Detection of Obstructive Sleep Apnea with Facial recognition – A Pilot Study

A PROJECT REPORT

submitted by

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BONAFIDE CERTIFICATE

This is to certify that the project report entitled " Detection of Obstructive Sleep Apnea with Facial recognition" submitted by Gautam S Ganesh (CB.EN.U4CSE16117) in partial fulfillment of the requirements for the award of the degree Bachelor of Technology in Computer Science and Engineering is a bonafide record of the work carried out under our guidance and supervision at Department of Computer Science and Engineering, Amrita School of Engineering, Coimbatore.

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INTERNAL EXAMINER	EXTERNAL EXAMINER

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ABSTRACT

Obstructive Sleep Apnea (OSA) is one of the common sleep relation breathing disorder in which the slow symptoms produce the abnormality of the peoples who are impacted. The proposed design model focused on age variants and face landmark variations. The impact of sleep apnea creates random changes in the facial features. The test inputs are collected from the clinical data from known sources. The subjects are insisted to take facial photographs at different lightings. The training dataset is created from the original facial data. An efficient MATLAB model is created in which the obtained images are labeled. The training dataset is then used in a feature extraction algorithm by which designated and intended features are extracted from the training image. In the proposed system the extracted features vectors are learned by the deep learning neural network which uses the training function through a convolutional neural network. The trained model is now able to identify the key features that any patient must possess in order to have OSA. The testing images are then inputted in the model with the activation function being the presence of the key features identified. Some of these key features are the distances between eyes, nose and cheek. Hence the model evaluates the patients for the unknown samples to predict the patient's status for presence of OSA or not. The system is then next evaluated on its performance by creating a performance matrix and measuring the accuracy, precision and recall. The output derived contained 98% accuracy, 96% precision and a 92% recall when the skewness was in favor of the apnea positive patients. When the skewness was reversed the output was 65% accuracy, 61% precision and 71% recall.

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CHAPTER 1

INTRODUCTION

1.1 Introduction to OSA

Obstructive Sleep Apnea (OSA) is the most common sleep-related breathing disorder. It is characterized by snoring and repetitive upper airway collapse resulting in oxygen desaturation, sleep fragmentation, nocturnal catecholamine surges, intrathoracic pressure swings, and excessive daytime sleepiness. [1]The 'gold standard' diagnosis of OSA is via overnight polysomnography (PSG), a labor intensive and expensive assessment method often available only in major medical centers. It is estimated that only 10% of the population with OSA are currently diagnosed. [2] Simple, cost-effective, and more accessible assessments for OSA are therefore required. Soft tissue and craniofacial structures have been shown to differ between individuals with and without OSA. For example, MRI and CT studies have shown that patients with OSA tend to have a larger tongue, higher soft palate, [3] more crowded posterior airway, [4] a retruded mandible, [5-7] and a more inferiorly placed hyoid bone [8,9] in comparison to individuals without OSA. Presumably, these changes predispose the upper airway to cause obstruction during sleep. While such MRI- and CT-based measurements provide valuable information on the anatomical factors that predispose individuals to OSA, they are unsuitable for routine clinical use, due to radiation exposure, costs involved, and/or limited access.

Photography of the face is a simple, convenient, safe, and easily accessible method to obtain information on craniofacial structure. Studies in Caucasian populations use craniofacial photogrammetry-derived measurements of face width, cervicomental angle, and mandibular length, together with Mallampati scoring; have been able to identify individuals at high risk of OSA. [10] Ethnicity modifies the precise combination of measurements that best characterize patients with OSA. For example, [11] showed that Asians from Hong Kong and Vancouver differed from Caucasians in Mallampati score, thyromental distance, and thyromental angle, while an Iranian study reported mandibular width to be the only craniofacial measure associated with

OSA severity. [12] In India, the reported prevalence of OSA ranges from 9.313 to 30%; [14] however, the craniofacial features that predict OSA in an Indian population are yet to be defined.

Obstructive Sleep Apnea is present when the airway at the back of the mouth repeatedly partly or completely obstructs during sleep. The breathing is reduced or may stop altogether. The oxygen level then falls and you wake up briefly to start breathing again. These episodes may happen many times across a night. Some people know that their breathing is not normal all night, but may be unaware that they have a problem. Fortunately, good treatments are available and help patients to lead a normal, active life.

1.2 Available Identification Techniques

While the available techniques (cephalometry, computed tomography [CT] and magnetic resonance imaging [MRI]) for craniofacial assessment allow detailed examination of bony and soft tissue structures, they are generally limited to research applications due to their expense, time-consuming analyses and/ or radiation exposure. Craniofacial anthropometry and photogrammetric are alternative craniofacial assessment techniques that have the advantages of being noninvasive and readily accessible. Furthermore, they allow quantification of the surface morphology which is generally not achievable with the other imaging modalities. Craniofacial photogrammetric, involving measurements from photographs, has been applied in the assessment of subjects with craniofacial anomalies. Application of photogrammetric to examine subjects with OSA may reveal new insights in the craniofacial morphological phenotype of this condition

1.3 Symptoms

If the patient has sleep apnea he/she may snore, toss and turn and/or stop breathing during the night. The patient's partner in bed is usually the one who notices this. He/ She may complain of waking up during the night gasping and choking. In the morning, the individual may still feel tired. As the day goes on, the individual may struggle to stay awake, especially in the afternoon.

Snoring can keep the individual's bed partner awake. Some partners try to stay awake to make sure that their partner with sleep apnea starts breathing again every time that they stop. Lack of sleep puts a strain on a relationship there is strong evidence that people with moderate to severe sleep apnea die prematurely. If a person has sleep apnea he/she is more likely to have cardiovascular disease than someone without sleep apnea. With each apnea the blood pressure may rise and heart beat becomes irregular. This may lead to daytime high blood pressure (hypertension). If the person is overweight he/she may also be at risk of diabetes and have high cholesterol. Taken together these risks will increase the chance of a heart attack or a stroke. Treating sleep apnea eliminates one of these risks.

