An Approach for Prediction of Obstructive Sleep Apnea

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Abstract- Conceptual—Obstructive Sleep Apnea (OSA) is a common disorder related to breathing, happens when obstruction occurred due to physical collapse of pharyngeal airways. Regular markers of OSA are snore throat at wake ups, dry mouth, poor night sleep and morning headaches. Determination of OSA is expensive in terms of time and money. So the patients not easily discovered and so they become unconscious for their condition. In this paper, we examine the utilization of profound learning methods to analyze the malady through the profundity guide of human facial outputs Instead of plain 2-D shading picture, profundity guide will give more data about facial morphology. We can get around 69validation exactness with less measure of test information by utilizing move learning.

Keywords- Classification, Obstructive Sleep Apnea, Transfer learning, Deep Learning, Facial Depth Map

I. INTRODUCTION

Social and individual exercises are altogether influenced by poor rest. There are various kinds of rest issue and it is costing us at various levels. As [1] shows that as it were in Australia rest issue costs the economy around $5.1 billion every year that contains social insurance, related medicinal conditions, efficiency, and non-therapeutic expenses. Furthermore, among all the rest issue, OSA is the most widely recognized reason [2]. Ordinarily, during rest, our upper aviation route stays open due to lose however sufficient muscles, covering the upper throat. Be that as it may, in OSA, somebody can have a common blockage in upper aviation route because of various reasons, for in excess of 10 sec for each blockage, which causes the lungs out of oxygen and individual to wake, which will reestablish the aviation route [3]. In the event that more than 15 apneas happen then the finding of OSA is made. History of the patient, physical assessment, polysomnography (PSG) test, and imaging are being utilized to analyze OSA. The best quality level to analyze is a PSG test. In which an individual needs to rest in a unit in a medical clinic with a few sensors to screen breathing examples, Oxygen level, heart rate, and body developments. A few gadgets are likewise making a difference to direct these tests at the patient's claim a home, yet there will be a question mark on the unwavering quality of the test and have not been demonstrated to be as exact as PSG [4]. After the test Apnea-Hypopnea Index (AHI) is processed. This list calls attention to the seriousness of rest apnea. Because of cost in terms of cash and time, the intrusiveness of the PSG, vague nature of side effects related to OSA and the restricted access to rest centers, numerous OSA patients stay undiscovered until critical indications show up [5]. Numerous endeavors have been made in the past to foresee OSA in view of polls. For instance, the Berlin poll predicts the degree of hazard depends on wheezing, tiredness, blood weight, and weight record data while the Epworth Sluggishness poll evaluates tiredness in different situations during the day. In spite of the fact that they are self-directed what more, ease, is they have deficiencies in precisely recognizing influenced people.

II. LITERATURE SURVEY

Sr. No.	Title	Author	Limitations	Proposed work
1	Deep Learning of Facial Depth Maps for Obstructive Sleep Apnea Prediction[10]	Syed MS Islam, Hassan Mahmood, Adel Ali Al-Jumaily, Scott Claxton	Pose correction problem will be solved through a 3D morphable model. Hole filled depth maps will be created through an automatic procedure. This work gets good results with a very small dataset and with more 3D scans of OSA and non-OSA patients, we will enhance the performance for diagnoses.	This paper propose the first facial depth map based sleep apnea detection. Patients dataset is small, to overcome this limitation took advantage of transfer learning. Paper analyze three pre-trained models and among them, VGGface performs the best.

2	Speech signal and facial image processing for obstructive sleep apnea assessment.[11]	F.Espinoza-Cuadros R.Fern´andez-Pozo, D. T. Toledano, J.D.Alc´azar Rammers, E. L´opez-Gonzalo, L. A. Hern´andez-G´omez.	Supervised automatic image processing is used instead of precise manual identification for the purpose of landmark identification.	In this paper prediction of OSA enhanced by combining both clinical and facial measurements. Also detection of OSA is possible in practical using mobile devices as well as image processing.
3	Relationship between surface facial dimensions and upper airway structures in obstructive sleep apnea.[12]	R. W. Lee, K. Sutherland, A. S. Chan, B. Zeng, R. R. Grunstein, M. A. Darendeliler, R. J. Schwab and P. A. Cistull	Instead at level of the lower face, correlations between thickness of surface soft tissue and upper airway soft tissue volumes occurred at the level of the mid-face.	This paper approach deal with finding relationship between surface facial dimensions and upper airway structures using magnetic resonance imaging (MRI) .
4	Craniofacial obesity in patients with obstructive sleep apnea.[13]	S. M. Banabilh, A. Suzina, S. Dinsuhaimi, A. Samsudin, and G. Singh.	There are Limitations conventional cephalometrics. In addition to problems associated with standardizing the radiographic equipment, technique and interpretative skills, it is difficult or impossible to perform volumetric analysis, patients are exposed to radiation, it cannot be performed in the supine position, it is a two-dimensional representation of a three-dimensional object.	This paper approach case–control study using three-dimensional magnetic resonance imaging cephalometry 55 apneic and 55 controls were matched for age, sex and race. The analysis was stratified by sex and controlled for age, race, height, neck visceral fat, skeletal type and tongue volume.
5	Online Obstructive Sleep Apnea Detection on Medical Wearable Sensors.[14]	Gr´egoire Surrel , Amir Aminifar , Francisco Rinc´on, Srinivasan Murali, and David Atienza	For the reason of lack in medical devices for long term ambulatory monitoring of OSA the current systems becomes more expensive.	In this paper author proposes the approach in which single-channel electrocardiogram signals are used for monitoring patients and time-domain analysis is developed which is used to compute the sleep apnea score.

