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Prediction of Diseases Based on Facial Diagnosis Using Deep Learning

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Abstract

Practitioners can diagnose diseases by looking at a patient's facial features, a process known as facial diagnosis. Doctors need to have a lot of real-world experience to diagnose facial conditions with high accuracy. Modern medical studies show that many diseases do, in fact, manifest matching unique traits on human faces. Due to the scarcity of medical resources, it is challenging to get a check-up today in many rural and undeveloped areas, which frequently causes treatment to be delayed. Limitations still exist, such as high expenses, lengthy hospital waiting-times, and conflicts between doctor and consulted patient that result in medical disputes, even in major cities. We can rapidly and easily do non-invasive screening and disease detection thanks to computer-aided face diagnosis. To perform CA facial-diagnosis of various diseases and test DTL methods for both single and multiple disease spotting on a short data-set, we therefore propose adopting deep transfer learning from face recognition.

Keywords: Deep learning, Facial Diagnosis, Computer-aided face diagnosis, Deep transfer learning.

1. Introduction

One of the earliest observational skills and diagnostic methods known to practitioners of Chinese medicine is Chinese face diagnosis. Since ancient times, the shen, or light emanating from the eyes, has been the first thing a doctor has assessed while treating a patient. The majority of current practitioners use pulse and tongue diagnosis in their clinical work, but full facial diagnosis has been underutilized throughout time because it is less frequently taught. A practitioner can identify the pathophysiology of many disorders early on by using face diagnosis alone or in conjunction with tongue and pulse diagnosis. This can help prevent disease. We therefore suggest utilizing DTL from face recognition to accomplish CA facial diagnosis of various diseases and evaluate DTL techniques for both single and multiple disease recognition on a small data-set.

The technology used to authenticate or validate a person's identification based on how they appear in photographs or videos is referred to as face recognition. In the world of computer vision, it is a contentious topic. Face verification is the technique of assessing whether two candidates' faces match by contrasting them. One to one mapping is used. The process of matching a given facial image to a face in a database of faces is known as facial identification. It is a one-to-many mapping. Both of these may be done using distinct algorithmic frameworks, or they can be combined using metric learning. As a result of recent breakthroughs in the industry, deep learning approaches have swiftly overtaken traditional facial recognition technologies. The most popular deep learning technique for face recognition is Convolutional Neural Network (CNN). CNN facial recognition architectures that excel in ILSVRCs are the inspiration for FaceNet, VGG-facial, DeepFace, and ResNet. Using a huge number of annotated face photos from open face recognition datasets, these CNN models are trained to automatically discover the optimum face representations for computer understanding and discrimination. When evaluated on particular datasets, they show excellent accuracy.

This project is driven by deep learning's achievements in the field of facial recognition. The tagged data, however, is woefully inadequate for face diagnosis. Overfitting will unavoidably result from training a deep neural network from beginning. Facial diagnosis and face recognition appear to be linked. Because there is a lot more tagged data in the field of facial recognition, transfer learning technology enters the picture. In traditional learning, we build independent, segregated models for specific tasks on specific datasets. Transfer learning is the process of applying information gained while addressing one problem to another, unrelated problem. Depending on whether the feature spaces of the two domains are the same or not, transfer learning is divided into two basic categories: homogeneous transfer learning and heterogeneous transfer learning. It is a component of homogenous transfer learning in our work. Deep neural network knowledge transfer is referred to as deep transfer learning. Deep learning can now recognise diseases from 2D face images via transfer learning, providing a non-invasive and useful way to realise early diagnosis and disease screening. To carry out the validation, four newly emerging diseases and their accompanying health controls are chosen.

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2. Related Work

Leandro Cruz et al. [1]In this study, the goal is to investigate whether using deep learning methods, it could be possible to detect diseases from uncontrolled 2D face photos. Methods include, preprocessing is utilized to provide more accurate findings, followed by two techniques fine-tuning pretrained model and CNN as the tool for extraction of features. Even with a dataset which is smaller this model produces results that are more accurate.

Theyazn H. H. Aldhyani et al.[2]This method employs a deep learning-based web application to assist in the diagnosis of autism condition . With the aid of transfer learning and the flask framework, CNN is employed to extract facial features. For classification, MobileNet, Xception, and InceptionV3 were used.

Mohammad Alamgir Hossain et al.[3]Face detection, pose estimation, and image segmentation are included in pre-processing. Feature extraction is done using an AROI-based CNN, while level synthesis is done using a decision tree which improved overall effectiveness and accuracy and produces better results in expression tracking which is of greater use.