People with sleep apnea are at least four times more likely to have a motor vehicle accident than others. The broken night-time sleep leads to less concentration and more chance of falling asleep at the wheel. If the patient's job involves operating machinery or transport the risk of accidents becomes high. Similarly for a person with OSA between the nose or mouth and the lungs becomes partly or fully blocked. Part of the problem is that the airway muscles relax when the patient sleeps. Central apnea is uncommon and is due to problems with the signals from the brain instructing to breathe.

Sleep apnea can occur at any age. In children apnea is often the result of enlarged tonsils or adenoids or of some problem with airway structures. In adults, apnea is more common in middle age. It is more common in men than in women, although after menopause women may be more at risk. Sleep apnea is often associated with being overweight and thus having more fatty tissue around the neck. Others are born with a narrow airway or have a facial structure which leads to narrow airways. Almost everyone who has obstructive sleep apnea snores. This is because snoring is the result of narrow or floppy upper airways.

Signs and symptoms such as snoring, obesity, observed apneas and sleepiness in the day may suggest that a person has sleep apnea. The best way to be really sure is with an Overnight Sleep Study. This measures the sleep, breathing and oxygen levels.

Sleep apnea may involve many episodes of disrupted breathing overnight with more than 30 partial or complete obstructions an hour in more severe cases.

The treatment of choice for obstructive sleep apnea is called nasal Continuous Positive Airway Pressure (CPAP). This involves a pump that provides air under gentle pressure to a mask that covers your nose. This provides pneumatic splint to the throat which holds it open through an air cushion effect. CPAP can be used only during bedtime. It is almost always very good in controlling the symptoms and the long term effects of sleep apnea. It stops the snoring and the machine noise is much quieter than the snoring was. Surgical treatments may not be effective in everyone and may have side effects. Devices that fit between the teeth and hold the jaw forward may help but these may not work for everyone .As yet there is no effective drug for treating sleep apnea. A number of other remedies have been marketed but none have been shown to be effective.

1.4 Introduction to Craniofacial Photogrammetry

Frontal and profile digital photographs of the head and neck were obtained with a standardized setup. A single-lens reflex digital camera (D70 with 18-70 mm lens and external flash unit SB-29s; Nikon Corp., Japan) was mounted on a tripod at a distance of 160 cm from the subject alignment plane. Standardized camera settings (focal length 70 mm, aperture 7.1, and shutter speed 1/100th, ISO 400) were used to ensure consistency of the JPEG images (resolution 3008 by 2000 pixels). Subjects were photographed standing upright while assuming the natural head position. Prior to the photographs, certain bony and cartilaginous landmarks were pre-identified on the subjects by palpation and marked with a white tape. Standardized methods were used to align subjects for the photographs. For the frontal photograph, the subject's facial landmark nation was aligned along the subject alignment plane while ensuring both ears were seen equally from the front. For the profile photograph, the subject was instructed to turn 90 degrees to the left after the frontal photograph was taken. This was aided by a laser pointer head-clip and calibrated markings on the side wall to ensure the profile views were perpendicular to the frontal views. The subject's mid-sagittal plane was aligned to the subject alignment plane.

Using image analysis software (Image J v1.36, NIH, Bethesda, MD), the photographs were examined for landmark digitization. Craniofacial landmarks of interest were captured as pixel coordinates (x, y) of the image which were then transferred to a custom-programmed spreadsheet for the computation of linear, angular, area, and polyhedral volume measurements. Pixel measurements were converted to metric dimensions (52 pixels/ cm). In this study, a total of 71 craniofacial measurements were computed using this photogrammetry technique. These measurements represented the dimensions and relationships of the various craniofacial regions including the face, mandible, maxilla, eyes, nose, head, and neck. Technique validation (landmark digitization accuracy and test-retest reliability) was performed in a subgroup of subjects.

1.5 Anthropometry

Height was measured by a wall-mounted stadiometer (±0.1 cm). Subjects were weighed using an analogue scale (±0.5 kg) with minimal clothing. Neck circumference was measured with a tape measure (±0.5 cm) at the level of the cricothyroid membrane. Waist circumference was measured at the level of the ischial tuberosities with the subject in the standing position. Body mass index (BMI) was calculated with the formula of weight (kg) divided by height squared (m2).

1.6 Polysomnography

Diagnostic Polysomnography (PSG) was performed in accordance with previous studies and recommendations as in [19, 20]. Sleep staging was determined using standardized definitions [21]. Apnea was defined as complete airflow cessation ≥ 10 seconds with oxygen desideration of at least 3% and/or associated with arousal. Hypopnea was defined as a reduction in amplitude of airflow or thoracoabdominal wall movement > 50% of the baseline measurement > 10 sec with an accompanying oxygen desaturation of at least 3%, and/or associated with arousals. Apnea-hypopnea index (AHI) was calculated as the total number of apneas and hypopneas per hour of sleep. Polysomnography scoring was performed by experienced accredited sleep technologists. The OSA cases were defined by AHI $\geq$ 10 events per hour. The controls were defined by an AHI < 10 events per hour.

1.7 Project Objective

The main objective of the project is to develop a tool that would detect obstructive sleep apnea by the use of facial photographs. Obstructive Sleep Apnea detection further extends the objective to develop a program that would determine facial gradients from facial images and utilize the information obtained to identify patients.

CHAPTER 2

LITERATURE SURVEY

2.1 Facial Recognition

Research on face recognition as an aspect of computer vision is significant in recent years. Face recognition is an important research problem covering numerous fields and disciplines such as bankcard identification, access control, mug shots searching, security monitoring, and surveillance system.

Facial expressions aids in understanding fundamental human behaviour that is essential for effective communications and interactions among people.

The rapid development of face recognition through computer vision/ visual imaging studies is due to a combination of factors [1]:

a. Active development of algorithms,

b. The availability of a large databases of facial images

c. A method for validating / evaluating the performance of developed face recognition algorithms

Face recognition problem can be analysed using either static (still) or video images of a scene, and identify or verify one or more persons in the scene by comparing with faces stored in database.