6	Distinguishing Obstructive from Central Sleep Apneas and Hypopnea Using Linear SVM and Acoustic Features[15]	Richard Hummel, T. Douglas Bradley, Devin Packer, Hisham Alshaer	The limitations are have implemented acoustic analysis of breath sounds to extract information about breathing patterns to help identify flow limitation, site of obstruction and caliber of the airway and distinguish habitual snoring from OSA, which can't be available from any other single transduce.	This paper analyses breathe sounds to distinguish central and obstructive events. This is the first study that distinguishes CSA from OSA with high reliability by recording breathe sound during sleep.
7	A prediction model based on an artificial intelligence system for moderate to severe obstructive sleep apnea.[16]	Sun LM, Chiu HW, Chuang CY	When more patients are recruited sensitivity and specificity of GA models may improve.	Paper aim to introduce an artificial intelligence methods that are used to find moderate to severe OSA patients (apnea-hypopnea index ≧15).
8	The application of hierarchical evolutionary approach for sleep apnea classification.[17]	Yi-nan lu, Hong zhang, Wei-tian zhang.	The limitations are most un-effective method for the diagnosis of SAS is based on a polysomnogram, defined as a continuous and simultaneous recording during sleep of a set of variables, which are described electro-encephalogram (EEG), electrocardiogram (ECG), electromyogram (EMG), airflow, oxygen saturation and respiratory effort (both abdominal and thoracic).	This paper presents the hybrid approach . Different hierarchical levels are expressed with complex hierarchical structures by combining Genetic Algorithm and Genetic Programming.
9	Automatic detection of obstructive sleep apnea using facial images.[18]	A. T. Balaei, K. Sutherland, P. A. Cistulli, and P. de Chazal.	This approach has limitations in dealing with variations of the images (scale, pose, illumination, etc.). In the second approach, face landmarks are localized by solving the regression problem which relates the features of the training datasets and their associated landmarks. The estimated parameters are then used to detect the landmarks of the test images.	Paper proposes landmarks to generate the facial features for the purpose of prediction of OSA. Using a neural network, we show that it is possible to detect OSA without the step of calculating facial landmarks and features.
10	Analysis of Sleep Fragmentation and Sleep Structure in Patients With Sleep Apnea and Normal Volunteers.[19]	T. Penzel, C.-C. Lo, P.C. Ivanov, K. Kesper, H.F. Becker C. Vogelmeier	Limitation that all sleep stage scoring is done in 30 second epochs. This may influence the properties of the duration distributions. Therefore we made an additional test using 10 second epochs for some subjects. But even using this short segments we	In this paper ,transitions using a statistical approach are evaluated. Transitions detected differences in the sleep stages and wake states during sleep. This difference is useful to investigate normal people and patients

			still found the same properties: exponential distribution for all sleep stages and power law distribution for the wake states.	with sleep apnea .And finally these differences were investigated in different species.

Paper propose the first facial depth map based sleep apnea detection. Patients dataset is small, to overcome this limitation took advantage of transfer learning. Paper analyze three pre-trained models and among them, VGGface performs the best. This method shows comparable performances to the state-of-the-art results in terms of getting prediction straight from depth facial data using end-to-end deep learning.

In this paper prediction of OSA enhanced by combining both clinical and facial measurements. Also OSA detection possible in practical using mobile devices and automatic speech and image processing.

This paper approach deal with finding relationship between surface facial dimensions and upper airway structures using magnetic resonance imaging (MRI) .

