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PREDICTION OF BODY MASS INDEX (BMI) USING SPEECH SIGNALS WITH WAVELET PACKET BASED FEATURES

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ABSTRACT

Adiposity nowadays is one of the most important causes which are responsible for the chronic maladies such as hypertension and diabetes and in the coming years, it is predestined to be responsible for many deaths. The body mass index (BMI) is a useful tool which is common in the field of medicine and experts of the wellbeing to determine whether the individual is underweight, normal, overweight or obese. BMI has some drawbacks in the assessment in the degree of obesity as it does not take into account the distribution of body fat, making it a skewed metric. In the recent years, researchers have started to pay attention on investigating the relationship between speech signals and BMI status. Thus, the paper reports the prediction/estimation of BMI status (normal, overweight, and obese) via speech signals using Wavelet Packet Transform (WPT) and Probabilistic Neural Network (PNN) with the omission of weight and height values. For this study, Daubechies orders of "db4", "db6", "db10" and "db20" are selected randomly. The speech signals (/ah/ sounds) are decomposed into five levels by WPT. Energy and Entropy features are calculated at various sub-bands. 10-fold cross validation technique has been implemented to examine the consistence of the classifier results. The experimental results reveal that the suggested features and classification algorithm give classification accuracy of > 87%.

Keywords: adiposity, BMI, wavelet packet transform, probabilistic neural network.

INTRODUCTION

The obesity nowadays is the major health issue which many countries around the world are encountering. Besides, the problem of overweighting has become the focus of the health experts' rather than the mal nutrition round the world. The official statistics reveal that the number of people who are obese is about 475 million compared with the people who are considered to be overweight which attain 1.5 billion among the adults (Kini, 2015). The problem of overweighting has become a rampant phenomenon even among the children and the kids who have not reached puberty and it is estimated that there are more than 200 million children who are overweight. This has impacted negatively their health and has had some consequences on them such as shortening their longevity compared with the previous generations (Deckelbaum and Williams, 2001; Reilly *et al.*, 2005). Obesity can be described as a medical phenomenon when the weight of the body increases dramatically which increases the amount of fat. The excess of the amount of fat in the body has a notorious effect on the health. Whenever there is instability of calories in the body which means that the amount we take as a form of food and nutrition fat exceeds the amount we spend then this definitely result to an extra weight which is fat. A myriad of elements are responsible for causing the problem of obesity and the imbalance of energy intake and energy spent for instance: the shift from the jobs which require brawn and physical strength to jobs that require brain and cognition, the number of people who own cars has augmented therefore they rarely walk and spend energy, electronic appliances and devices which enable people's lives and make it hassle free therefore not too much energy is consumed, idleness which

lead to abandonment of working out and less activity, over consumption of food; high calories and fat in the ingredients (Kini, 2015; Newburgh, 1931). There are other factors which contribute to the issue of obesity such as social, economic and cultural ones where the impact vary from one country to another and the discrepancies can be easily perceived (Ng *et al.,* 2014). It is highly recommended the person who has started to become obese and gain extra weight to consult a medical treatment since this issue will lead to other health complications and numerous studies have been carried out to investigate the relation between the body mass index and the diseases caused as an aftermath of this and the results were positively endorsing this theory (Pasco, Nicholson, Brennan, and Kotowicz, 2012). Quetelet index (BMI) is determined as a proxy which helps to determine the ratio of the person's weight according to his height (Muralidhara, 2007). The BMI is a useful tool which is common in the field of medicine and experts of the wellbeing to determine whether the individual is underweight, overweight or obese. BMI is a proxy and is computed by the dividing the mass of the body (Kg) by the height (in meters) power of two (Rothman, 2008). The World Health Organization has labeled overweight when the person's BMI falls within a range of 25.0 and 29.9 and if it exceeds 30 then the person is obese. When the BMI is within the interval of 18.5 and 24.9 so the person is in a state of equilibrium which means neither fat nor