An incoming image is thus compared to a small number of model images of the person whose identity is validated in the database, which is the case in the recognition scenario, with every image in a significantly larger database.

In the case of an automatic authentication system, it must operate in near-real time to be acceptable to users.

In the case of recognition experiments, only images of people from the training database are presented to the system, whereas the case of an imposter is of utmost importance for authentication [2].

Face recognition starts with the detection of face patterns in sometimes cluttered scenes, proceeds by normalizing the face images to account for geometrical and illumination changes, possibly using information about the location and appearance of facial landmarks, identifies the faces using appropriate classification algorithms, and post processes the results using model-based schemes and logistic feedback [2].

The application of face recognition technique can be categorized into two main parts: security application and commercial application [3]. In security applications, especially mug shot albums and video surveillance. The commercial applications range from static matching of photographs on credit cards, ATM cards, passports, driver's licenses, and photo ID to real-time matching using still images or video image sequences for access control. Each application presents different constraints in terms of processing [3].

All face recognition algorithms consistent of two major parts:

1. Face detection and normalization
2. Face identification.

Algorithms that consist of both parts are referred to as fully automatic algorithms and those that consist of only the second part are called partially automatic algorithms. Partially automatic algorithms are given a facial image and the coordinates of the centre of the eyes. Fully automatic algorithms are only given facial images.

The development of face recognition over the course of time classifies it into three types of recognition algorithms, namely frontal, profile, and view tolerant recognition, depending on the kind of images and the recognition algorithms.

While frontal recognition certainly is the classical approach, view-tolerant algorithms usually perform recognition in a more complex fashion by considering some of the underlying physics, geometry, and statistics. Profile schemes as stand-alone systems have a rather marginal significance for identification. However, they are very practical either for fast coarse pre-searches of large face database to reduce the computational load for the next sophisticated algorithm, or as part of a hybrid recognition scheme.

Another way to categorize face recognition techniques is to consider whether they are based on models or exemplars. Models are used to compute the Quotient Image, and to derive their Active Appearance Model. These models capture class information (the class face), and provide strong constraints when dealing with appearance variation. At the other extreme, exemplars may also be used for recognition [4].

Recently, a way of combining models and exemplars for face recognition was proposed, in which, models are used to synthesize additional training images, which can then be used as exemplars in the learning stage of a face recognition system.

Face recognition is also performed by independently matching templates of three facial regions (eyes, nose and mouth). The configuration of the components during classification was unconstrained since the system did not include a geometrical model of the face. A similar approach with an additional alignment stage was proposed [5].

Face recognition research still face challenge in some specific domains such as pose and illumination changes. Although numerous methods have been proposed to solve such problems and have solved and demonstrated positive results, the difficulties still remain. For these reasons, the matching performance in current automatic face recognition is relatively poor compared to that achieved in fingerprint and iris matching, yet it may be the only available measuring tool for an application. Error rates of 2-25% are typical. It is effective if combined with other biometric measurements. Current systems work very well whenever the test image to be recognized is captured under conditions similar to those of the training images. However, they are not robust enough if there is variation between test and training images. Changes in incident illumination, head pose, facial expression, and hairstyle (include facial hair), cosmetics (including eyewear) and age, all confound the best systems today.

Facial recognition is also used in medicine in a multitude of ways. FRT, short for Facial Recognition Technology, is a method used to identify a person based on their specific facial features like bone structure and skin texture. Its functional algorithm relies on existing databases which it dives into to compare those features in order to output a result.

Such software has been in use to identify law offenders or to visualize how missing children might look like as adults but not really in the healthcare sector until recently. This is because with time FRT became more sophisticated (due to the presence of larger database of faces) and, and is now becoming increasingly attractive in medicine thanks to the numerous ways it can be implemented in this sector from cutting down on paperwork to helping physicians in diagnosis [6].

A future prospect in this field is the Smart Mirror: By combining FRT into a seemingly simple mirror with a built-in camera and existing technologies like SkinVision's skin analysis and Nuralogix's transdermal optical imaging technique to measure blood pressure and stress level, a quick scan can reveal a lot by simply looking at your own reflection [4].

Real-time emotion detection is yet another valuable application of face recognition in healthcare. It can be used to detect several emotions patients exhibit during their stay in the facility and analyse the data so as to determine how they are feeling. The results of the analysis may help identify where the patients need more attention in case they're in pain or sad.

Hospitals can also use face recognition technology to detect patterns that entail overall statistics around visitors and patients based on gender and age. This system can help the facility track patients without using physical tracking devices. This can come in handy to locate patients within a nursing home or in outpatient assisted living facilities. Face recognition has been proven efficient for security among other uses. It’s now slowly gaining momentum in healthcare facilities to track patients and keep their records safe without mismatching. Biometric facial recognition is very useful when it comes to visitors’ authentication, which can help secure the facility and prevent patient fraud [7].

2.2 Obstructive Sleep Apnea

One third of everybody’s life is spent on sleep. Despite the high prevalence of sleep disorders in the population and primary care settings. Sleep complaints are often under addressed by physicians.

Sleep Apnea is a condition in which absence of spontaneous breath occurs for more than 10 seconds during sleep. Sleep apnea is classified into 3 types:

- Obstructive sleep apnea(occlusion of the airway)
- Central sleep apnea(absence of respiratory effort)
- Mixed sleep apnea(combination of these factors)

Obstructive sleep apnea (OSA) is sleep related breathing disorder associated with snoring, repetitive upper airway collapse during sleep leading to oxygen desaturation and sleep fragmentation, nocturnal catecholamine surges, intra-thoracic pressure swings, and excessive daytime sleepiness. Obstructive Sleep Apnea Syndrome (OSAS) is defined as coexistence of excessive daytime sleepiness with at least five obstructed breathing events (apnea or hypopnea) per hour of sleep. In India, prevalence of OSA is 9.3% in males and 4.5% in females [8].

