

Deep Facial Diagnosis: Deep Transfer Learning from Face Recognition to Facial Diagnosis

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ABSTRACT

The link between the face and disease has been debated for thousands of years, leading to the development of facial diagnosis. The goal of this study is to see if deep learning techniques can be used to diagnose diseases from uncontrolled 2D facial photos. In this research, we suggest that computer-aided facial diagnosis on various diseases be performed utilising deep transfer learning from face recognition. In the trials, we use a relatively limited dataset to perform computer-aided facial diagnosis on single and multiple disorders (beta-thalassemia, hyperthyroidism, Down syndrome, and leprosy). Deep transfer learning from face recognition can achieve overall top-1 accuracy of over 90%, outperforming both classic machine learning approaches and clinicians in the studies. Collecting disease-specific facial photos is difficult in practise.

Keywords *Number plate, Computer Vision, Pattern Recognition, Python, OCRvehicle number plate detection, edge detection, python, Open CV.*

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I. INTRODUCTION

Cloud Electrical utility organizations are locked "Qi and blood in the twelve Channels and three hundred and sixty-five Collaterals all flow to the face and infuse into the Kongqiao (the seven orifices on the face)," said Huangdi Neijing, the main doctrinal source for Chinese medicine, thousands of years ago. It implies that abnormal alterations in the internal organs can be seen in the relevant areas' faces. In China, a skilled doctor can examine a patient's facial features to determine the patient's overall and local lesions, a process known as "facial diagnosis." Similar notions were also popular in ancient India and Greece. Nowadays, the term "facial diagnosis" refers to the practise of diagnosing diseases based on the appearance of the patient's face. The drawback of face diagnosis is that it takes a lot of time to obtain a high level of accuracy.

People in many rural and undeveloped areas still find it difficult to get a medical checkup due to a lack of medical resources, which leads to treatment delays in many cases. Even in metropolises, limits such as high costs, long hospital wait times, and the doctor-patient conflict that leads to medical disputes persist. We may use computer-aided face diagnostics to perform non-invasive disease screening and detection swiftly and efficiently. As a result, if face diagnosis can be proven to be effective with a low error rate, it has a lot of potential. With artificial intelligence, we may use a quantitative technique to investigate the association between face and disease.

Deep learning technology has improved the state of the art in several fields in recent years, particularly in computer vision. Deep learning uses a multi-layer structure to do nonlinear information processing and abstraction for feature learning, which is inspired by the structure of human brains. From 2012, it has demonstrated its greatest performance in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). Several traditional deep neural network models, such as AlexNet, VGGNet, ResNet, Inception-ResNet, and

SENet, arose as the challenge progressed. The findings of the ILSVRCs have demonstrated that deep learning approaches for learning features can communicate the data's intrinsic information more effectively than artificial features. Deep learning has become one of the most recent trends in artificial intelligence.

II. LITERATURE REVIEW

[1] Y. Gurovich, Y. Hanani, O. Bar, G. Nadav, N. Fleischer, D. Gelbman, L. Basel-Salmon, P. M. Krawitz, S. B. Kamphausen, M. Zenker, and colleagues, "Identifying facial phenotypes of genetic illnesses using deep learning," *Nature medicine*, vol. 25, no. 1, pp. 60–64, 2019.

In total, 8% of the population is affected by syndromic genetic conditions¹. Clinical geneticists can learn a lot about a syndrome by looking at its facial features². Recent research have shown that facial analysis technologies can match the ability of experienced doctors in identifying syndromes. These technologies, on the other hand, only detected a few illness phenotypes, limiting their utility in clinical situations where hundreds of diagnosis must be considered. We introduce DeepGestalt, a face image analysis framework that assesses similarities to hundreds of syndromes using computer vision and deep-learning techniques. DeepGestalt outperformed physicians in three preliminary tests, two of which were aimed at discriminating people with a target condition from those with other syndromes, and one of which was aimed at distinguishing various genetic subtypes in Noonan syndrome. On the last trial, which was conducted in a real-life clinical environment

[2] "A deep cnn based transfer learning method for false positive reduction," *Multimedia Tools and Applications*, vol. 78, no. 1, pp. 1017–1033, 2019. Z. Shi, H. Hao, M. Zhao, Y. Feng, L. He, Y. Wang, and K. Suzuki, "A deep cnn based transfer learning method for false positive reduction," *Multimedia Tools and Applications*, vol. 78, no. 1, pp. 1017– When using a Computer Aided Detection (CAD) system to detect pulmonary nodules in thoracic computed tomography, a low false positive (FP) rate is critical (CT). However, obtaining a low FP rate remains a difficult challenge because to the wide range of nodule appearance and size. We present a deep Convolutional Neural Network (CNN)-based transfer learning approach for FP reduction in pulmonary nodule diagnosis on CT slices in this research. To collect nodule features, we employed VGG-16, a state-of-the-art CNN model, as a feature extractor, and a support vector machine (SVM) for nodule classification. To begin, we moved all of the layers from an ImageNet pre-trained VGG-16 model to our target networks. Then we fine-tuned

[3] "Robust sparse linear discriminant analysis," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 29, no. 2, pp. 390–403, 2018. J. Wen, X. Fang, J. Cui, L. Fei, K. Yan, Y. Chen, and Y. Xu, "Robust sparse linear discriminant analysis," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 29, no. 2, pp.