N.Syed Siraj Ahmed et al.[4] Convolution Neural Network (CNN) along with the transfer learning methods of CNN such as InceptionV3, Xception, VGG16, VGG19 and ResNet50. This model produces reliable results, but its only drawback is that it only supports a small set of features.

Shuai Ding et al.[5] This models main objective is to detect negative emotions. The methodologies included are EdgeER is one of the strategies used to recognise unpleasant emotions and screen data. while C-DpressNet is utilised to estimate the extent of dejection at the edge and cloud server. This model provide reults with higher precision and performance.

Farhoumandi, Nima .,[6] The study's goal was to identify the most suitable ML model for differentiating between healthy and alexithymic people. Based on the FER challenge, they applied ML to predict alexithymia. Their results are consistent with the idea that applying ML approaches enhances the capacity to identify alexithymia using FER scores. The quality of life for these individuals can be improved by therapists by identifying and presenting a professional, timely therapy and by enhancing the diagnostic techniques for alexithymia, such as by employing ML models.

Castela Forte et al,[7] In this experiment, four separate CNNs, each instructed on a distinct component of the facial images, were combined to a single, stacked-CNN that classifies persons as well or seriously unwell. The results demonstrate how face feature analysis algorithms might help in acute illness diagnosis. The data might inadvertently be biased in favour of the disease characteristics.

Hallgrimsson[8] For each individual, they got 3D photogrammetric images of their face. They utilized a Creaform Gemini camera for 436 subjects. A 3dMDface camera system was used to capture images of the remaining subjects. They employed both parametric (CVA) and machine learning techniques to classify faces. DNN, RF, PLS, k-NN, and regularized high-dimensional discriminant analysis model were some of the machine learning techniques they explored. Of these, HDRDA was found to perform the best. They demonstrated the significant potential for facilitating the identification of syndromes by deep phenotypic analysis based on quantitative 3D facial imaging. The accuracy stated here can also be increased by incorporating other data on phenotypes

Jin Bo [9] In the pre-processing step, they used a face-detector in Open-CV that is based on Histo-gram of Oriented-Gradients features and a linear SVM-classifier to conduct face detection on the original 2D face photos. Upon successful face-detection, a box containing the face which is detected is produced. Then , to obtain the coordinate information, they collected 68 facial landmarks from the Dlib collection that are situated on the jaw lines, brows, eyes, bottom of the nose, margins of the lips, and chin. Next, they executed face alignment using the transformation, which includes a variety of transformations like rotation scaling, and translation, with the assistance of the 68 facial landmarks that were extracted. The frontolyzed face - image is then cropped and scaled using the C-Neural Networks that was utilized. They have proven that, for the short dataset of face diagnosis, CNN is the most suitable DTL technique.

T. M. Rutkowski [10] In the study, they used input characteristics Fi,s to test classifiers from the scikit-learn library and Tensorflow for binary classification of MCI versus normal cognition in the 35 patients. In each cross-validation run, they utilised a LOPO method with appropriately balanced-labels from the MCI and normal cognition-classes. The use of such an ML or AI-based dementia onset fore-cast will result in lower healthcare costs, which will benefit all ageing societies throughout the world.

C. Duan et al [11] In this study, a DL model was created to separate patients with acromegaly from healthy individuals using hand-images. Because of less patient population and because of high price of diagnosis, there are only a limited number of training data sets for acromegaly identification available. They applied two efficient approaches to deal with overfitting problems: transfer learning and data augmentation. This method's F1-score, NPV, and sensitivity (recall)e appeared to be greater than doctors' predictions with nearly identical specificity and PPV, indicating that it could assist the general population without medical training in successfully and accurately self-detecting acromegaly.

Fawaz Waselallah Alsaade et al.,[12]Xception, NASNETMobile, and VGG1-9 were among the deep learning models built on transfer learning that were trained to identify autism using the facial traits of autistic and regular kids.In terms of categorization accuracy, the Xception model had the highest results (91%). However, less than 80% of the final two models were accurate.

Marco Leo et al. [13] Many CNNs work together to detect human faces on each image. Also used was the Convolutional Experts Constrained Local Model (CECLM) Algorithm. The pipeline is more accurate than the present techniques, according to the results. The suggested course of action was determined without knowing the final result in advance.