Long term effects of untreated OSA has got a positive influence of morbidity rates. OSA on long run leads to impaired glucose iterance, type-II diabetes mellitus, depression, uncontrolled hypertension, acute coronary syndrome, cardiac arrhythmias mostly atrial fibrillation, heart failure, sudden cardiac death and stroke [9].

2.3 Diagnosis of OSA

The gold standard for the diagnosis of OSA is overnight polysomnography which records electroencephalography (EEG), electrooculography (EOG), surface electromyography (EMG), electrocardiography, pulse oximetry, respiratory effort, end tidal or transcutaneous CO2, sound recordings to measure snoring and surface EMG monitoring of limb muscles (to detect limb movements, periodic or other) [10]. This is very expensive and availability of sleep labs is also limited. Due to the need of consultant and specialist in sleep medicine, sleep technologist, call for the overnight polysomnography as the diagnostic test for OSA is to tedious process. In India the scenario is even worse. The sufferers hardly care about their symptoms due to ignorance. Hence most of the OSA cases remain hidden in the community. Hence, there is acute need for a cheaper and non-invasive method to improve recognition and diagnosis of OSA in the community.

2.4 Obstructive Sleep Apnea and Facial Features

Patients with OSA manifest a continuum of irregularities of craniofacial anthropometry which leads to upper airway obstruction during sleep. Restriction of hard-tissue dimensions and enlargement of upper-airway soft tissue are both likely to compromise upper-airway space, resulting in a smaller and more collapsible airway. A small and shallow mandible is an independent risk factor for OSA in male but not in female. Mid face length was shorter and upper lip to mid plane length was longer significantly in the OSA patients. Significant difference in maxillary and mandibular length was found in the OSA patients when compared to non OSA [11].

Cephalometric method is a novel method using two dimensional assessment of the three dimensional craniofacial bony structure. It has been proven to be an efficient in the diagnosis of OSA. In [12], the study of craniofacial measurement like mandibular measurements, assessment of the facial profile, making a decision rule for the diagnosis of OSA was done. [13] has done an extensive study on the predictors of OSA through craniofacial photogrammetry. These measurements represented the dimensions and relationships of the various craniofacial regions including the face, mandible, maxilla, eyes, nose, head and neck. Perusal of literature has shown that there is an article from Indian population using manual analysis of facial photographs in the detection of OSA [14].

2.5 Lacuna

Facial features vary with ethnicity. Hence data from other populations cannot be used in our country. Perusal of literature shows dearth of such simplistic method development using facial features in our country which probably would be very useful in the early detection of OSA.

2.6 Impact of OSA on Economy

OSA is recognized as a major public health issue with potential social consequence: accidents, increased morbidity and cognitive deficits impairing work efficiency [14]. OSA lead on to loss in productivity due to premature workforce separation and mortality, absenteeism. OSA imposes a burden that extends beyond health care system and broader economic costs. Hence there is an imperative need in simplistic detection tool suitable for our Indian population.

CHAPTER 3

SYSTEM ARCHITECTURE

3.1 Block Diagram

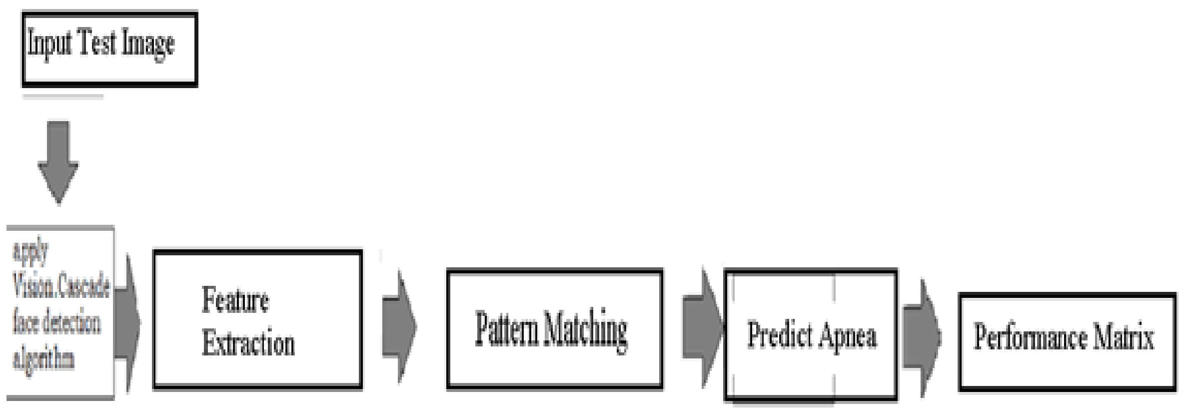


Fig 1 : Architecture Diagram

In this model (Fig 1), initially obtain the images that is to be used for the testing and training of the model. Once the input images are collected it is then further split into testing images and training images. This procedure is done in accordance to a 70-30% split between testing and training. Once the images have been classified into testing and training the Viola-Jones algorithm is applied, this is used for the face detection algorithm, this process then further extends to feature extraction. In the feature extraction step, the model utilizes the iBUG-300W dataset in order to train the model for gradient plotting and to mark the essential points required for the further calculations. Once the features have been extracted, and then move into pattern matching step, in which the model is to use the gradients for the creation of input vectors that contain the distances between points that are identified to have the greatest influence on the model. This is identified by the use of Haar features, an extension of the Viola-Jones algorithm. The process is made very efficient by the addition of Ada boost technique by which careful selection of the features that have the greatest importance to the overall objective are considered. Once this is done and has successfully created the input vectors it is passed to obtained results to a CNN model that contains 5 convolution layers and 3 pooling layers. This enables to model to compute the information more quickly and accurately. The activation functions for the model are the features that have been extracted in the previous steps, those which possess the greatest impact on the model. Through this process the model is successfully able to identify the patients and classify them based on the presence of Sleep Apnea. Once a model is complete one is to evaluate it, thus evaluate the given classification model by the use of a confusion matrix which is then further extended and utilized to find the accuracy, precision and recall. In this project an addition of the inbuilt MATLAB functions to create error histograms, and calculate a gradient against the number of epochs are utilized. In order to further evaluate the model, proceed to change the skewness of the input, this is done by changing the number of input images of patients that have apnea to patients that do not possess apnea.

