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FACIAL DISEASE DETECTION VIA TRANSFER LEARNING: BRIDGING FACE RECOGNITION AND MEDICAL DIAGNOSIS

[1]Mr K. Koteswara Chari, [2]Amberi Jayanth, [3]Boredha Anusha and [4]Challa Mounika

[1](Assistant Professor), CSE. Teegala Krishna Reddy Engineering College Hyderabad

[2, 3, 4]B-Tech, Scholar, CSE. Teegala Krishna Reddy Engineering College Hyderabad

kkchari530@gmail.com[1], jayanthamberi@gmail.com[2], anushaboredha236@gmail.com[3] and challamounikareddy10@gmail.com[4]

ABSTRACT

The ancient practice of facial diagnosis, which associates facial features with diseases, has inspired modern research. In this study, we explore the feasibility of identifying diseases from uncontrolled 2D facial images using deep learning techniques. Specifically, we propose leveraging deep transfer learning from face recognition models for computer-aided facial diagnosis across various conditions. Our experiments cover both single-disease cases (e.g., beta-thalassemia) and multiple diseases (including hyperthyroidism, Down syndrome, and leprosy) using a relatively small dataset. Remarkably, deep transfer learning achieves an impressive top-1 accuracy of over 90%, surpassing traditional machine learning methods and clinician performance. Despite challenges in collecting disease-specific face images, this approach holds promise as a low-cost and noninvasive method for disease screening and detection.

Keywords: Facial diagnosis, deep switch learning (DTL), face recognition, beta-thalassemia, hyperthyroidism, Down syndrome, leprosy.

1. INTRODUCTION

Locked groupings of software on Cloud Electrical A qualified doctor can use facial features in China's "facial diagnostic" process to recognise a patient's common lesions and surrounding lesions. Ancient India and Greece also comprehended concepts of a similar nature. Locked groupings of software on Cloud Electrical According to Huangdi Nailing, the founding text of Chinese medicine, "Qi and blood withinside the twelve Channels and three hundred and sixty-five Collaterals all glide to the face and infuse into the Kongqiao (the seven orifices at the face)" was said to flow to the face and into the seven orifices hundreds of years ago.

It implies that odd alterations to the internal organs may be discernible in the facial features of the pertinent places. In China, a licenced physician can identify a patient's typical lesions and surrounding lesions using facial traits. "Qi and blood withinside the twelve Channels and three hundred and sixty-five Collaterals all glide to the face and infuse into the Kongqiao (the seven orifices at the face)," according to Huangdi Nailing, the foundational text of Chinese medicine, was said to flow to the face and into the seven orifices hundreds of years ago. It suggests that peculiar changes to the internal organs might be visible in the face features of the relevant locations.

A qualified doctor can use facial features in China's "facial diagnostic" process to recognise a patient's common lesions and surrounding lesions.

Similar ideas were also understood in ancient India and Greece.The term "facial analysis" now refers to the practise of diagnosing diseases exclusively from the patient's face.The disadvantage of face analysis is that it takes a while for it to become overly precise. Due to a lack of clinical resources, it is still difficult for people to get healthcare in many rural and underdeveloped areas, which frequently causes treatment delays.Limitations still persist, such as high costs, lengthy hospital wait times, and the doctor-patient conflict that causes disputes in the medical industry. Using laptop assisted face diagnostics, we can also carry out non invasive disorder screening and identification rapidly and successfully. Therefore, face analysis has a lot of potential if it can be shown to be reliable with little error. We can use artificial intelligence to quantitatively analyse the connection between face and disorder. Deep learning technology has advanced the state of the art in a number of fields recently, especially in computer vision..Deep learning, which is inspired by the structure of human brains, uses a multi-layer shape to perform nonlinear statistical processing and abstraction for characteristic learning. Within the ImageNet Large Scale Visual Recognition Challenge, it has obtained its best overall performance since 2012. (ILSVRC). As the project developed, a number of well-known deep neural network models emerged, including Alex Net, VGGNet, Resent, | The ILSVRCs' findings have demonstrated that deep learning methods for learning capacities can communicate the data's intrinsic statistics more accurately than synthetic methods. One of the most recent developments in artificial intelligence is deep learning.