Jiankang Deng et al.,[14]employing an Additive Angular Margin Loss, highly discriminative features for facial recognition were obtained (Arc-Face).They developed an Arc-Face function for face recognition that can considerably increase the discriminative strength of feature embeddings learned using DCNNs.

Babak Taati et al., [15] There were five distinct landmark identification methods used, all of which could be easily coded and modelled. AAM, FAN, CFSS, MDM, and OpenFace.Demonstrated the biases in the algorithms used by the most modern facial land-mark and expression-recognition methods. The study is constrained because it only examines the automatic recognition of two facial action components.

Mohamad Al Jazaery et.al.[16] Instead of employing C2D features separately, C3D features were used to simultaneously describe spatial and temporal salient featuresTrials using the AVEC2013 and AVEC2014 datasets have demonstrated the viability of the visual-based method.Future evaluations of the RNN-C3D can focus on additional issues related to human behaviour comprehension

Anping Song et al.[17] The Inception-v3 architecture serves as the foundation for the entire model. IDFNP concatenated the parameters of the two portions using a concat layer in addition to the core elements of Inception-v3 and DeepID.Reached a level of accuracy that is on par with that of neurologists. Applying IDFNP performance to additional face disorders or conditions that can be recognised visually will require future research..

Dinh Viet Sang et al.[18] This method makes use of recent deep learning developments to propose effective deep CNNs that can accurately and automatically assess the semantic information contained in faces. In order to extract the temporal relationship between video frames, we first learn facial features from VGG faces using convolutional neural networks (CNNs), and then connect the results to a lengthy short-term memory.

Zhen Yu et al.[19] The most crucial prerequisite for diagnosis and measurement is the foetal facial standard plane (FFSP). With the use of a Deep Convolutional Neural Network (DCNN) architecture, to enhance the recognition performance of FFSP. The transfer learning method and a data augmentation method designed specifically for FFSP are both used to increase recognition.Due to use of the data augmentation technique, encoding the descriptors takes up the greatest time.

Dan Yang Li et al.[20] The suggested model first extracts the facial image's attributes using a convolutional neural network, and then it mixes those elements with colour features. The Softmax classifier receives the fusion characteristics at the end to produce the classification outcome. They extracted the pulse's properties using a CNN, which they then utilised to categorise the body constitution type in order to achieve high accuracy.

3. Challenges faced by existing system

Most of the current systems use handcrafted features and conventional machine learning algorithms with an accuracy range of 60% to 75%. For example thermal scanning devices, video cameras, and mobile devices outfitted with photography software have all been used for image capture. However, the present shortcomings of the existing systems are that small image sizes make facial recognition, which is employed for facial diagnosis, more challenging. This experiment faces a significant dataset issue. Hospitals and other healthcare organisations value patient privacy more than other organisations do, and they are unable to defy medical orders. As a result, getting patient datasets for this project would be challenging, and even if they were, the dataset size would be modest. We cannot apply the conventional machine learning algorithms due to the tiny dataset

4. Methodology

The proposed system as shown in Figure 1 is to predict the disease from the facial features. It accepts as input a picture of the patient's face. It collects the characteristics from the input image and uses them to determine whether the patient is ill or not.

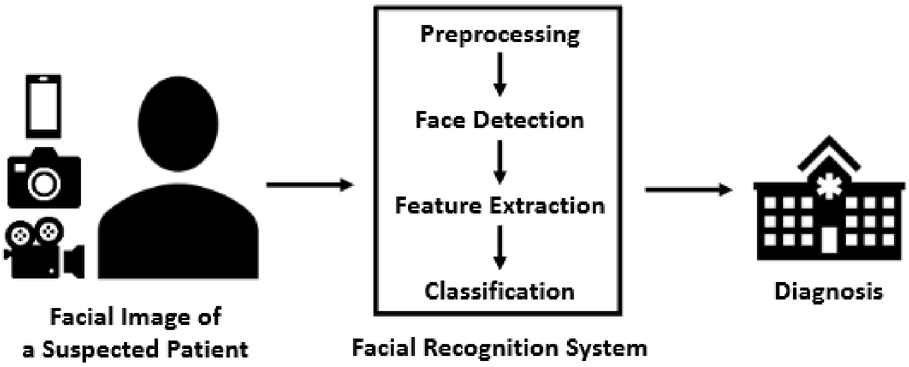

Fig. 1: Proposed System

5. Algorithm

The VGG-16 is a CNN model that is composed of 16 levels. The ImageNet database, which has been trained on more than a million images, has a pretrained version of the network. The well-known object identification and classification algorithm VGG16 achieved a classification accuracy of 92.7% when classifying 1000 photos into 1000 distinct groups. It is a popular method for classifying images due to its ease of use with transfer learning. VGG-16 applies 1x1 convolutional layers to decrease the linearity of the decision function, but it does not alter the receptive fields. Because the convolution filters are small, VGG-16 can incorporate multiple weight layers, which typically results in enhanced efficiency. However, this is a common characteristic of neural networks

6. System Architecture

The system architecture is shown in the Figure 2.