This paper approach case–control study using three-dimensional magnetic resonance imaging cephalometry. 55 apneic and 55 controls were matched for age, sex and race. The analysis was stratified by sex and controlled for age, race, height, neck visceral fat, skeletal type and tongue volume.

In this paper author proposes the approach in which single-channel electrocardiogram signals are used for monitoring patients and time-domain analysis is developed which is used to compute the sleep apnea score.

This paper analyses breathe sounds to distinguish central and obstructive events. This is the first study that distinguishes CSA from OSA with high reliability by recording breathe sound during sleep.

Paper aim to introduce an artificial intelligence methods that are used to find moderate to severe OSA patients (apnea-hypopnea index ≧15).

This paper presents the hybrid approach. Different hierarchical levels are expressed with complex hierarchical structures by combining Genetic Algorithm and Genetic Programming.

Paper proposes landmarks to generate the facial features for the purpose of prediction of OSA. Using a neural network, we show that it is possible to detect OSA without the step of calculating facial landmarks and features.

In this paper, transitions using a statistical approach are evaluated. Transitions detected differences in the sleep stages and wake states during sleep. This difference is useful to investigate normal people and patients with sleep apnea .And finally these differences were investigated in different species.

III. RESEARCH GAP IDENTIFIED

The previous system in which pose correction problem will be solved through a 3D morph able model. Hole filled depth maps will be created through an automatic procedure. This work gets good results with a very small dataset and with more 3D scans of OSA and non-OSA patients, we will enhance the performance for diagnoses[10]. The major limitation is to study used a neural network approach to detect obstructive sleep apnea that can't be handle large number of dataset. The main problem was the great number of variables and the needed number of data sets (405 patients) required for training and testing the neural network. The study also reported a poor specificity rate (80%). A. T. Balaei, K. Sutherland, P. A. Cistulli, and P. de Chazal developed approach has limitations in dealing with variations of the images (scale, pose, illumination, etc.). In the second approach, face landmarks are localized by solving the regression problem which relates the features of the training datasets and their associated landmarks. The estimated parameters are then used to detect the landmarks of the test images [18].

IV. PROPOSED METHOD

Recently, new artificial intelligence (AI) technologies, including deep neural networks (DNNs), are being increasingly used for medical diagnosis with successful results.6 For the diagnosis of OSA, AI analyses of clinical features facial photographs, oximetry, and electrocardiogram data11 have been proposed. A few studies have applied machine learning to acoustic analyses for the diagnosis of OSA.

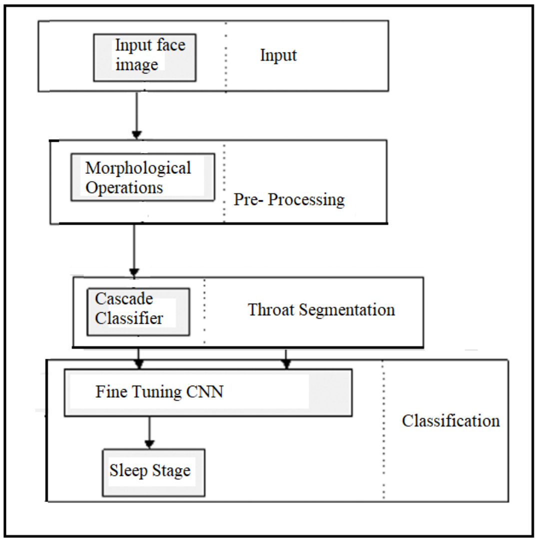

Fig.1: block diagram of proposed system

In proposed system Pre-processing is used to improve image data which is taken as input also Pre-processing suppresses unwanted distortions or enhances some image features which are important for further processing. In Pre-processing different morphological operations are takes place: 1)Dilation which makes object more visible and fills in small holes in object. 2)Erosion removes small object so that only substantive remains.

In next step cascade classifier utilizes some training data to understand how given input variable relate to the class. These classifier involve several stages that are applied subsequently to a region of interest until at some stage the region is rejected or accepted.

Convolutional Neural Network(CNN) commonly applied to analyzing visual imagery. Fine tuning is used to improve accuracy of the result. It is a process to take a network model that has already been trained for particular task. It is a process of identifying to which set of categories a new observation belongs on the basis of a training set of data containing observations.

V. CONCLUSION

In this paper, Depth map of human facial scans are used to diagnose the disease using the application of deep learning techniques. As compared to the plain 2-D color image depth map will provide more information about facial morphology. 3D morphable model have some advantages because of their ability to model intrinsic properties of 3D faces. So prediction of Obstructive Sleep Apnea using the deep learning approach with the help of morphological operations results in better accuracy.

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