2. LITERATURE SURVEY

[1] Y. Gurovich, Y. Hanuni, O. Bar, G. Nadav, N. Fleischer, D. Gelbman, L. Basel-Salmon, P. M. Krawitz, S. B. Kuhnhausen, M. Zemke, and others,

8% of the population is affected by syndromic genetic disorders overall1. Numerous syndromes have recognisable facial characteristics2, which could be very instructive to professional geneticists. According to recent studies, face evaluation technology was just as effective at identifying syndromes as trained physicians. However, those technologies could only identify a small subset of disease phenotypes, which limited their application in scientific settings where a large number of diagnoses must be taken into account. Here, we present DeepGestalt, a system for evaluating face photos that makes use of computer vision and deep learning techniques to quantify similarities to numerous disorders. In three preliminary trials aimed at differentiating patients with a target syndrome from patients with other syndromes and one in each of identifying unique genetic subtypes in Noonan syndrome, DeepGestalt outperformed physicians. In the last test, which simulated a real-world scientific placement challenge, DeepGestalt achieved 91% top-10 accuracy in identifying the appropriate diagnosis on 502 unique images. The version was trained using a dataset of more than 17,000 images covering more than 200 syndromes, which p-ISSN: 2395-0072 version to our target networks. Then, we adjusted the final, entirely related layers to control the CNN version that was trained on computer vision tasks to perform pulmonary nodule type tasks. The initial CNN threshold weights were then improved using the training data— namely, the pulmonary nodule patch images and accompanying labels—through back-propagation in order to better take into account the modalities contained within the pulmonary nodule image dataset. Finally, an SVM classifier has been taught using functions discovered inside the tweaked CNN. The educated SVM's output was utilised for the very last kind. Experimental results show that the proposed approach's overall sensitivity was 87.2% with 0.39 FPs consistent with test, which is better than the 85.4% with 4 FPs consistent with test attained using a different state-of-the-art approach. was curated using a community-driven phenotyping platform. Without a doubt, DeepGestalt adds a significant financial burden to phenotypic assessments in scientific genetics, genetic testing, research, and precision medicine.

[2]K. Suzuki, L. He, Y. Wang, Z. Shi, H. Hao, M. Zhao, Y. Feng, and Y

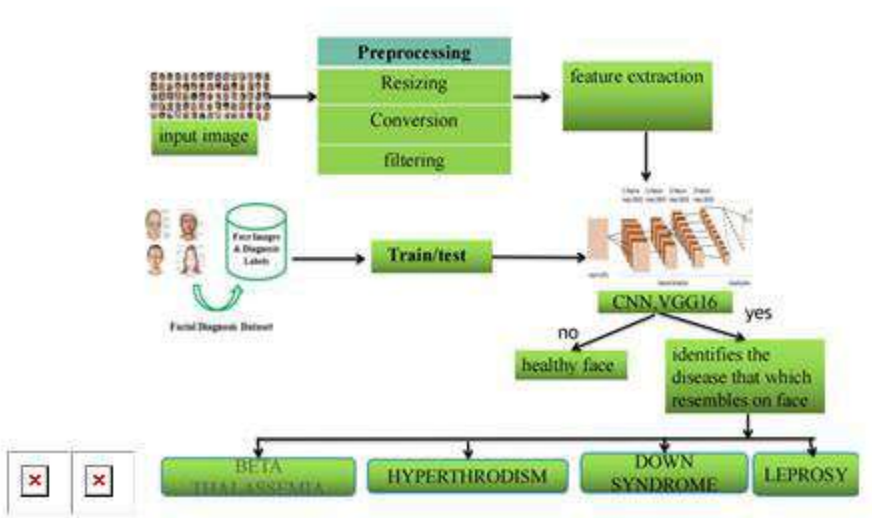
Using a Computer Aided Detection (CAD) device to identify pulmonary nodules in thoracic Computed Tomography is of outstanding significance (CT). However, achieving a low FP rate is still a very difficult task due to the variations in nodules' appearance and size. In this report, we propose a deep fully switch learning method based on Convolutional Neural Networks (CNN) for FP discount in CT slice-based pulmonary nodule diagnosis. We employed a help vector machine (SVM) for nodule type and one of the contemporary CNN models, VGG-16, as a characteristic extractor to obtain nodule functions. First, we copied all the layers from an ImageNet VGG-sixteen pre-educated version to our target networks. Then, we adjusted the final, entirely related layers to control the CNN version that was trained on computer vision tasks to perform pulmonary nodule type tasks. The initial CNN threshold weights were then improved using the training data— namely, the pulmonary nodule patch images and accompanying labels—through back-propagation in order to better take into account the modalities contained within the pulmonary nodule image dataset. Finally, an SVM classifier has been taught using functions discovered inside the tweaked CNN. The educated SVM's output was utilised for the very last kind. Experimental results show that the proposed approach's overall sensitivity was 87.2% with 0.39 FPs consistent with test, which is better than the 85.4% with 4 FPs consistent with test attained using a different state-of-the-art approach.

