

Disease Identification System using Image Analysis

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Abstract: Artificial Intelligence (AI) and Sensor Technologies making a point-of-care delivery possible which was considered impossible. The human body shows early indicators of disease manifestation before actual clinical symptoms appear. These indicators can be picked up by analyzing the optical face image, which can be used for rapid and cost-effective screening of life-threatening health conditions. This article focuses on how health status can be tracked using optical image analytics. Early identification of disease plays a vital role in therapeutics of a patient. In accordance with review of secondary data available in literature, this article proposed a model to rapidly screen the health conditions at point-of-care. The patterns in the optical image have the potential to act as digital disease markers.

Keywords: Artificial intelligence, image analysis, disease marker, optical images.

1. Introduction

It is evident that early treatment provided to any patient recovers rapidly as compared to the patient who has been treated after the disease has taken control over the body. In some cases, there is no cure available, only medications have been formulated to control the disease that exists in the patient. Diseases take place because of the lifestyle which a person follows every day, whose outcome is developed over the years.

Technology is advancing every day, which can act as a helping hand for the people not only in diagnosing the ailment at an early stage, but will also be cost efficient for those who cannot afford hefty charges demanded by healthcare officials. It is a time-consuming process to visit hospital and take appointments for checkups, because generally without any major symptoms nobody visits a doctor.

Our model focuses on achieving the above objective, using image analysis of optical images of the person. Generally, a person cannot detect various changes taking place in our body until and unless they visit a doctor. Thus, the model brings simple applications which can be used by anyone who wants to check their early signs of symptoms that could lead to serious consequences later. The model is fed with the optical images of patients who are suffering from diseases and taking treatments for the same. Feature extraction process will withdraw features in the form of RGB values, these are stored against the patient record. After collecting this data for all the patients, data will be grouped based on the organ that is infected.

The person is required to upload an image, which will be used for feature extraction. These features will be compared with the data that was processed before and based on that appropriate output will be prompted to the person. This will be implemented using Keras and TensorFlow models. For image processing, OpenCV libraries will be used to extract features in the form of RGB values. This computer-aided analysis will be more accurate than the manual analysis done by the doctors. It will add value to the diagnosis that is done in laboratories, which will in turn help the person recover from the ailment.

2. Procedure

2.1. Pre-processing

Pre-processing is an integral part of our model because it makes the image easier to interpret and evaluate computationally. As the real-world dataset is almost accessible in different formats, it is not available as per our requirement. Therefore, our model uses various techniques out of which one is resizing technique which helps in shaping all the images in standard size required by the model. Geometric transformations and enhancement techniques will also be used to reduce the intricacies and improve the performance of the proposed algorithm. After cleaning and processing of the images is complete, this dataset will be provided as an input for the model.

We have used the standardization approach for pre-processing the dataset to translate the dataset into a functional format.

2.2. Neural Networks

A system is needed to process and train images to classify new, unknown images. The system consists of a web of neural networks. Neural network algorithms that identify images can classify any types of files including texts, videos, and images. Each pixel of the image is carried by a neuron that uses a basic calculation to give the result known as an activation function. The result is then sent to other neural layers before the final output is given and the process is completed.

This process is repeated in case of a large number of images. Backpropagation is a process in which the network learns the most suitable weights for each neuron that provide accurate predictions. The model is then fed with another set of images that did not participate in training. Thus, the model is prepared to process real-world images.