CHAPTER 4

METHODOLOGY

4.1 Introduction

The model aims on detecting the presence of apnea in patients by utilizing only the individual's photograph. The procedure by which one can achieve this is through three steps namely:-

4.1 Face Detection

4.2 Feature Extraction

4.3 Deep learning analysis & Prediction

By completing the above mentioned steps, a result as to the presence of sleep apnea is present or not in the patient is obtained.

4.2 Face Detection

The Viola-Jones algorithm is a widely used mechanism for object detection. The main property of this algorithm is that training is slow, but detection is fast. The efficiency of the Viola-Jones algorithm can be significantly increased by first generating the integral image. Traditional algorithms involving face recognition work by identifying facial features by extracting features, or landmarks, from the image of the face. For example, to extract facial features, an algorithm may analyze the shape and size of the eyes, the size of nose, and its relative position with the eyes.

The problem to be solved is detection of faces in an image. A human can do this easily, but a computer needs precise instructions and constraints.

To make the task more manageable, Viola–Jones requires full view frontal upright faces. Thus in order to be detected, the entire face must point towards the camera and should not be tilted to either side.

While it seems these constraints could diminish the algorithm's utility somewhat, because the detection step is most often followed by a recognition step, in practice these limits on pose are quite acceptable.

IBUG- 300w data set is used for facial landmark localization.

4.2.1 Introduction to Viola-Jones Algorithm

The Viola-Jones Algorithm has four stages:

- Haar Feature Selection
- Creating an Integral Image
- Adaboost Training
- Cascading Classifiers

All humans possess certain identical properties. These are identified and noted by the haar features. Some of them include darker region under eyes and difference of colour when compared with the cheeks.

Haar features takes into account the features as rectangles, these are segregated into 2, 3, 4 – rectangle features. These features are then matched in order to obtain a shape or a feature such as cheeks or chin for example.

The learning algorithm then subsequently shrinks the image to a 24*24 image to look for trained features within the image. The model utilizes an ada-boost in order to speed up the classification and thus selecting the best features and to train classifiers to utilize them.

$h(x)=\mathrm{sgn}\left(\sum^{M}{}_{j=1}\ \alpha_j h_j(x)\right)$ (x^i,y^i). If image i is a face $y^i=1$, if not $y^i= -1$ The threshold value Θ_j and the polarity s_j ±1 are determined in the training , s well as the coeffectients $a_{j.}$

1. Initialization: assign a weight $w^i_1 = 1/N$ to each image i.

2. For each feature F_i With $j = 1,\ldots,M$

a. Renormalize the weight such that they sum to one.

b. Apply the feature to each image in the training set, then find the optimal threshold and polarity Θ_j , s_j that minimizes the weight classification error. That is

$\Theta_j s_j =$ arg min $\sum^N_{i=1} w_j^i E_j^i$

Where $E^i_j = \begin{cases} 0 \text{ if } y^i = h_j(x^i , \Theta_j , s_j) \\ 1 \text{ otherwise} \end{cases}$

3. Assign a weight a_j to h_j that is inversely proportional to the error rate in this way best classifiers are considered more.

4. The weights for the next iteration, i.e. w^i_{j+1} Are reduced for the images I that were correctly classified.

4.2.2 Algorithm Framework

A simple framework for the learning algorithm is given below.

- f = the maximum acceptable false positive rate per layer.
- d = the minimum acceptable detection rate per layer.
- Ftarget = target overall false positive rate.
- P = set of positive examples.
- N = set of negative examples.

F(0) = 1.0 ; D(0) = 1.0 ; I =0;

While f(i) > Ftarget

Increase I;

n(i) = 0; F(i) = F(i-1);

While F(i) > f x F(i-1)

Increase n(i)

Use P and N to train a classifier with n(i) features using Ada boost. Evaluate current cascaded classifier on validation set to determine F(i) and D(i). decrease threshold for the ith classifier (i.e. how many weak classifiers need to accept for strong classifier to accept)) until the current cascaded classifier has a detection rate of at least d x D(i-1) (this also affects F(i))

N = 0

If F(i) > target then

Evaluate the current cascaded detector on the set of non-face images and put any false detection into set N

4.3 Feature Extraction

Facial landmark features are locations which act as important points of the facial vectors. These locations are trained through various test images and average value is being accumulated with the MAT file loaded. The database file for extracting the features is loaded initially.

This process is divided into multiple steps:-

4.3.1 Landmark Creation

A shape predictor attempts to localize key points of interest along the shape (Fig 2).

Fig 2 : Landmark creation using shape predictor

4.3.2 Gradient Creation

Using the facial landmark the model establishes gradients (Fig 3). These annotations are part of the 68 point iBUG 300-W dataset which the dlib facial landmark predictor was trained on.

Fig 3: Gradient creation using iBUG 300-W dataset

4.3.3 Canonicalizing

Using this format the model localizes the necessary features that are required: Eyes, Eyebrows, Nose, Mouth, and Jawline (Fig 4)

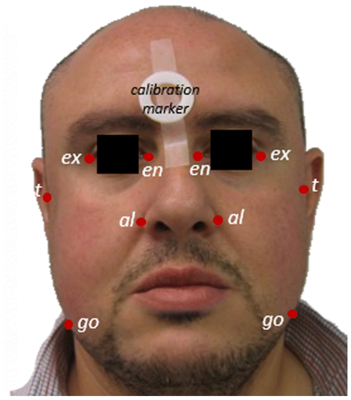


Fig 4: Localizing key features

4.3.4 Pixel Count

Count of pixels from one destination to another thereby computing the approximate distance features.

4.4 Deep Learning Analysis and Prediction

4.4.1 Introduction to the Model

This module compare the existing input cumulative distances with the database features and configure the pattern matching analysis for 10 hidden layers and 100 input vectors at a time frame. The resultant prediction provides good accuracy and precision recall. For the classification of normal subjects and sleep apnea affected subjects.