[3]X. Fang, J. Cui, L. Fei, K. Yan, Y. Chen, and Y. Xu

The widely used supervised characteristic extraction method known as linear discriminant analysis (LDA) has been extended to various variants. However, the following issues exist with conventional LDA: 1) LDA is sensitive to noise; 2) LDA is sensitive to the choice of amount of projection directions; and 3) LDA is sensitive to the acquired discriminant projection's genuine interpretability for functions. The challenges mentioned above are addressed in this study via a novel characteristic extraction method called strong sparse linear discriminant evaluation (RSLDA). Specifically By incorporating the l 2,1 norm, RSLDA adaptively chooses the most discriminative functions for discriminant evaluation. RSLDA can perform better than other discriminant methods because an orthogonal matrix and a sparse matrix are simultaneously added to ensure that the extracted functions can maintain the fundamental strength of the unique information and enhance the robustness to noise. Extensive tests on six databases show that the suggested strategy performs aggressively when compared to other ultra-modern feature extraction techniques. The suggested approach is also robust against noisy information.

[4]Squeeze-and-excitation networks by J. Hu, L. Shen, and G. Sun.

Using a Computer Aided Detection (CAD) device to identify pulmonary nodules in thoracic Computed Tomography is of outstanding significance (CT). However, achieving a low FP rate is still a very difficult task due to the variations in nodules' appearance and size. In this report, we propose a deep fully switch learning method based on Convolutional Neural Networks (CNN) for FP discount in CT slice-based pulmonary nodule diagnosis. We employed a help vector machine (SVM) for nodule type and one of the contemporary CNN models, VGG-16, as a characteristic extractor to obtain nodule functions. First, we copied all the layers from an ImageNet VGG-sixteen pre-educated © 2022, IRJET | Impact Factor value: 7.529 Convolutional neural networks are built on the convolution process, which derives informative functions by combining spatial and channel-clever characteristics in close-by receptive fields. The benefit of enhancing spatial encoding has been demonstrated in various recent processes to increase the representational power of a network. In this work, we look at the channel dating and propose a single architectural element, which we call the "Squeeze-and-Excitation" (SE) block, that explicitly models the interdependencies among channels to adaptively adjust channel-clever function responses. By arranging the blocks in a stack, we may demonstrate thatWe can put together Senet designs that generalise incredibly well across challenging datasets. Importantly, we find that SE blocks discoveries are mapped out, we can also speak characteristic maps. Step significantly improve performance for contemporary ultra-modern deep systems with little additional computational cost. Our ILSVRC 2017 class submission, which achieved first place and significantly reduced the top five errors to 2.251%, was inspired by SENets. This resulted in a 25% relative improvement over the winning access of 2016. You may download the code and designs for SENet.



The Schematic Diagram of Facial Diagnosis by Deep Transfer Learning.

SCOPE OF THE PROJECT

We are using Deep learning and Neural network to capture the faces of people and detect any possible disease associated to them. Deep learning offers increased accuracy for detection of disease and it is highly scalable. We used data augmentation technique to handle imbalance of data in the system. It is also allows us to reduce over fitting and hence generate better accuracies than ever before.We depict the advancement used in the method. For getting an unrivaled show on the contamination acknowledgment, a portion of the time we maintain that a pre taking care of procedure should dispose of really look at variables to make For the CNN input, frontalized face pictures of reasonable scale are utilized to stress the facial finish positively.