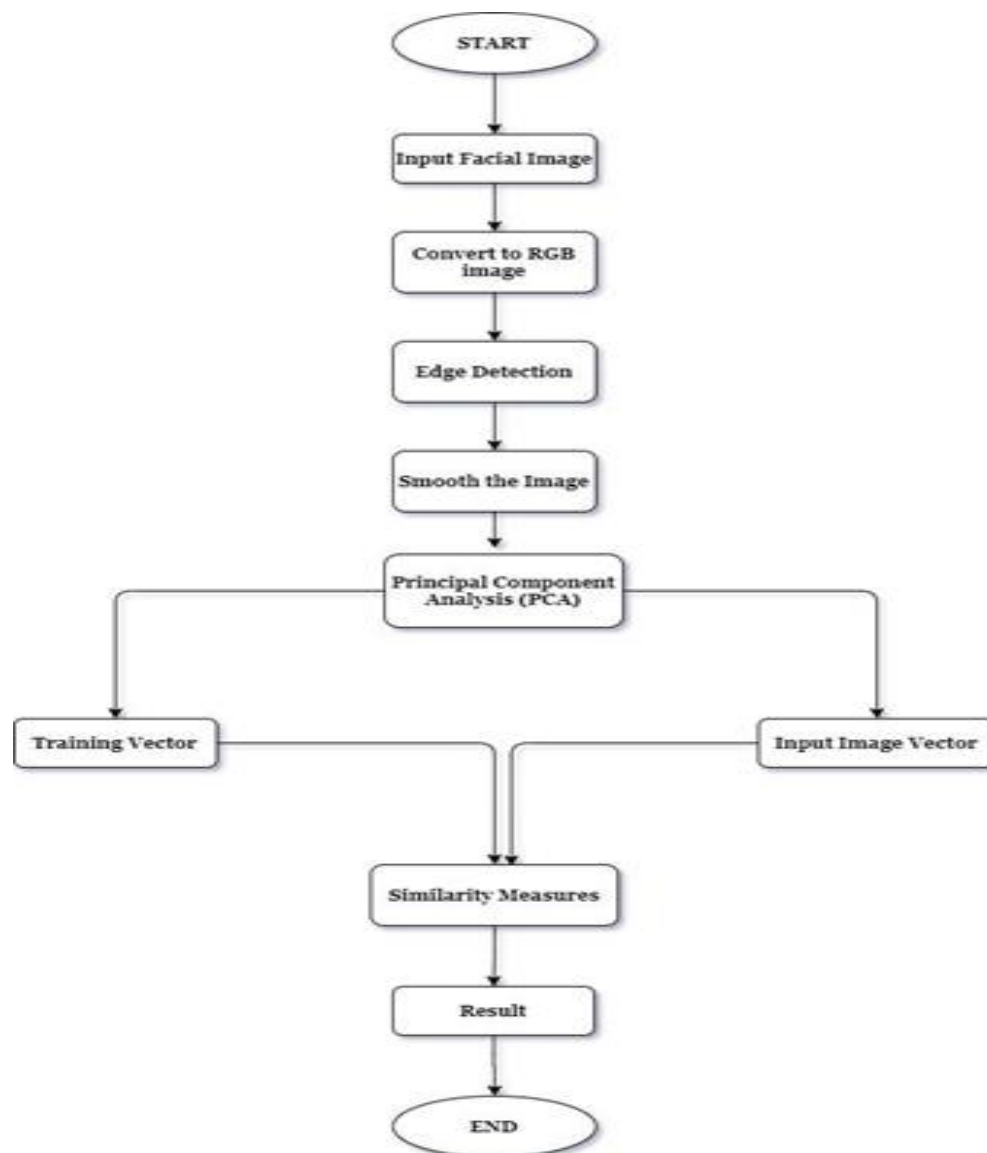


Figure 1. Steps to process Facial Image

2.3. Facial Image Recognition

In the case of minute observations, the human eye has limitations. The device proposed is to diagnose different health conditions where the facial image is presented as an input to the system. The input image is segmented by applying digital image processing techniques and certain features in the segmented images are

extracted. To predict probable diseases, the knowledge base of medical palmistry is used to evaluate the features extracted.

3. Proposed methodology

Feature extraction of facial markers will be implemented using OpenCV. Landmarks of the required region will be defined and RGB values of that region will be extracted. It will be stored for feature analysis and helps in providing distinction between the various diseases. OpenCV is well-suited for our model because it focuses on real time applications due to its computational efficiency and has a comprehensive collection of algorithms. It can work very well with multi-core processing. It is portable and includes pre-trained models that can be used effectively for inference.