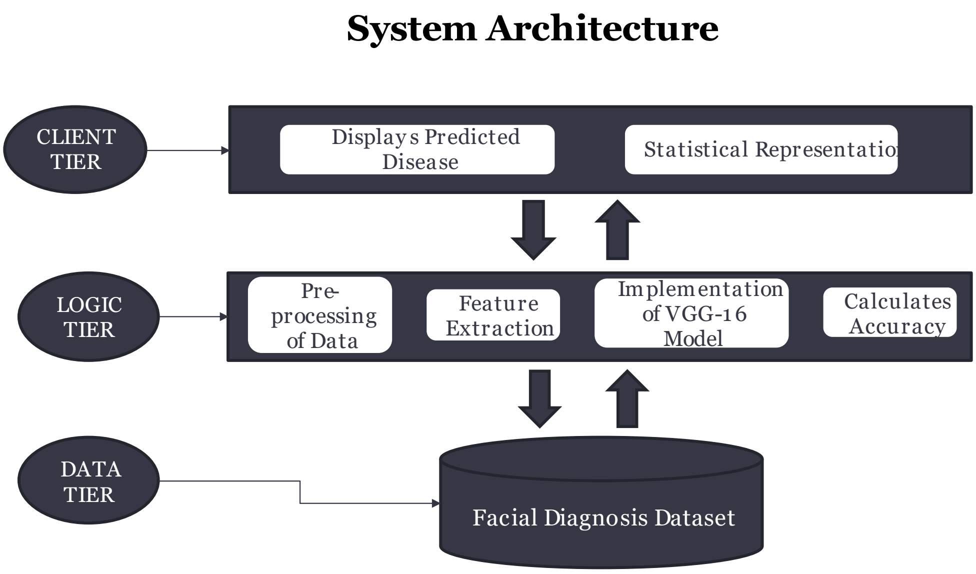

Fig. 2: System Architecture

7. Results

Computer-aided facial diagnosis is a promising method for disease screening and detection, according to an increasing number of research. In this study, we propose a deep transfer learning approach using methods of face recognition to achieve efficient computer-aided facial diagnosis and test it on single and multiple diseases together with healthy controls. The results of experiments with an accuracy of over 90% have shown that CNN is the preferred deep transfer learning technique as a feature extractor. In the future, by taking the help of data augmentation methods, deep learning models will be developed further to enable efficient facial diagnosis. The Predicted Leprosy Disease, Predicted Beta thalassemia Disease, Predicted Down syndrome Disease, Accuracy, Accuracy loss graph is shown in Figure 3, 4, 5, 6 and 7 respectively.

