce activation maps or feature maps that reflect low level features like edges or curves, the input facial image data is convolved using a variety of kernels. This feature map is sent into the next convolutional layer, producing activations that represent high-level traits and face landmarks. The convolutional layer basically defines a set of filter weights that are modified throughout network training. A ReLU, which introduces nonlinearity into the system, follows each convolutional layer in the algorithm. This layer applies the function to the input data of the layer. By using appropriately scaled down sampling, the pooling layers merge similar properties into a single layer. Afeature's position in relation to other features counts more than its exact placement, according to the pooling layer'score tenet. It reduces the size of feature maps and network parameters.

HAAR ALGORITHM:

The HAAR algorithm is a well-liked technique for face detection and recognition in pictures and videos, and it can also be used to identify missing children. Finding faces in the photographs is the first step. The HAAR cascadeclassifier, a pre-trained machine learning model that can recognise faces based on a set of Haar-like features, can be used for this. A sizable dataset of both positive (faces) and negative (non-faces) images is used to train the classifier. The OpenCV package, which offers a pre-trained HAAR classifier for face identification, can be used to implement the HAAR classifier in Python. Here is some sample code that uses the HAAR classifier to find faces:Object detection is the process of locatinga certain object inside a picture. Many methods may be used to complete this work, however in this post we'll employ a haar cascade using pre-trained XML files. The easiest way to detect objects is via this technique. One of the most widely utilised object identification methods in OpenCV, Haar cascades have been employed for object detection on low-edge devices. Because Haar Cascade requires relatively little computing, it is popular for compact devices with limited processing power. A feature-based object detection systemcalled Haar Cascade is used to identify things in photos. For detection, a cascade function is trained on a large number

of both positive and negative images. The approach can run in real-time and doesn't call for a lot of computing. We are able to train a custom cascade function for items like human faces, animals, vehicles, bicycles, and more. As Haar Cascade only recognises objects with the same shape and size, it cannot be used to recognise faces. The cascade function and cascading window are used in the Haar cascade. Every window's features are calculated, and positive and negative values are assigned. Positive if it's possible that the window is a component of an object; otherwise, negative.

PSEUDO CODE FOR HAAR ALGORITHM

1. Load training data

2. Initialize a Haar cascade classifier with default parameters

3. For each stage in the classifier:

a. For each weak classifier in the stage:

i. Train the weak classifier using AdaBoost algorithm.

ii. Select the threshold that minimizes classification error.

iii. Update the weights of the training samples based on classification error and retrain the classifier until convergence.

b. Calculate the stage threshold that minimizes classification error.

c. If the stage threshold is greater than the current stage's threshold, update the current stage's threshold to the stage threshold.

d. If the stage threshold is less than the required detection threshold, stop training and return the classifier.

4. Apply the classifier to detect objects in new images by scanning the image at different scales and positions using asliding window technique.

IX. RESULT AND DISCUSSION

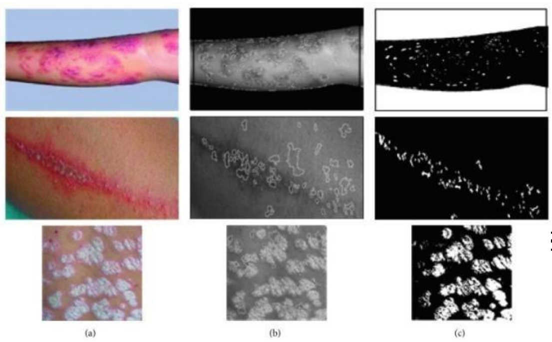


Fig 1. Sample image during pre-processing

Fig 1. Home Page

Fig 1. shows the main page of the project model.

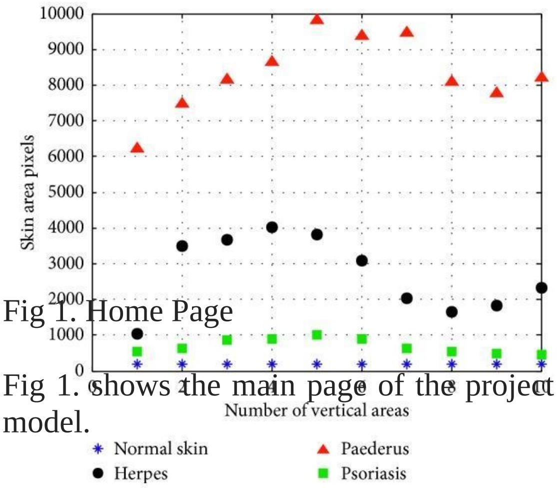
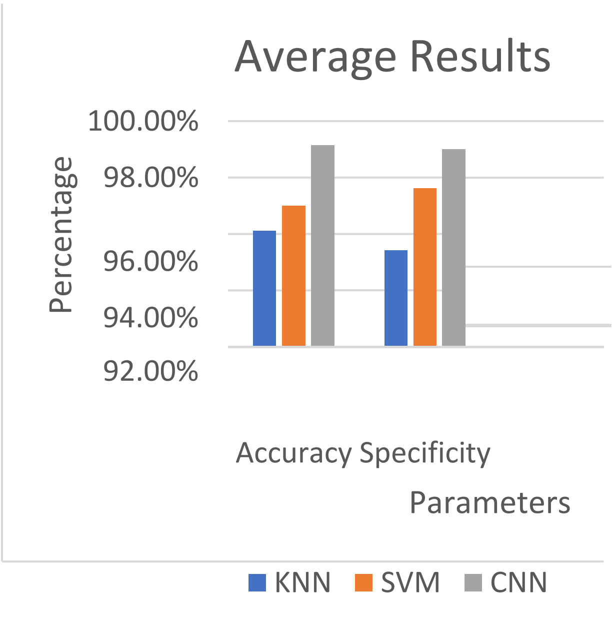