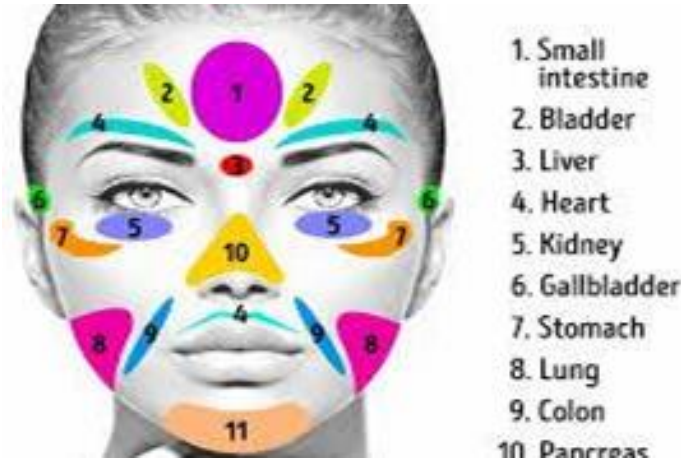


Figure 2. Facial Landmarks

According to the above diagram, landmarking of liver, heart, lungs, and brain diseases can be analyzed by performing feature extraction on mapped regions. Early signs of any disease can be detected by studying pathological behaviour on the face. We will be focusing on the following points-

- Point 3- Liver diseases
- Point 4- Heart diseases
- Point 8- Lungs disease

Feature extraction of these points will be done, the pathological pattern which follows in the dataset will be analyzed by our model based on which user’s image will be classified.

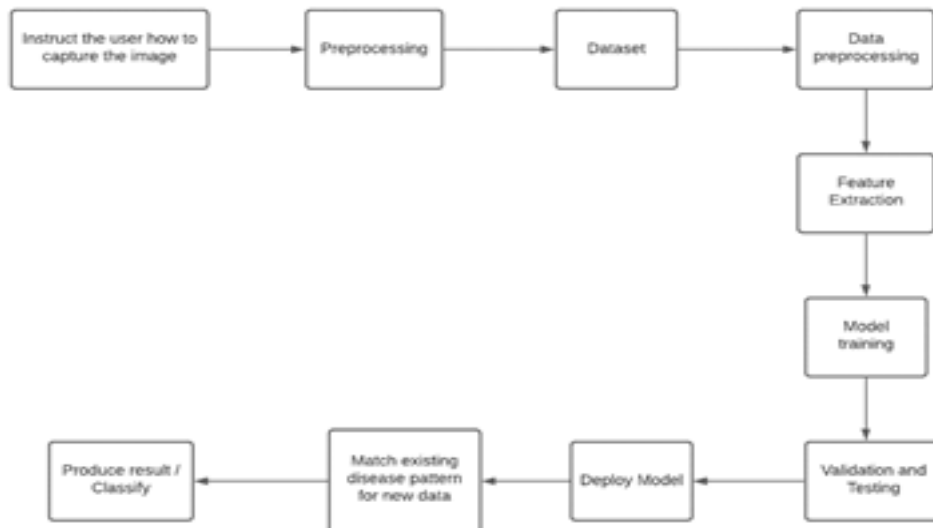


Figure 3. Methodology

The methodology adopted by our model is neural nets which transfers one neuron to another, which further makes the decision based on the input stored. We will use the data which the user will provide to the model. Preprocessing of the images takes place after the input is given, it is done by extracting pixel values and storing it in a matrix and image is stored against those values. Image Preprocessing is required because it is the amplification of image data that reduces distortions or improves those image features that are relevant for further processing. Image scaling is the process of rescaling an image. It assists in lessening the density of pixels from a picture and that has many benefits. It also supports enlarging images. Numerous times we require to rescale the image i.e., either contract it or increase to fulfill the size conditions. OpenCV delivers us with many methods for resizing a picture.