4.4.2 Neural Network

Than a traditional approach of a back propagation, the use a CNN (Convolutional Neural Networks) was taken. This module compare the existing input cumulative distances with the database features configure the pattern matching analysis for 10 hidden layers and 100 input vectors at a time frame (Fig 5)/ The resultant prediction provides good accuracy and precision recall. For the classification of normal subjects and sleep apnea affected subjects. A total of 3 pooling layers are used in order to further improve and get a better result through the CNN network. The CNN once the input vectors are fed to the system a common activation function as the features that gives us the sign for the presence of OSA is given at each subsequent step. Once the data is processed using the given functions the model then proceeds to classify if the individual has OSA or not from the overall operation. Once it has been classified the model then prints the output that if the patient has OSA or not.

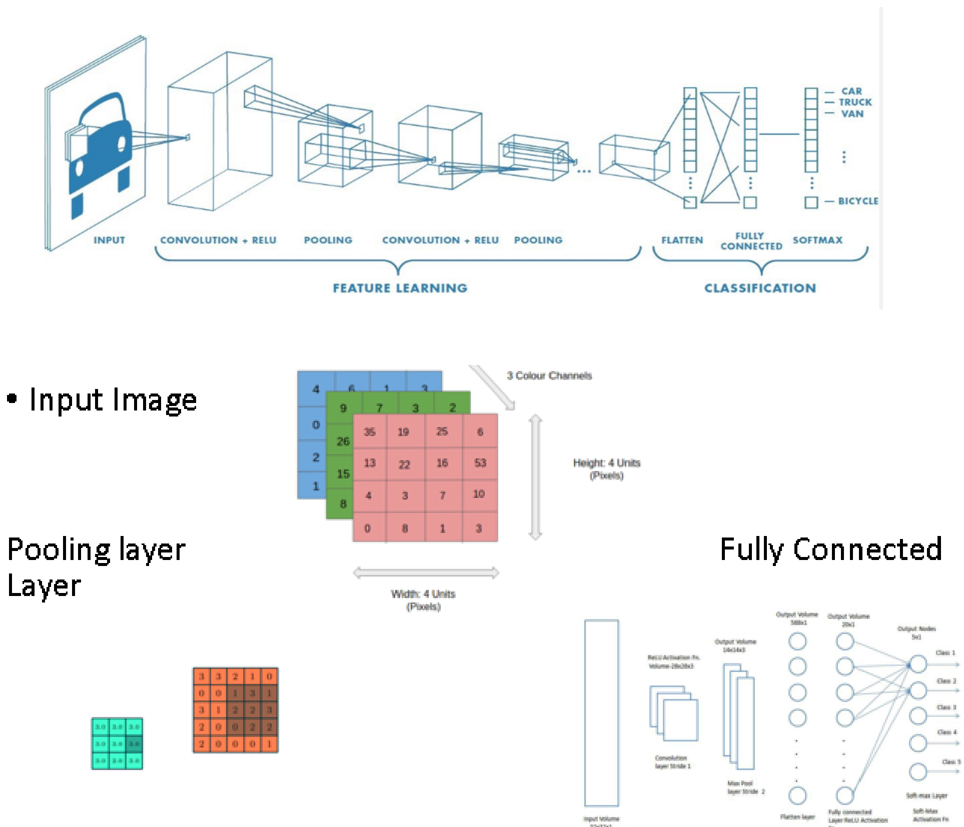


Fig 5: Schematic representation of neural network of CNN

4.4.3 Why CNN?

The reason to why the use CNN in this case is due to the fact that: the convolutional layer uses a convolutional operation on the input. Due to this convolutional operation, the network can be much deeper but with much fewer parameters. Due to this ability, convolutional neural networks show very effective results in image and video recognition, natural language processing, and recommender systems. Evaluating the model’s performance. Let’s say you have 100 examples in your dataset, and you’ve fed each one to your model and received a classification. The predicted vs. actual classification can be charted in a table called a confusion matrix .The model is also experimented by changing the skewness on our data set by increased the number of non-apnea patients to the apnea patients.

CHAPTER 5

RESULTS

5.1 Result

Thus from the model have successfully created a prototype that takes into account a person's face and thus thereby converting the inputs derived to vectors, these vectors are then converted to inputs for neural networks which can identify patients with and without sleep apnea. We also tested for skewness in the dataset i.e. I changed the number of non-apnea patients with the apnea patients thus changing the skewness of the data. We were able to observe a drastic difference in the accuracy, precision and recall parameters when taken into account. We were also able to distinguish and identify the different parts of the face such as nose, eyes and cheeks using the Viola-Jones algorithm.

5.2 Simulation Result

TEST INPUT

FACE DETECTED

Fig 6: Image of Test input

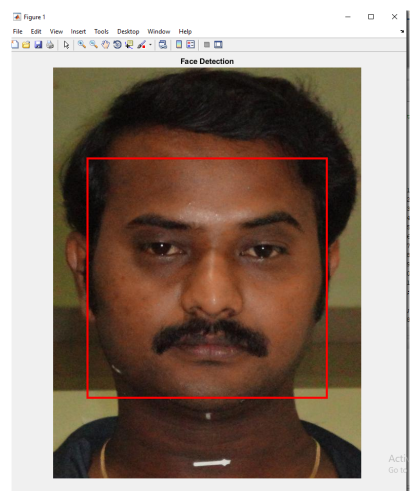
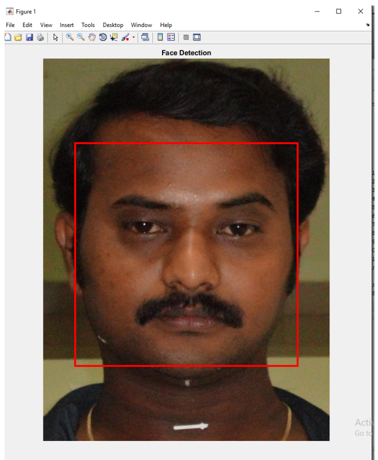


Fig 7: Face detected on the input image

-

Initially detection of the face from the given input image (Fig 6), this is done using a basic usage of Haar feature detection thus we are able to segregate the face from the input image (Fig 7).