Linear discriminant analysis (LDA) is a prominent supervised feature extraction method that has been branched out into other variations. Classical LDA, on the other hand, has the following drawbacks: 1) The resultant discriminant projection has poor feature interpretability; 2) LDA is susceptible to noise; and 3) LDA is sensitive to the number of projection directions used. To tackle the challenges mentioned above, a novel feature extraction method termed robust sparse linear discriminant analysis (RSLDA) is suggested in this study. By incorporating the $l_{2,1}$ norm, RSLDA adaptively selects the most discriminative features for discriminant analysis. An orthogonal matrix and a sparse matrix are also introduced at the same time to ensure that the extracted features can hold the original data's main energy and improve the quality of the data.

III. PROPOSED METHOD

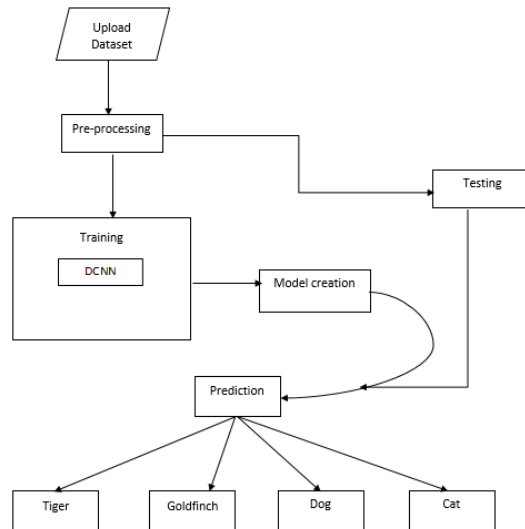
We use Deep Learning and Neural Networks in the suggested system to record people's faces and detect any ailment that may be related with them. Deep learning improves disease detection accuracy while also being highly scalable. To deal with data imbalances in the system, we used a data augmentation technique. It also enables us to reduce overfitting and, as a result, achieve higher accuracies than ever before.

ADVANTAGES:

ADVANTAGES:

1. High Accuracy.
2. Low computational usage.
3. Does not require costly equipment's and easy to scale.

IV. SYSTEM ARCHITECTURE



4.1 System Architecture

(i).Send Query: The user must be registered and **Modules:**

System

User

Admin

1.System:

1.1 Create a Dataset:

A dataset containing photos of the desired items to be recognised is divided into training and testing datasets, with the test size set at 20-30%.

1.2 Pre-processing: Resizing and reshaping the photos into the proper format for our model to learn from.

1.3 Training: Our model is trained using the CNN method using a pre-processed training dataset.

2.User:

2.1 Register The user must register, and the information must be saved in the MySQL database.

2.2 Login To utilise an application, a registered user must login to the website using valid credentials.

2.1 Project Overview

We have successfully constructed an application that classifies photographs in this application.

2.2 Add an image

The user must upload an image, which must then be classified.

Prediction (2.3)

Our model's outcomes are displayed as Down syndrome, hyperthyroidism, beta-thalassemia, or leprosy.

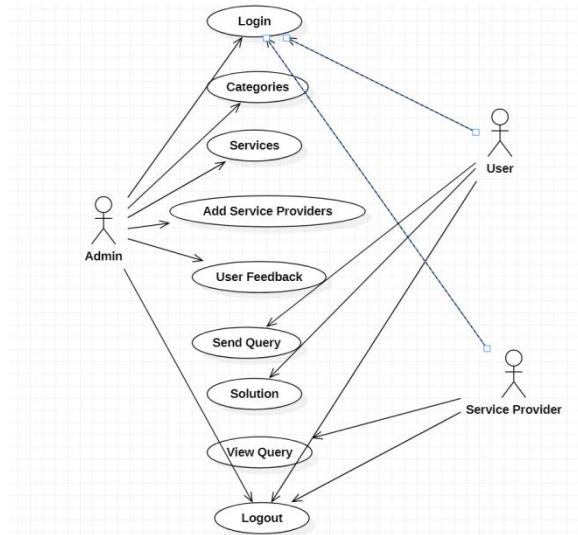
2.6 Logout When the prediction is finished, the user can exit the programme.