After the above process is completed, a normalization process is adopted where it changes the range of pixel intensity values. This type of image subtraction feature is required to level uneven sections of image. PCA algorithm will be used for feature extraction because it takes original data as input and finds such a combination that best summarizes the original data distribution to achieve dimensionality reduction. The information is ranked in order of significance and based on that the prominent feature is selected through which features are extracted. Gradient boosting technique will be applied on these features to identify each valuable feature within the model which will be used in decision making. This will also help in improving the quality of the algorithm by reducing overfitting.

After these stages are successfully implemented, the model training process takes place. If the dataset is vast, models will predict more efficient results since they will store each feature precisely for one ailment which will help in predicting accurate results for patients. To assess the results, we will perform validation and testing on the results that are provided by the model. If the model passes the testing phase, it will be deployed on various platforms for doctors and people. If it does not pass the accuracy metrics, then we will re-train our model by eliminating all the discrepancies present. Later, the targeted audience will provide images of themselves or patients who have not yet contracted any disease related to heart, lungs, liver, or brain, and classify them based on the model dataset. Over the period of time to improve the accuracy of the model, it will be trained once every 6 to 8 months with recent dataset, because diseases evolve periodically.

4. Review analysis

4.1. Breast cancer detection from histopathological images using deep learning-

Cancer, which is particularly effective for women, is the deadliest disease in the world. So, through clinical testing, the authors primary aim is to cure the cancer. Early detection of cancer should be the second primary target because early cancer detection can be helpful for the complete removal of cancer. This paper focuses on the application of deep learning technology to the MIAS Database and it is noted that with 98 percent accuracy it is very beneficial for breast cancer diagnosis. Some preprocessing algorithms such as Watershed Segmentation, Color-based segmentation and Adaptive Mean Prior to training with a scaled dataset, filters were added to the model, then the model was implemented, and accuracy was achieved.

In this analysis, the MIAS dataset that is freely available for download was used. The dataset was pre-processed in the second stage. For scaled and pre-process datasets, three distinct methods were used in the pre-processing. Later, DNN was implemented and computed for precision. 98 percent precision was achieved by CNN.

The convolutional neural network approach of deep learning is primarily used for the classification of image datasets and that is why this paper used a CNN. 98 percent precision was achieved after the implementation of this paper. As described, this paper only worked on 12 characteristics only. The authors will explore new features in the future and try to work with the real image dataset so that they can achieve the best cancer diagnosis outcome and precision for cancer diagnosis. [1]

4.2. A deep facial landmarks detection with facial contour and facial components constraint-

This paper proposes a new facial landmark recognition approach focused on deep learning with limitations on facial contours and components of the face. For facial landmark detection, the proposed DCNNs contains two deep networks: first DCNN is to detect landmarks restricted to the facial contour, and second one is to detect landmarks that are confined to facial elements. A new DCNN architecture is suggested for the identification of landmarks with facial component constraints, which branches the network to higher layers to capture the intricate features of local facial components. In addition, a novel learning technique is proposed to learn the DCNN by

leveraging the relationship between facial contour landmarks and those on facial components to detect the landmarks on the facial contour. Experimental studies have shown that the proposed solution outperforms the state-of-the-art FLD approaches.

A new FLD approach based on DCNN with facial contour and facial part constraints is proposed in this paper. It is extremely difficult to detect landmarks on the facial contour. To learn the DCNN for FLD, facial part constraints are considered. The proposed deep network is composed of two separately trained DCNNs: DCNN-C, trained to detect facial contour landmarks, and DCNN-I, trained to detect facial component landmarks. Authors. Enhance the identification of landmarks on face components by separately studying DCNN-C and DCNN-I. In addition, by jointly studying the facial contour landmarks with the facial components, they enhance the facial contour identification of landmarks.