Fig 2. Classifying Skin disease type

Average Results



DATA BASED CHALLENGES

The calibre and quantity of training data samples strongly influence how well deep neural networks operate. Consequently, the creation of task-specific cross-age datasets continues to be a patterns. Collecting face pictures from groups who are generally underrepresented in public datasets, such as small children and elderly people, is a significant difficulty. For instance, the majority of the current child-based FAPmethods are based on private datasets, which restricts their potential to be replicated and compared to other efforts. Hence, by enabling users to learn patterns from the entire lifetime age span, the creation of new public datasets focusing on underrepresented age groups accelerates new research and enhances existing FAP methods. The collection of face images labelled with these factors allows for conducting intriguing experiments to further understand the relationship between the human face ageing process and external factors because the ageing process of the human face also depends on external factors like lifestyle, nutrition, or working conditions. Images with higher resolutions are being synthesised more and more in modern FAP technologies. The most well-known cross-age datasets, however (CACD and MORPH-II), only contain photos with a maximum resolution of 400x480 pixels. FFHQ has 70,000photos with a size of 1024x1024, but the gathering of more data will make use of deep generative networks'

capacity for generation.

X. CONCLUSION

In this paper, the analysis method

necessary prerequisite for deep generative models to be able to learn pertinent ageing of vertical image segmentation isemployed to identify the common skin diseases by dividing image into ten vertical image regions. Based on this, the grey- level co-occurrence matrix is adopted toextract the texture feature, and the area pixel method is applied to extract the characteristics of the lesion area. Finally, the support vector machine is utilized to classify the data of three different skin diseases according to the features of the texture and the lesion area, achieving a more ideal accuracy of recognition.

XI. REFERENCES

[1] A check on facial recognition ways and quested algorithms-S.Balaji, R Saravanan,P Pavadharani, J Inter discipcycle., 2020-jicrjournal.com

[2] D. Heinsohn, E. Villalobos, L. Prieto, and D Mery. 2019. Face Recognition in Low-Quality Images using Adaptive Sparse Representations. Image and Vision Computing (2019).

[3] D. Mery, I. Mackenney, and E. Villalobos. 2019. Student Attendance System in Crowded Classrooms using a Smartphone Camera. In 2019 IEEE Winter Conference on Applications of Computer Vision (WACV2017)

[4] Pacha Shoba Rani ,A Vasantharaj, , Sirajul Huque, KS Raghuram, R Ganeshvkumar, Sebahadin Nasir Shafi "Automated Brain Imaging Diagnosis and Classification Model using Rat Swarm Optimization with Deep Learning based Capsule Network" Publication date2021/7/12 International Journal of Image and Graphics Pages 2240001 Publisher World Scientific Publishing Company

[5]Michalitsi-Psarrou, A. et al, 2019. "Complementing Amber Alert: Increasing the Social Sensors'Effectiveness through Focused Communication Channels." In Institute of Electrical and Electronics Engineers (IEEE), 1–7 Focused Communication Channels." In Institute of Electrical and Electronics Engineers (IEEE), 1–7

[6] J. Despois, F. Flament and M. Perrot, "AgingMapGAN (AMGAN):High-resolution controllable face aging with spatially-aware conditional GANs" in arXiv:2008.10960, 2020, [online] Available: http://arxiv.org/abs/2008.10960.

[6] M. Zhang, R. Wang, X. Gao, J. Li and D. Tao, "Dual-transfer face sketch–photo synthesis", *IEEE Trans. Image Process.*, vol. 28, no. 2, pp. 642- 657,

[8] Advanced Parametrization of Graphomotor Difficulties in School-Aged Children ZOLTAN GALAZ 1 , JAN MUCHA 1 , VOJTECH ZVONCAK 1 , JIRI MEKYSKA 1 , ZDENEK SMEKAL 1 , (Senior Member, IEEE),2021

[9] *Visa Information System (VIS)*, Nov. 2020, [online] Available: https://ec.europa.eu/home-affairs/what-we-do/policies/borders-and-visas/visa-information-system_en.

[10] Y. Shen, J. Gu, X. Tang and B. Zhou, "Interpreting the latent space of GANs for semantic face editing", *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, pp. 9243-9252, Jun. 2020

[11] P.Shobha Rani, Vamsidhar Enireddy, S.Finney Daniel shadrach, R.Anitha, SugumariVallinayag ,T.Maridurai, T.Sathishf, .Balakrishnan "Prediction of human diseases using optimized clustering techniques" https://doi.org/10.1016/j.matpr.2021.03.068

Feb. 2019..

[7] H. Wang, D. Gong, Z. Li and W. Liu, "Decorrelated adversarial learning for age-invariant facerecognition", *CVPR*, 2019.