FACE DETECTED



NOSE DETECTION

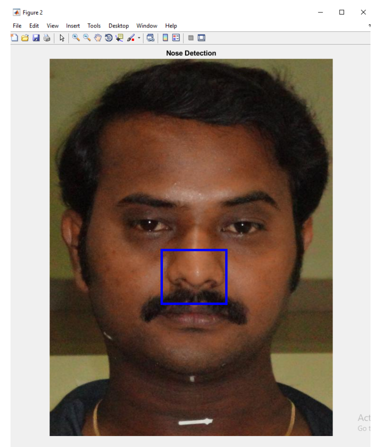
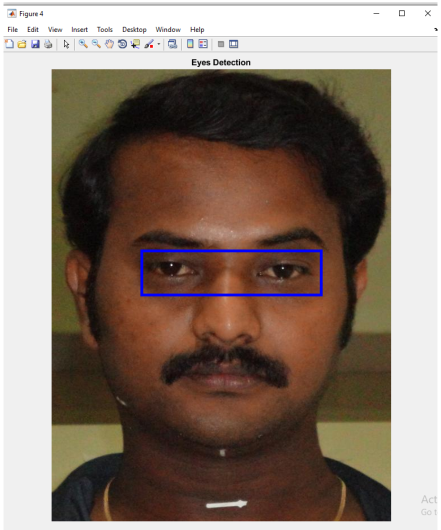


Fig 8: Detection of the nose in the input image

Further processing when done on the face segment, on apply the viola-jones algorithm to its fullest potential to obtain segments of the desired parts of the face such as nose (Fig 8), eyes (Fig 9). Using the above algorithm we are able to locate and identify the required and important features (Fig 10). From this we can frame input vectors that can be used to search for identification for presence of Obstructive Sleep Apnea.

EYE DETECTION

LANDMARK DETECTED



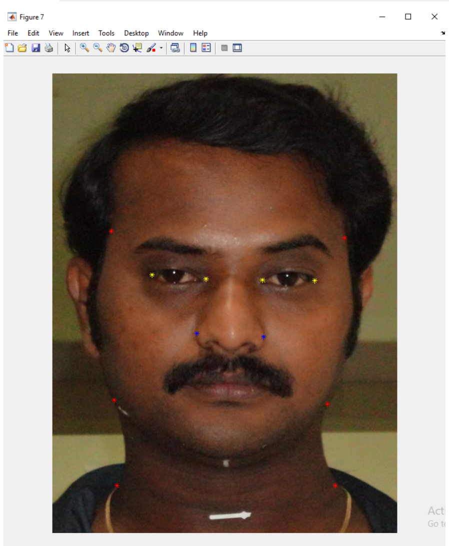
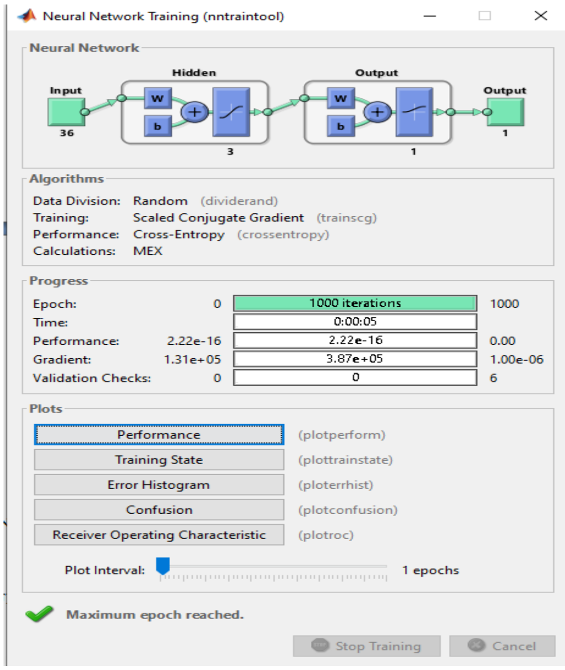


Fig 9: Eye detected on the input image

Fig 10: Various landmarks detected and marked on the input image

The Input vectors obtained after the application of Viola-Jones algorithm is then fed to the neural network, this is done with the help of MATLAB and its supporting tools of Neural Network (Fig 11). Once vectors have been inputted to the system the users are able to determine/identify if a person has Sleep Apnea or not. Evaluation takes place over 1000 epoches and has a performance value of 2.22e-16 for value ‘c’. the time taken for the system to completely run is 0:00:25sec.

NEURAL NETWORK PROCESSING PREDICTION RESULT



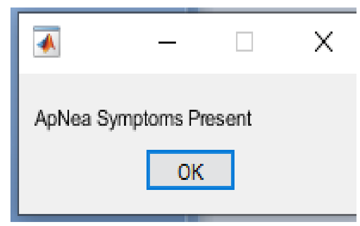


Fig 11: Screenshot of neural network process and predicted result

Once the Results have been printed an evaluation of the system is done to check how well the system performs under certain inputs, thus change in the skewness of the data, and several other performance matrices were implemented. Through this method the users are able to find out if the system is performing optimally under speculated conditions or not.

Once the evaluation methodology of ROC curves (Fig. 12) and error histogram (Fig. 13) has been determined the skewness of the input test images are changed in order to check the efficiency of the module. In the case where there are number apnea positive patients we obtained:

```
accrcy =

    98
```

```
Precisi =

    96
```

```
Recll =

    92
```

This indicated that the system works exedingly well for the cases where there are larger number of apnea positive patients when compared with apnea negative patients. When the above skewness was revereresed we obtained:

accrcy = 65

Precisi = 61

Recll = 71

This indicated that the system works poorly for the cases where there are larger number apnea negative patients when compared with apnea positive patients.