DCNN-C adopted a traditional DCNN design, but it was pre-trained to enhance the identification of facial contour landmarks along with facial components. On the standard 300-W dataset, the efficacy of the approach proposed was checked. Experimental findings showed that state-of-the-art methods are outperformed by the proposed process. [2]

4.3. Chest pathology detection using deep learning with non-medical training-

Different pathology detection techniques in chest radiographs were discussed in this paper. Dataset which is not medically extracted was used to recognize the various kinds of pathologies in x-rays. X-rays are fit for the model because they help in findings which include lung infiltrates and anomalies of size. Human observation is a difficult task to observe such pathologies, thus images are read by the computer system to assist radiologists. Deep learning approach was adopted to identify the pathologies that exist, and later healthy and infected lungs were also categorized. Decaf pre-trained CNN model was used, which learned the images and were categorized accordingly. Bag-of-Visual-Words (BoVW) was used for image depiction of text documents. Thus, image was treated as the distribution of visual components to represent an image. A given image was clustered into K groups to build a unique dictionary which can identify various pathologies. GIST was used to capture information which accurately categorizes the problem. Decaf5 was used as a baseline descriptor. They demonstrated feasibility of detecting pathology using x-ray data. [3]

4.4. Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs-

This disease accounts for 18% of people in India, which needs regular treatments so that severe conditions can be avoided. Manually, a screening tool is used to identify this disease. Automated testing can increase efficiency, reproducibility and early detection and treatment of this ailment. Deep convolutional neural network was applied in retinal fundus photographs to build such algorithm which can detect automatically. Images were graded by ophthalmologists to recognize diabetic retinopathy and diabetic macular edema. During training, the parameters were at first set to random integers and later for each picture intensity given by the function if compared with the training dataset. This process is repeated so that the model learns to compare the images based on pixel intensity which is combined to form features. Inception-V3 was used to build this model. Lesions are not identified by this algorithm. Severity index was also categorized based on the pixel reading, i.e. how severe the ailment is will be graded by this model to provide the treatment accordingly. [4]

4.5. Early detection of Parkinson's disease using image processing and artificial neural network-

Special photon emission tomography (SPECT) images are interpreted by humans using I-Ioflupane to indicate the presence of Parkinson's disease (PD). To train this model 200 images were used to process the area of caudate and putamen. Area of caudate and putamen values were fed to ANN so that it can be used as a model of prediction. After making the model, images of healthy and unhealthy patients were provided to the model which detected PD in them. SVM and Regression models were used for building this algorithm and SVM provided best results. Calculation of caudate and putamen values was done using RGB values of the image and pixels that relate to each other, further these values are stored for analysis. This model can assist doctors to provide best medications for their patients and severity of PD could be lesser if treated at an early stage. [5]

4.6. Early Detection of Alzheimer's Disease using Image Processing –

One of the prominent causes of Dementia, which is an irreversible disorder that slowly destroys cognitive function of the brain. To detect such disease at the earliest, image processing can be useful for doctors and patients. MRI images of the brain from axial plane, coronal plane and sagittal plane were taken to analyze the

affected areas of the brain. It first affects the hippocampus region and till final phase brain size is shrunked significantly. Input of MRI image was provided, extracted RGB values of each image of specified regions and black pixel is considered as cavity region and white pixel is cortex region. If the cavity region is more than 30% to 50% person is classified in stage1, if it is more than 50% then the person is in stage 2, if less more than 10% and less than 30%, then person is suffering from mild cognitive impairment and if less than 10%, then gradient image is obtained from the MRI of complete image. If the pixel intensity exceeds the threshold then the patient is suffering from AD else, they belong to a healthy group. [6]

4.7. Human Skin Disease Detection-

Skin detection deals with the identification in a given picture of skin-colored pixels and regions. RGB color models (Red, Green, Blue), YCbCr (Luminance, Chrominance) and HSV (Hue, Saturation, Value) are the three key parameters for identifying a skin pixel. The aim of the proposed algorithm is to enhance the identification of skin pixels by providing greater precision in some images.