MOTIVATION FOR THE WORK

Nowadays, it is still difficult for people to take a medical examination in many rural and underdeveloped areas because of the limited medical resources, which leads to delays in treatment in many cases. Even in metropolises, limitations including the high cost, long queuing time in hospital and the doctor-patient contradiction which leads to medical disputes still exist. Computer-aided facial diagnosis enables us to carry out non-invasive screening and detection of diseases quickly and easily. Therefore, if facial diagnosis can be proved effective with an acceptable error rate, it will be with great potential. With the help of artificial intelligence, we could explore the relationship between face and disease with a quantitative approach.

AIM:

It is at this point difficult for people to do a clinical evaluation on various commonplace in juvenile locale due to the limited clinical resources, the prompts concedes in treatment overall. Indeed, even in cities, constraints including the significant expense, long lining time in clinic and the specialist patient inconsistency which prompts clinical questions actually exist. PC supported facial determination empowers us to complete harmless screening and identification of illnesses rapidly and without any problem. In this way, in the event that facial conclusion can be demonstrated successful with a satisfactory blunder rate, it will accompany extraordinary potential. With the assistance of man-made consciousness, we could investigate the connection among face and illness with a quantitative methodology.

OBJECTIVES:

- The main objective of the Deep facial diagnosis is to predict the disease more accurately and fast without any
  – Thalassemia , Hyperthyroidism, Down syndrome,
  an be predicted more accurately using Deep facial diagnosis.

EXISITING SYSTEM:

Traditional facial diagnosis relies on manual observation and inspection by dermatologists or healthcare professionals.

Limited accuracy and reliability due to subjectivity and potential human errors.

Lack of standardized diagnostic criteria and inconsistency in diagnosis across different experts.

Time-consuming process, specially for complex or rare skin conditions.

Limited accessibility to expert dermatologists in remote or underserved areas.

DRAWBACKS:

High cost

long queuing time in hospital

doctor-patient contradiction

high probability of causing error

PROPOSED SYSTEM:

Deep Facial Diagnosis is a proposed system that aims to diagnose facial conditions using deep transfer learning from face recognition algorithms.

The system will utilize deep learning techniques to extract facial features and patterns from images.

It will employ transfer learning, a technique where a pre-trained face recognition model will be fine-tuned to perform facial diagnosis.

It will prioritize accuracy and reliability by training the model on a large and diverse dataset of facial images.

ADVANTAGES:

More dataset

With in the less time we will get good accuracy

Easy to classify the human facial skin disease

Privacy and data security will be a primary focus, with encryption and secure data handling protocols implemented to protect users' sensitive facial images.

FUTURE SCOPE

In future, we will keep on finding profound facial determination successfully with the assistance of information expansion strategies. believe that a steadily expanding number of contaminations can be distinguished gainfully by face photographs and also this application could be extended to include multiple facial diseases as well as new models like MobileNet, AlexNet, Xception and Inception can also be included for model performance comparison.

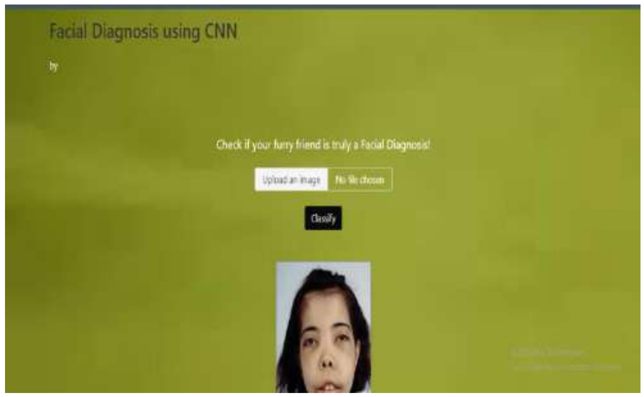
CONCLUSION

More and more studies have shown that computer-aided facial diagnosis is a promising way for disease screening and detection. In this paper, we propose deep transfer learning from face recognition methods to realize computer aided facial diagnosis definitely and validate them on single disease and various diseases with the healthy control. The experimental results of above 90% accuracy have proven that CNN as a feature extractor is the most appropriate deep transfer learning method in the case of the small dataset of facial diagnosis. It can solve the general problem of insufficient data in the facial diagnosis area to a certain extent. In future, we will continue to discover deep learning models to perform facial diagnosis effectively with the help of data augmentation methods. We hope that more and more diseases can be detected efficiently by face photographs ACKNOWLEDGMENT