ROC CURVE

ERROR HISTOGRAM

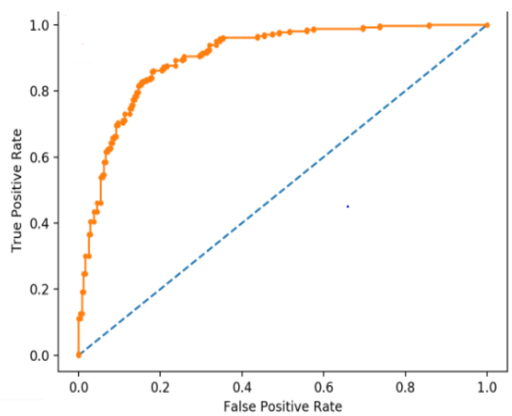


Fig 12: The Receiver Operating Curve (ROC) clearly shows the performance matrix within acceptable levels

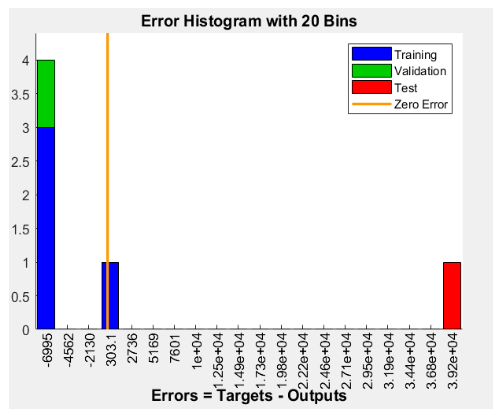


Fig 13: Error Histogram

Confusion Matrix

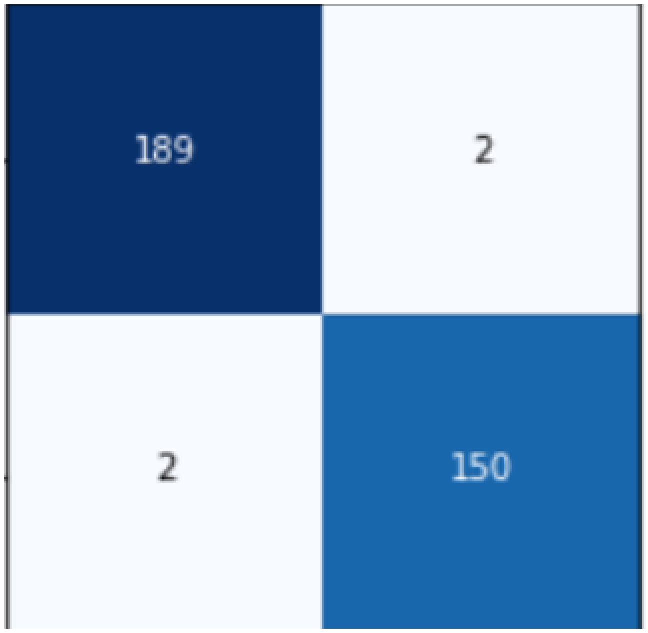


Fig 14: Confusion matrix

Gradient per Epoch

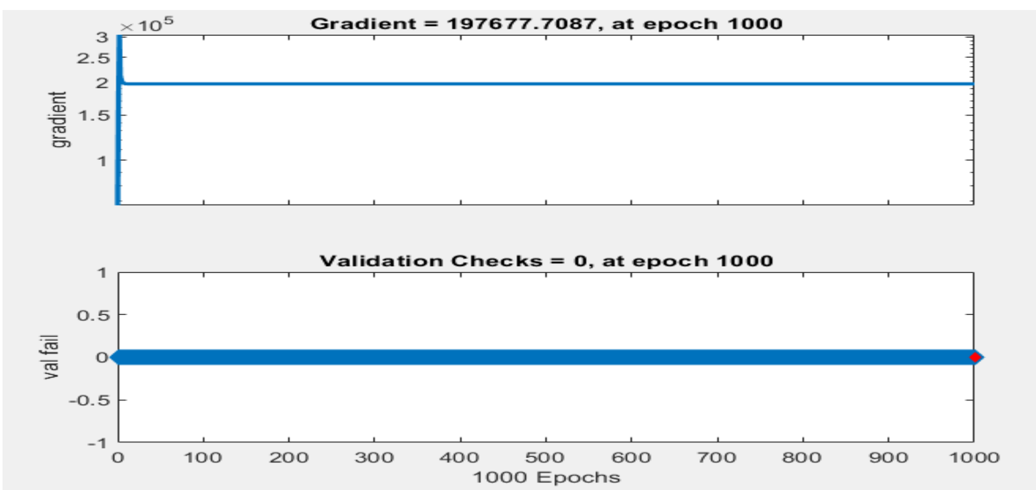


Fig 15: Gradient per Epoch

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Conclusion

From this project, it is possible to conclude the following. Facial characteristics can be utilized in order to facilitate and detect the changes, abnormalities as well as the conditions that patients possess. The model is successfully capable of extracting features from the frontal images that is provided by the user using the Viola-Jones algorithm. Important features such as eyes, nose, and lips are further segregated from the image. Landmarks are then created and displayed to the user. This process in turn allows room for the system to calculate the vectors which can be used in the CNN. The CNN is a basic model with 100 input vectors and 10 hidden layers. The procedure contains 3 pooling layers intended to bring maximum efficiency in the detection for sleep apnea. The highly intricate networking formed by the convolution layers further encodes the data thus allowing for secure storage in the model. On changing the skewness of the training dataset, the effectiveness of the current model drops significantly by 30% i.e. the model works very efficient for the case where the number of apnea positive patients is more than the apnea negative patients.

6.2 Future Work

This project is done with a sample size of 200 images and a total of 46 patients. Scope of the project could be increased by implementing a larger sample size and a greater number of volunteers for the testing of OSA.

Time complexity for the given model could be improved and made better for faster computation and more efficient results.

Another improvement that could be done on the project is the conversion to a mobile application as it would enable the free usage of the users and allow for a more wide spread awareness of such diseases and conditions.

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