Skin color is the primary key to the identification of skin from an image. But because of the difference in skin tone according to different races, color may not be the only determining factor. The findings are often affected by other variables, such as light conditions. The findings are often affected by other variables, such as light conditions. Parameters such as light, contrast, clarity, lighting, and saturation affect skin identification. The skin tone is also paired with other signs, such as texture and edge features. This is done by splitting the image into individual pixels and classifying them into colored skin and non-colored skin.

This paper reveals a threshold-based algorithm that uses the RGB-HSV-YCbCr model to identify skin images and which can produce positive results in terms of precision and accuracy relative to the baseline dataset under various conditions. The potential scope of this algorithm is to recognize movements of the face, hand and hand that may be used for surveillance purposes or for the identification of skin diseases. [7]

4.8. Using facial images to detect Adenoviral Conjunctivitis using ML-

Using image recognition, scientists are working on diagnosing such eye disorders. Adenoviral conjunctivitis is one of the major eye infections that should be identified and cured. For an automatic, quick, and cost-effective diagnosis, digital image processing (DIP) is implemented. The diagnosis of conjunctivitis, vascularization and redness severity in pink eyes following segmentation the region of infection in corneal images was evaluated. 93% of the time, they note, corneal photographs obtained using the proposed DIP technique successfully diagnose eye infections. The technique correctly isolates 93 percent of highly infectious patients efficiently.

Acute conjunctivitis diagnosis is also dependent on clinical signs and symptoms and is generally diagnosed as redness and inflammation within the eyes' sclera area, and elevation of sclera vascularization.

The goal of this research is to build an automated framework for the analysis of facial images that analyses sclera and feature extraction of essential characteristics which will be used in the disease diagnosis. Such a device could be used for a monitor mounted outside the doctor's office to check patients for the chance of having adenoviral conjunctivitis.

Findings were presented for the automated diagnosis of adenoviral conjunctivitis using facial photos of the patient's face. The sclera regions of the eye are first separated using the automatic Grab-Cut algorithm using facial images. Using RGB thresholding, Hessian Matrix and GLCM, redness, vascularization and contrast are calculated. Among these functions, the best classification accuracy (96%) is given by RGB thresholding and vascularization. [8]

4.9. Digital image processing based on hand image to detect diseases-

As an application of digital image processing and analysis in the field of health care, this paper explains an Automated Disease Prediction Method (ADPS). In medical research, medical professionals study a patient's nails and palms to get a primary understanding of the human body's illnesses and health conditions.

In the proposed method, the algorithm is constructed such that the nail and palm regions are segmented from the dorsal and palmar sides of the digital hand image input. ADPS relies on the extraction from the segmented palm image of colors, textures, form from the segmented nail image and symbols, color, shape, and texture. ADPS can predict the diseases and health status of human beings based on 7 parameters. Neural networks are used to improve the performance of the whole ADPS. It assists in the preliminary detection of diseases without

human involvement. It provides outcomes with sufficient cautionary measures and remedies. It also saves the user's costs and time by reducing the expense of health risk and care. ADPS uses only a hand picture as input and does not require the patient's presence. It would be helpful in many respects compared to the techniques used today. [9]

4.10. Face Detection Based on Skin Colour Segmentation and Neural Network-

This paper proposes a human face recognition system based on the segmentation of skin colour and neural networks. They differentiate facial photos in two parts: face candidate and non-face block. According to the position of two eyes, which is called a face nominee, a region is cropped; else it is a non-face block. A 3-layer back-propagation neural network is used to validate facial images of candidates. Combined RGB, normalized RGB and HSV colour spaces are used to detect skin pixels. The colour space of both RGB and HSV will help reduce the impact of lighting on a picture. These three constraints are used to check if a skin region contains face: Area size, aspect ratio, and occupancy. Possible face block will satisfy these constraints otherwise, a non-face region. This system has a few limitations such as the device will fail to identify skin color if the light is too bright or too dark and the effective detection of eyes is not done, face detection will fail. [10]

4.11. Detecting Visually Observable Disease Symptoms from Faces-

Popular facial characteristics that are normally shared between human beings regardless of race, gender and age were analyzed and trained in this paper by applying statistical analysis and computer vision algorithms on databases of faces.