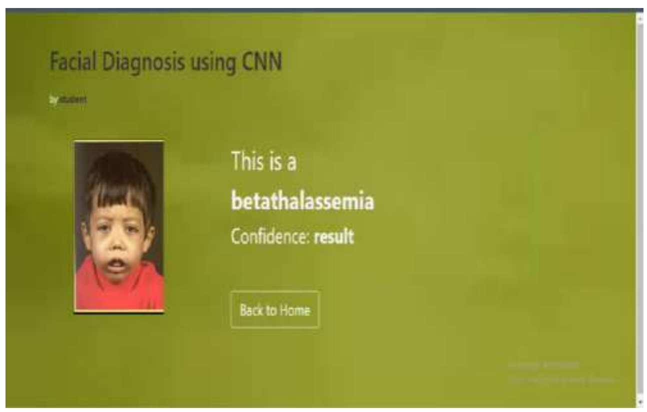
We express our gratitude to Teegala Krishna Reddy Engineering college management for providing infrastructure and services to complete the project. I also acknowledge with a deep sense of reverence, my gratitude towards our guides for their valuable suggestions given to our team in completing the project.

OUTPUT SCREENS

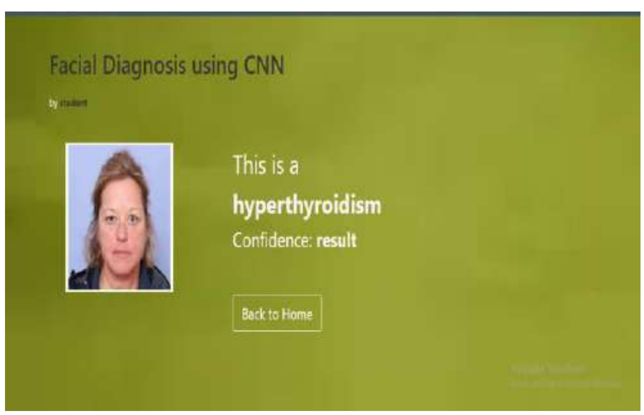
User Interface:



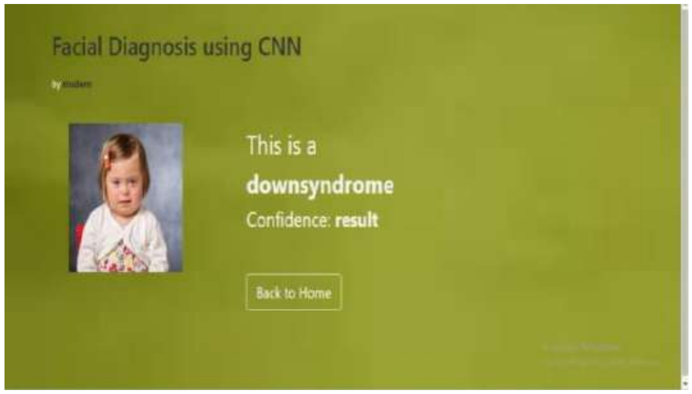
Identifies the Disease Betathalassemia:



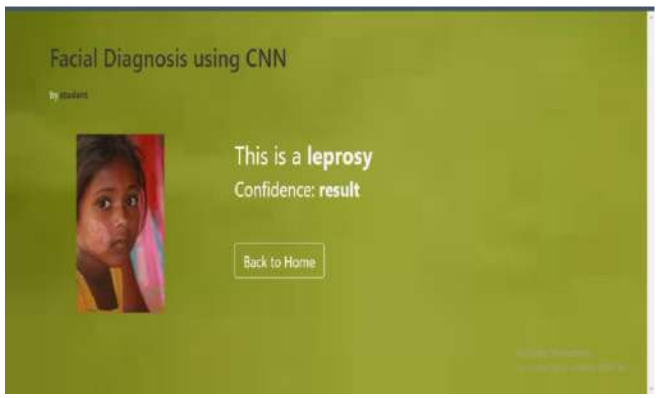
Identifies the Disease Hyperthyriodism:



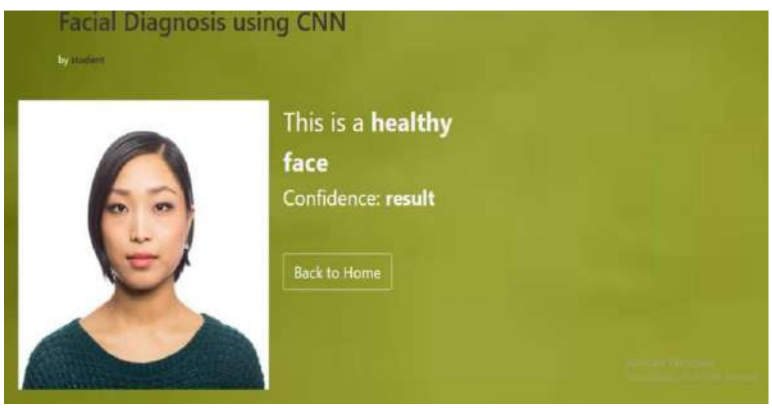
Identifies the Disease Downsyndrome:



Identifies the Disease Leprosy:



Identifies the Non-Diseased Person:



REFERENCES

[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 Jing Su Wen. Univ of California Press, 2003.

[2] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” in Advances in neural information processing systems, 2012, pp. 1097–1105.

[3] [3] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, “Going deeper with convolutions,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2015, pp. 1–9.

[4] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” arXiv preprint arXiv:1409.1556, 2014.

[5] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 770–778.

[6] C. Szegedy, S. Ioffe, V. Vanhoucke, and A. A. Alemi, Inception-v4, inception-resnet and the impact of residual connections on learning, in Proc. 31st AAAI Conf. Artif. Intell., 2017, pp. 112.

[7] F. Schroff, D. Kalenichenko, and J. Philbin, FaceNet: A uni ed embedding for face recognition and clustering, in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2015, pp. 815823.

[8] Y. Taigman, M. Yang, M. Ranzato, and L. Wolf, DeepFace: Closing the gap to human-level performance in face veri cation, in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2014, pp. 17011708

[9] B. Jin, Disease-speci c faces, IEEE Dataport, 2020. Accessed: Jun. 29, 2020. [Online]. Available: http://dx.doi.org/10.21227/ rk2v-ka85 [10] J. Liu, Y. Deng, T. Bai, Z. Wei, and C. Huang, Targeting ultimate accu racy: Face recognition via deep embedding, 2015, arXiv:1506.07310. [Online]. Available: http://arxiv.org/abs/1506.07310

[11] J. Fanghänel, T. Gedrange, and P. Proff, The face-physiognomic expres siveness and human identity, Ann. Anatomy-Anatomischer Anzeiger, vol. 188, no. 3, pp. 261266, May 2006.

[12] B. Zhang, X. Wang, F. Karray, Z. Yang, and D. Zhang, Computerized facial diagnosis using both color and texture features, Inf. Sci., vol. 221, pp. 4959, Feb. 2013.

[13] E. S. J. A. Alhaija and F. N. Hattab, Cephalometric measurements and facial deformities in subjects with-thalassaemia major, Eur. J. Orthodontics, vol. 24, no. 1, pp. 919, Feb. 2002.

[14] P. N. Taylor, D. Albrecht, A. Scholz, G. Gutierrez-Buey, J. H. Lazarus, C. M. Dayan, and O. E. Okosieme, Global epidemiology of hyperthy roidism and hypothyroidism, Nature Rev. Endocrinol., vol. 14, no. 5, pp. 301316, 2018.

[15] Q. Zhao, K. Rosenbaum, R. Sze, D. Zand, M. Summar, and M. G. Linguraru, Down syndrome detection from facial photographs using machine learning techniques, Proc. SPIE, vol. 8670, Feb. 2013, Art. no. 867003.