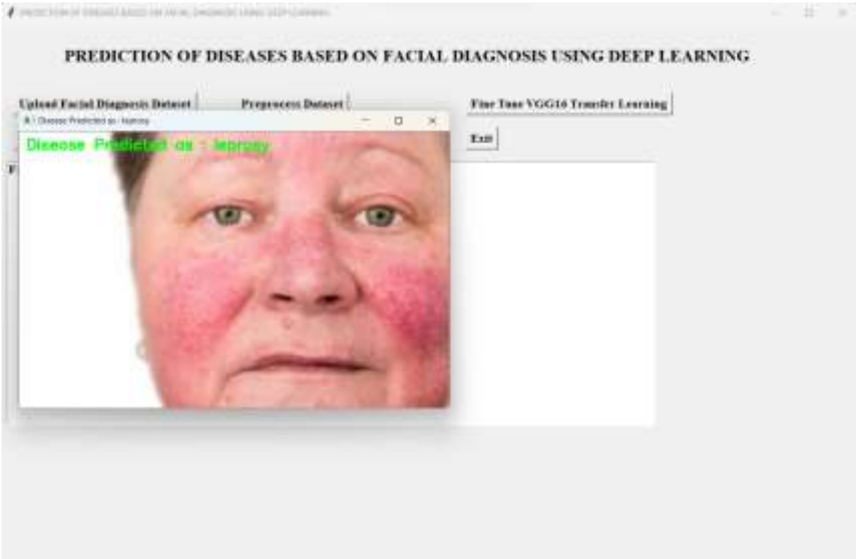

Fig. 3: Predicted Leprosy Disease

Fig. 4: Predicted Beta thalassemia Disease

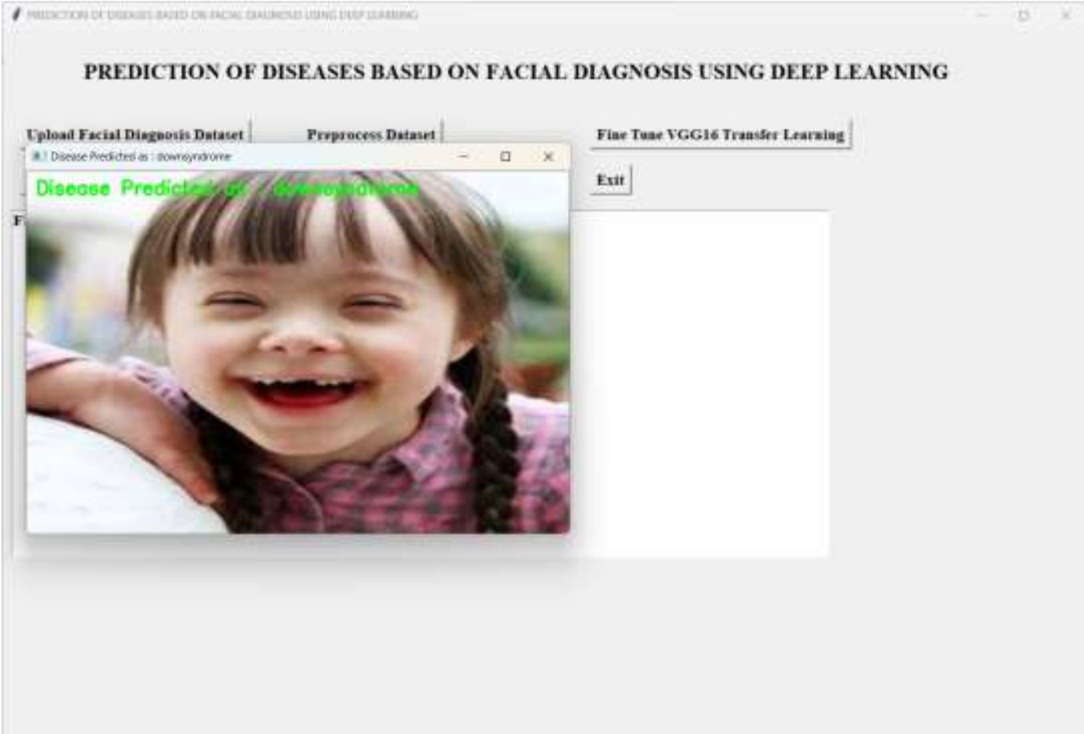

Fig 5: Predicted Down syndrome Disease

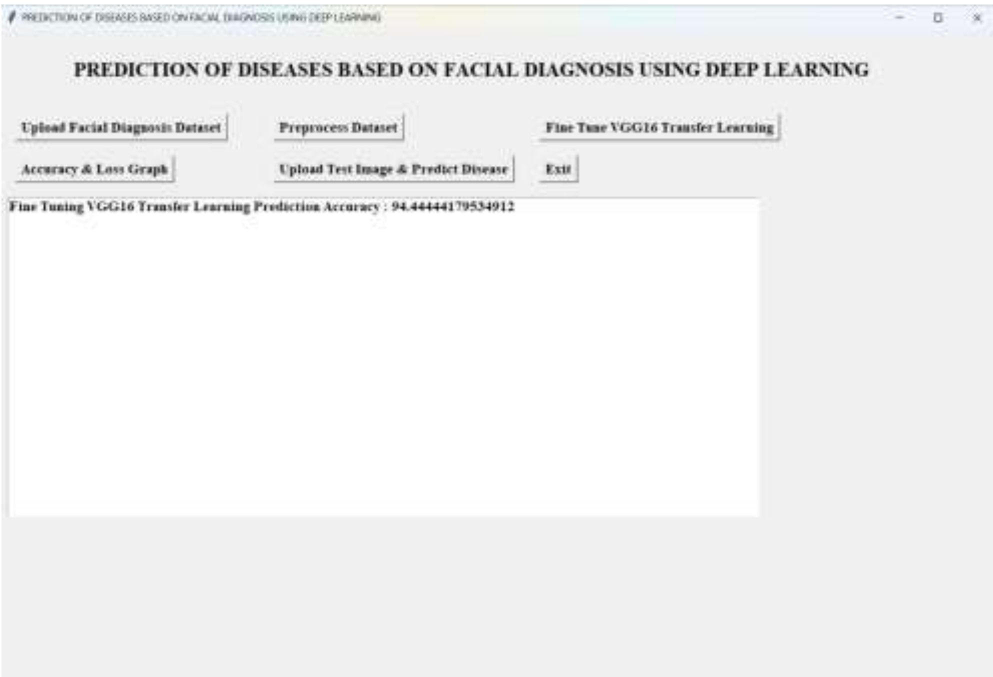

Fig 6: Accuracy

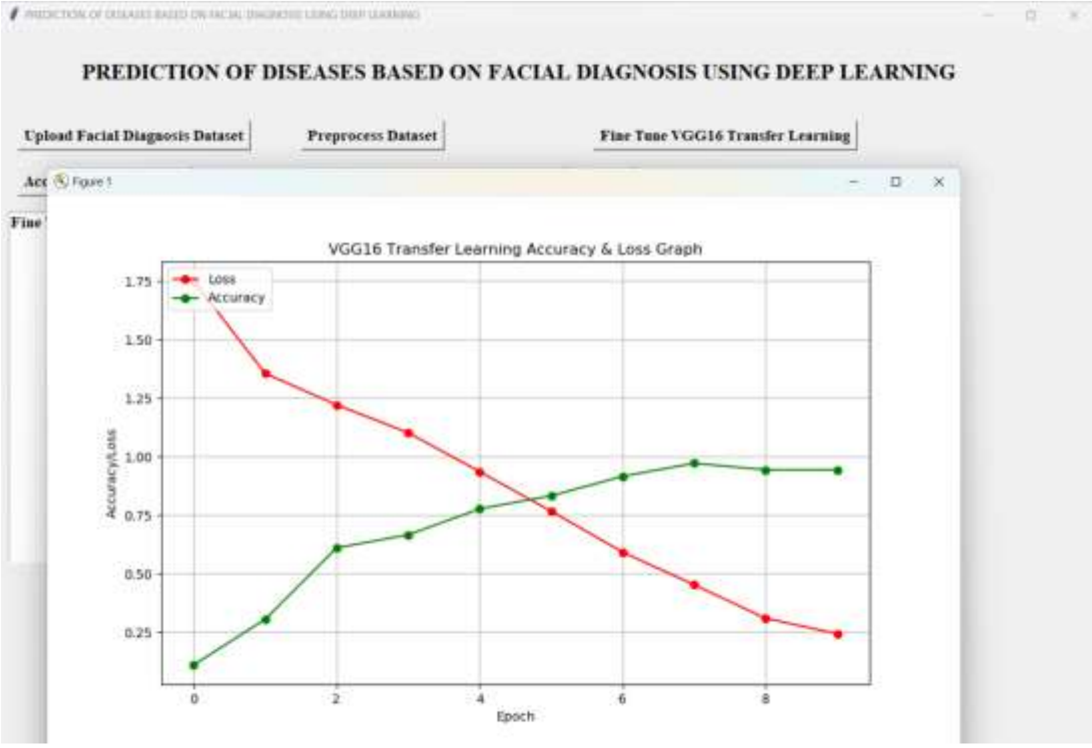

Fig. 7: Accuracy & Loss Graph

8. Future Scope

In the world of medicine, facial diagnosis is still a relatively new concept. Of course, the medical sector takes some time to implement this computer-aided facial diagnosis. We may define the illness in greater detail, classifying it as low, moderate, or high severity. For example, beta-thalassemia is divided into thalassemia major and thalassemia intermedia. can also establish changes in the health percentage of the human body. We can also suggest drugs and therapies for recovering from sickness.

9. Conclusion

We present a thorough literature review to examine the current state Facial Diagnosis. This study examines all models used in facial diagnosis and illustrates the need for more study so that the models can forecast disease in faces they have never seen before. In this study, we also examined other datasets associated with this problem, as well as their complexity and model performance on various related datasets. We are able to convince ourselves that out of all the methods mentioned, using a deep learning model that also includes implicit information and can also boost the accuracy by resolving problems faced by other models on our own is the best option.

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