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underweight but if the BMI falls less than 18.5 then the person is considered underweight (Dinsdale, Ridler, and Ells, 2011). These threshold values were agreed upon based on empirical studies and medical research which concluded that BMI is linked to maladies and early death. BMI has been proven and it has shown that it is the most useful tool to prove whether the individual is suffering from any kind of obesity (Rothman, 2008). BMI is very common in use and has many advantages such as accuracy, swiftness and efficiency; furthermore it can be used for both genders and all age categories. BMI is a vital means that enables us to evaluate the mass of the body and help to categorize its weight. It is an important tool to calculate the amount of fatness rather than just the weight and another privilege is that to be classified within the normal category, your weight does not have to be of precisely measured. BMI has some drawbacks in the assessment in the degree of obesity, for instance if a person has brawn and is physically well built then he is considered fat since he belongs to the group of the overweight but in fact he is not (Celli *et al.*, 2004; Pope, Sowers, Welch, and Albrecht, 2001). Moreover, BMI may be somehow misleading when it comes to categorizing people who have some muscular problems and they classified within the people whose weights is good. Besides, BMI is not a suitable measure and cannot be applied for people who are small in size and during the time of pregnancy. Fat in the body can cause serious implications on the health especially the hips and the thigh's fat. As a new area of interest, scientists have begun to focus and study the link between the signals that are generated by the speech and BMI status. A myriad of ways have been introduced and suggested in order to forecast the different categories of weight (normal, overweight and obese) which relies on a mixture of the characteristics of voice that are related to the BMI status. Besides, in the latest time, uncomplicated methods have been implemented by researchers for prediction of body mass index through shimmer, jitter, pitch, rate of speech, formant, HNR, PLCC and Mel frequency cepstral information (Arsikere, Leung, Lulich, and Alwan, 2013; Lee, Kim, Ku, Jang, and Kim, 2013; Lee, Ku, Jang, and Kim, 2013; Sedaaghi, 2009). From the previous review, it have been showed that many extraction features method were used to characteristics' deduction and classification algorithms were also suggested (Arsikere *et al.*, 2013; Lee, Kim, et al., 2013; Lee, Ku, *et al.*, 2013; Sedaaghi, 2009). The utilizations of Wavelet and Wavelet Packet Transform (WPT) have not been the focus of the categorization of BMI status. In fact few studies have tried to shed light on the issue using wavelet and wavelet packet transform. The use of wavelet and WPT analysis is broad, vast and varying and it is common in use when it comes to image and signal processing applications (Avci and Avci, 2008). This research which uses wavelet packet transform with energy and entropy characteristics and Probabilistic Neural Network is designed to foresee and have an early overview on the individual's BMI status when the calculations of weight and height are omitted. The /ah/ sound signals are constituted of five components. The elements of entropy and energy are calculated from the wavelet packet coefficients and are utilized to illustrate /ah/ sound signals. A probabilistic neural network has been implemented to examine the efficiency of the characteristics of wavelet packet (WP) energy and entropy. The results reveal and conclude that the characteristics of wavelet packet and PNN classifier can be of high importance help to assist the people who are in the field of medicine to forecast and foresee the BMI status.

METHODOLOGY

In this work, classification of BMI status contains of two important phases as showed in Figure-1, acoustic feature extraction and classification. By using wavelet packet transform, the speech signals (/ah/ sounds) are decomposed into five levels. Energy and entropy features are extracted at each level to describe the /ah/ sound. PNN classifier is implemented to estimate the efficiency of the entropy and energy characteristics for classifying the three BMI statuses (normal, overweight and obese). However, the researchers have used different databases for that it is difficult to liken our findings with earlier research.

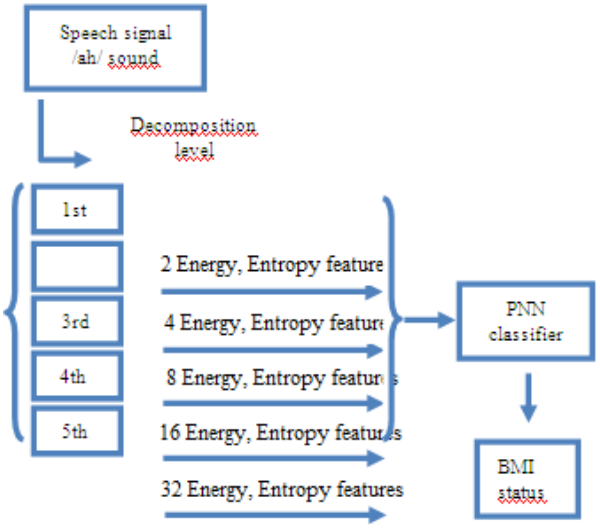

Figure-1. Scheme blocks of the feature extraction and classification stage.

DATABASE

A total of 75 people without any voice-associated problems participated in this study with ages ranging from 20 to 40 years. The clinical info of all the subjects was recorded (Table-1). Using /ah/ sound, the microphone was positioned at a distance of about 12 cm from the mouth of the subjects at the moment of recording the voice.

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Table-1. Standard deviation, mean of age and number of subjects.