V. IMPLEMENTATION

The problem of gaining knowledge on service utilities is difficult, but it can be easily done with a Knowledge Sharing on Electrical Utilities application like this. Well experienced Service providers given knowledge on Electrical Utilities to the Customer. So that customer can get knowledge on Electrical Utilities.

Knowledge engineering methods were initially developed for the design of knowledgebased systems (KBS). The application of knowledge engineering techniques have diversified into related areas such as requirements engineering and knowledge management. Knowledge engineering has a significant role to play in the management of knowledge as a resource within organizations. Through the application of knowledge engineering techniques, existing organizational processes and procedures can be appreciated and captured, enabling streamlining and optimization of existing processes and knowledge resources. Knowledge management within an organization can also receive support in the form of knowledge-based systems, often requiring a more detailed knowledge engineering approach than that required for process modelling.

The graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases.



5.1 Functionality of the System

VI. Experimental Results:

By using this web application, we got the results successfully with the help of admin, users and service providers. The following are the screenshots of the required results.

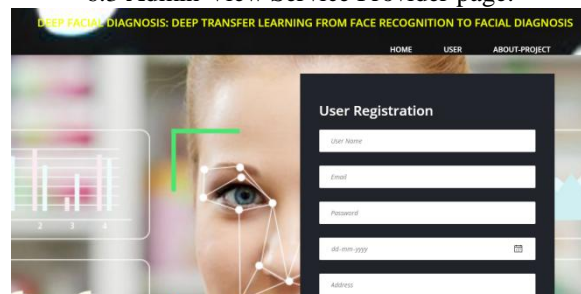
6.1 Home Page:



6.2 Admin Home Page:



6.3 Admin View Service Provider page:



6.4 User Registration Page:



6.5 User Home Page:



6.6 Service Provider Login Page:



6.7 Service Provider Home Page:



6.8 View User Queries:

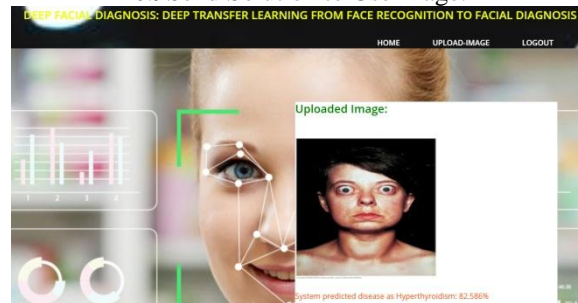
Insight: Effective Way of Knowledge Sharing

Home View Queries Back

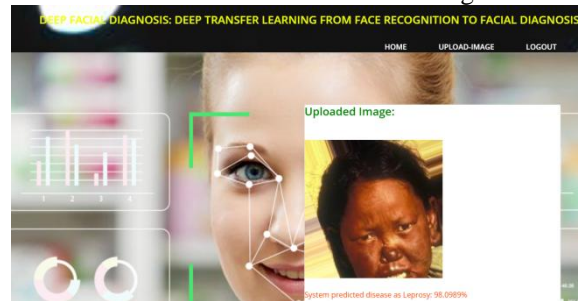
View User Queries

id	uname	email	cname	location	service	query	solution	Send
1	keerthi	akulakeerthana000@gmail.com	Mobile	tpt	redmi	higug	dhvdctv	Sended
2	gayathri	gayathri@gmail.com	Ac	Nellore	L.G	problem	klpofg	Sended
3	Harika	harika@gmail.com	pcs	Guntur	Microsoft	jhyuolim	hghadff	Sended
4	Rasi	rasi@gmail.com	Ac	Vijayawada	L.G	bnmcd	lkhyfjh	Sended
5	nandini	nandini2301@gmail.com	Fan	puttur	Usha	asofgh	rbvcmk	Sended
6	sirisha	sirisha@gmail.com	Refrigerator	korlagunta	Godrej	noooo	kkool	Sended
7	joothi	joothi@gmail.com	Mobile	Banglore	redmi	hkl	bbbbb	Sended
8	vanaja	vanaja@gmail.com	Mobile	Nellore	Vivo Y50	Wifi Problem	Fault in your wifi router	Sended
15	ramya	ramya@gmail.com	Mobile	gudur	Oppo f17 Pro	How to root f17 Pro?	You need to turn on USB Debugging.	Sended
16	roopa	roopa@gmail.com	Ac	Banglore rd no:34	Volta	why is not working wifi	pending	Send

6.9 Send Solution to User Page:



6.9.1 Sended Solution to User Page:



VII. CONCLUSION

Computer-aided face diagnosis has been shown in a growing number of studies to be a potential method for illness screening and detection. We propose deep transfer learning from face recognition algorithms in this research to achieve computer-aided facial diagnosis with certainty and validate them on single disease and multiple diseases with a healthy control. In the instance of the tiny dataset of facial diagnosis, the experimental results of above 90% accuracy have proved that CNN as a feature extractor is the best suited deep transfer learning approach. To some extent, it can tackle the general problem of insufficient data in the facial diagnosis domain. With the support of data augmentation approaches, we will continue to discover deep learning models to perform face diagnosis efficiently in the future. We are hoping for the best