[16]E. Turkof, B. Khatri, S. Lucas, O. Assadian, B. Richard, and E. Knolle, Leprosy affects facial nerves in a scattered distribution from the main trunk to all peripheral branches and neurolysis improves muscle function of the face, Amer. J. Tropical Med. Hygiene, vol. 68, no. 1, pp. 8188, Jan. 2003.

[17] Q. Zhao, K. Okada, K. Rosenbaum, D. J. Zand, R. Sze, M. Summar, and M. G. Linguraru, Hierarchical constrained local model using ICA and its application to Down syndrome detection, in Proc. Int. Conf. Med. Image Comput. Comput.-Assist. Intervent. Berlin, Germany: Springer, 2013, pp. 222229.

[18] 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, Med. Image Anal., vol. 18, no. 5, pp. 699710, Jul. 2014.

[19] H. J. Schneider, R. P. Kosilek, M. Günther, J. Roemmler, G. K. Stalla, C. Sievers, M. Reincke, J. Schopohl, and R. P. Würtz, A novel approach to the detection of acromegaly: Accuracy of diagnosis by automatic face classi cation, J. Clin. Endocrinol. Metabolism, vol. 96, no. 7, pp. 20742080, Jul. 2011.

[20] X. Kong, S. Gong, L. Su, N. Howard, and Y. Kong, Automatic detection of acromegaly from facial photographs using machine learning methods, EBioMedicine, vol. 27, pp. 94102, Jan. 2018.

[21] T.Shu,B.Zhang,andY.Y.Tang, Anextensiveanalysis of various texture feature extractors to detect diabetes mellitus using facial speci c regions, Comput. Biol. Med., vol. 83, pp. 6983, Apr. 2017. [22] S. Hadj-Rabia, H. Schneider, E. Navarro, O. Klein, N. Kirby, K. Huttner, L. Wolf, M. Orin, S. Wohlfart, C. Bodemer, and D. K. Grange, Automatic recognition of the XLHED phenotype from facial images, Amer. J. Med. Genet. Part A, vol. 173, no. 9, pp. 24082414, Sep. 2017.

[23] P. Kruszka, Y. A. Addissie, D. E. McGinn, A. R. Porras, E. Biggs, M. Share, and T. B. Crowley, 22q11. 2 deletion syndrome in diverse populations, Amer. J. Med. Genetics A, vol. 173, no. 4, pp. 879888, 2017.

[24] S. Boehringer, T. Vollmar, C. Tasse, R. P. Wurtz, G. Gillessen-Kaesbach, B. Horsthemke, and D. Wieczorek, Syndrome identi cation based on 2D analysis software, Eur. J. Hum. Genet., vol. 14, no. 10, pp. 10821089, Oct. 2006.

[25] Y. Gurovich, Y. Hanani, O. Bar, G. Nadav, N. Fleischer, D. Gelbman, L. Basel-Salmon, P. M. Krawitz, S. B. Kamphausen, M. Zenker, L. M. Bird, and K. W. Gripp, Identifying facial phenotypes of genetic disorders using deep learning, Nature Med., vol. 25, no. 1, pp. 6064, Jan. 2019.

[26] G. Bradski and A. Kaehler, Learning OpenCV: Computer Vision With the OpenCV Library. Newton, MA, USA: OReilly Media, 2008.

[27] O. M. Parkhi, A. Vedaldi, and A. Zisserman, Deep face recognition, in Proc. Brit. Mach. Vis. Conf., 2015, pp. 112.

[28] J.-G. Wang, J. Li, C. Y. Lee, and W.-Y. Yau, Dense SIFT and Gabor descriptors-based face representation with applications to gender recognition, in Proc. 11th Int. Conf. Control Autom. Robot. Vis., Dec. 2010, pp. 18601864

[29] C. Shan, S. Gong, and P. W. McOwan, Robust facial expression recognition using local binary patterns, in Proc. IEEE Int. Conf. Image Process., Sep. 2005. pp. II 370.

[30] D. Wu, Y. Chen, C. Xu, K. Wang, H. Wang, F. Zheng, D. Ma, and G. Wang, Characteristic face: A key indicator for direct diagnosis of 22q11. 2 deletions in Chinese velocardiofacial syndrome patients, PLoS ONE, vol. 8, no. 1, 2013, Art. no. e54404.