Semi-supervised outliers were formed using statistical facts were captured from normal faces dataset and used to categorize and detect suspected illness features on the testing data. They used active shape models to label this dataset of Face Alignment by Explicit Shape Regression. The original picture was transformed into the CIELAB colour space from the RGB colour space. A roughly Linear scale describing the redness and yellowness of the features to mark the possible symptoms on the faces makes CIELAB colour space.

They extracted six possible binary characteristics for one image of a face: skin, lower lip, left eye, nose, upper lip and right eye, and the information obtained from these was used in future steps to produce variants for the algorithm of anomaly detection. [11]

4.12. An Intelligent Model for Facial Skin Colour Detection-

This paper, based on comprehensive studies on human face recognition, focuses primarily on the colour of facial skin. Users can receive their skin colour and the face region's colour position, which will help them pick the correct colour to match their skin. Although it does not help us directly with our project, it can help us to learn how to correctly capture the colour variation on a person's face. A particular absolute colour space must be used to transform the RGB values. After a device-dependent RGB colour space is characterized, resulting in the transformed values that would be device-independent. The 6 points on the face are selected and the results of the colour detected are shown as the number for each, after which the average values of the 6 data will be captured using a FaceRGB program. The Gaussian distribution principle and standard deviation of the outliers are often omitted for efficient debugging, in addition to the restricted value, as six points that are used might have come due to part of the hair or shadow because of different brightness variations. [12]

5. Challenges

Challenges that might be faced while developing system like disease identification system:

- i. Acquiring dataset i.e., facial images with a medical background can be a challenge due to security reasons.
- ii. Images should meet the minimum requirements: -
 - State and History for Lighting
 - Saturation
 - No blurriness
 - Variations in the plane of the image and pose
 - Face Colour and other aspects of composition
 - Pre-processing should help us filter data.

iii. Training a model using a neural network requires a large set of data which could cause a resistance as mentioned above.

iv. The human face undergoes fundamental changes through development. In facial photographs, we can examine and model longitudinal changes. To achieve the specific result, multiple longitudinal studies will be performed.

v. In order to facilitate healthy patient behaviour and adoption of the model, patient interaction would be needed in order to balance patient awareness and ability.

vi. As specified in the minimum criteria, image acquisition is accomplished by the required camera.

vii. In order to extract features from the image without any difficulties, the details, i.e., facial images that we will work with should be noise free.

viii. Keeping the data safe is one of the most critical considerations which means protection should be there and the data must be secured to deter third parties from misusing the data for fraud or identity theft.

6. Research gap

i. Enhancement in image pre-processing, including feature extraction.

ii. Literature review discusses about detecting diseases from hand images, but our project explores on how to detect diseases from facial images.

iii. Formulate highly coherent and expansible image mining algorithms.

iv. There has been sufficient research in areas like facial landmarks detection, Deep learning algorithms for detection of diseases and detection of diseases using hand images based on colour reading, but our project aims to combine all this knowledge and explore more Deep learning algorithms to make a model which can detect diseases using the RGB reading on the landmarks present in facial images.

v. Additional explorations' center of attention should be widening the characteristic of image to differentiate images more precisely.

7. Conclusion

One of today's hot research subjects is the identification of various forms of diseases using Digital Image Processing. Expert doctors diagnose the disease and, from practice, determine the stage of the disease. Surgery, targeted care, etc. are part of the treatment. Such therapies are lengthy, expensive, and painful. In this research, we present our findings by monitoring digital disease markers located on the face for multiple organs i.e., liver, heart and lungs disease recognition using facial images. Initially, the model will not be able to identify ailments related to other organs. Over the period of time, if the model provides accuracy in the existing diseases, it will be retrained for other ailments. The future scope of this algorithm is that it will add value to the diagnosis that is done in laboratories and an advancement in existing models for accurate identification.

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