REFERENCES

- [1]. Huang Di Nei Jing Su Wen: Nature, Knowledge, Imagery in an Ancient Chinese Medical Text: With an Appendix: The Doctrine of the Five Periods and Six Qi in the Huang Di Nei Jing Su Wen. [1] P. U. Unschuld, Huang Di Nei Jing Su Wen: Nature, Knowledge, Imagery in an Ancient Chinese Medical Text: With an Appendix: The Doctrine of the Five Periods and Six Qi in the Huang Di Nei J 2003, University of California Press.
- [2]. A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification using deep convolutional neural networks," Advances in neural information processing systems, vol. 2, no. 1, pp. 1097–1105, 2012.
- [3]. C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, "Going deeper with convolutions," IEEE conference on computer vision and pattern recognition, 2015, pp. 1–9.

- [4]. "Very deep convolutional networks for large-scale image recognition," arXiv preprint by K. Simonyan and A. Zisserman.
- [5]. "Deep residual learning for image recognition," in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 770–778, by K. He, X. Zhang, S. Ren, and J. Sun.
- [6]. C. Szegedy, S. Ioffe, V. Vanhoucke, and A. A. Alemi, "Inception-v4, inception-resnet, and the impact of residual connections on learning," AAAI Conference on Artificial Intelligence, Thirty-first AAAI Conference on Artificial Intelligence, 2017.
- [7]. F. Schroff, D. Kalenichenko, and J. Philbin, "Facenet: A unified embedding for face recognition and clustering," IEEE conference on computer vision and pattern recognition, 2015, pp. 815–823.
- [8]. "Deepface: Closing the Gap to Human-Level Performance in Face Verification," in Proceedings of the IEEE conference on computer vision and pattern recognition, Y. Taigman, M. Yang, M. Ranzato, and L. Wolf.
- [9]. J. Liu, Y. Deng, T. Bai, Z. Wei, and C. Huang, "Targeting ultimate accuracy: Face recognition via deep embedding," arXiv preprint arXiv:1506.07310, 2015. [11] J. Liu, Y. Deng, T. Bai, Z. Wei, and C. Huang, "Targeting ultimate accuracy: Face recognition via deep embedding," arXiv preprint arXiv:1506.07310, 2015.
- [10]. "The face-physiognomic expressiveness and human identity," Annals of Anatomy-Anatomischer Anzeiger, vol. 188, no. 3, pp. 261–266, 2006. [11] J. Fanghänel, T. Gedrange, and P. Proff, "The face-physiognomic expressiveness and human identity," Annals of Anatomy-Anatomischer Anzeiger, vol. 188, no. 3, pp. 261–266, 2006.
- [11]. "Computerized facial diagnosis utilising both colour and texture features," Information Sciences, vol. 221, pp. 49–59, 2013. B. Zhang, X. Wang, F. Karray, Z. Yang, and D. Zhang, "Computerized facial diagnosis using both colour and texture features," Information Sciences, vol. 221, pp. 49–59, 2013.
- [12]. Alhaija, E. S. A., Hattab, F. N., and Al-Omari, M. A., "Cephalometric measures and facial abnormalities in persons with -thalassaemia major," The European Journal of Orthodontics, vol. 24, no. 1, pp. 9–19, 2002.
- [13]. P. N. Taylor, D. Albrecht, A. Scholz, G. Gutierrez-Buey, J. H. Lazarus, C. Lazarus, D. Albrecht, D. Albrecht, D. Albrecht, D. Albrecht, D. Albrecht, D. Albrecht, D. Albrecht, D. Albrecht, D. Albrecht, D.
- [14]. Q. Zhao, K. Okada, K. Rosenbaum, L. Kehoe, D. J. Zand, R. Sze, M. Summar, and M. G. Linguraru, "Digital facial dysmorphology for genetic screening: Hierarchical constrained local model using ica," Medical image analysis, vol. 18, no. 5, pp. 699–710.
- [15]. H. J. Schneider, R. P. Kosilek, M. Günther, J. Roemmler, G. K. Stalla, C. Sievers, M. Reincke, J. Schopohl, and R. P. Würtz, "A new technique to the identification of acromegaly: accuracy of diagnosis by automatic face categorization," The Journal of Clinical Endocrinology & Metabolism, vol. 96, no. 5, pp. 1642–1650, 2007.
- [16]. EBioMedicine, vol. 27, pp. 94–102, 2018. X. Kong, S. Gong, L. Su, N. Howard, and Y. Kong, "Automatic detection of acromegaly from facial images using machine learning approaches," vol. 27, pp. 94–102, 2018.