Gender	Class	Number of subjects	Mean age (Std)	BMI	signal recording	Sample rate
Female	Normal	15	23.53 (2.13)	20.90±1.60	Philips LFH3500 SpeechMike Premium microphone	44 KHz
	Overweight	3	26.66 (6.35)	29.46±2.05		
	Obese	4	24.75 (4.19)	35.27±3.49		
Male	Normal	13	26.61 (3.25)	22.01±2.27		
	Overweight	18	28.77 (4.94)	27.36±1.33		
	Obese	22	28.77 (4.94)	34.86±4.68		

FEATURE EXTRACTION

During (DWT) discrete wavelet transform dissolution is in process, signal is constituted into two frequency bands such as higher and lower frequency (Paiva and Galvão, 2012; Zhang and Li, 2012). Low frequency band is utilized for more process which is related to decomposition. Thus discrete wavelet transform gives a left recursive binary tree structure. Through wavelet packet decomposition procedure, higher and lower frequency bands are decomposed into two sub-bands. Therefore WP gives a stable binary tree structure. In the tree, by the number of subspaces p and its depth i (following forms) (Hariharan, Yaacob, and Awang, 2011; Paiva and Galvão, 2012) every subspace is indexed:

$$\psi_{i+1}^{2p}(k) = \sum_{n=-\infty}^{\infty} l[n]\psi_i^{p}\left(k - 2^i n\right) \text{.....(1)}$$

l[n] is a low-pass (scaling) filter

$$\psi_{i+1}^{2p+1}(k) = \sum_{n=-\infty}^{\infty} l[n]\psi_i^{p}\left(k - 2^i n\right) \text{.....(2)}$$

Where h[n] is the high pass (wavelet) filter. WP decomposition assistances to divider the high frequency side into smaller bands which cannot be achieved by applying the general DWT (Kumbasar and Kucur, 2012; Zhang and Li, 2012). The speech signals (/ah/ sounds) are split in to five levels in this study. The number of features at the fifth level of decomposition was 32. The sampling frequency fs is 16,000 Hz. The /ah/ sounds are filters and four different orders of Daubechies wavelets “db4”, “db6”, “db10” and “db20” are used by using the WP filters. The speech signals are tested at 16 kHz giving an 8 kHz band-width signal. Due to the following characteristics, Daubechies wavelet has been chosen in this study: Fast computation, time invariance, Sharp filter transition bands (Cohen, Daubechies, and Feauveau, 1992; Hariharan *et al.*, 2011). In this work, using the extracted WP coefficients, entropy and energy are computed. Through the following Eq. (3) using the extracted WP coefficients, the sub-band energy can be calculated:

$$Energy_{\ n} = \sum_{i=1}^{n} \left| C_{n,k}^{\ p} \right|^2 \text{ ....(3)}$$

Where the number of decomposition levels is n=1, 2,…., N and k=0,1,….2^N-1 and “p” is the measure index.

Entropy can be utilized as a joint measure to quantify uneven pattern of the /ah/ sound signals. Using the extracted WP coefficients, by the following Equation (4), the measure of entropy can be calculated.

$$Entropy_{\ n} = -\sum_{i=1}^{n} \left| C_{n,k}^{\ p} \right|^2 \log \left| C_{n,k}^{\ p} \right|^2 \text{ ....(4)}$$

Where the number of decomposition levels is n=1, 2,…., N and k=0,1,….2N-1 and “p” is the measure index.

Figures 3(a), 3(b) and 3(c) show the two levels WP decomposition of the speech signals (/ah/ sounds) relating to the BMI status (normal, overweight and obese). According to the graphs, it is difficult for us to discriminate among three speech signals (/ah/ sounds) that was recorded from the normal, overweight, and obese" subjects. Therefore, to determine WP coefficients, energy and entropy are used. A feature database is created, after the calculation of entropy measures from each subband wavelet packet coefficients and used for classification purpose.

The block diagram of the feature extraction and classification stage is shown in Figure-2.

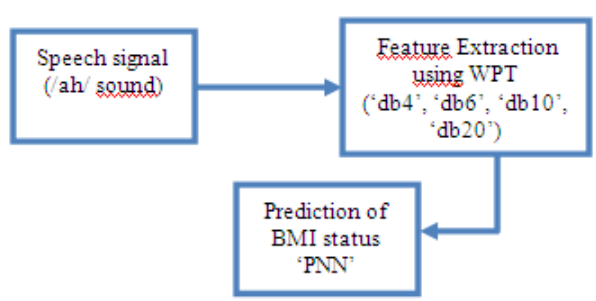

Figure-2. Feature extraction and classification stage.

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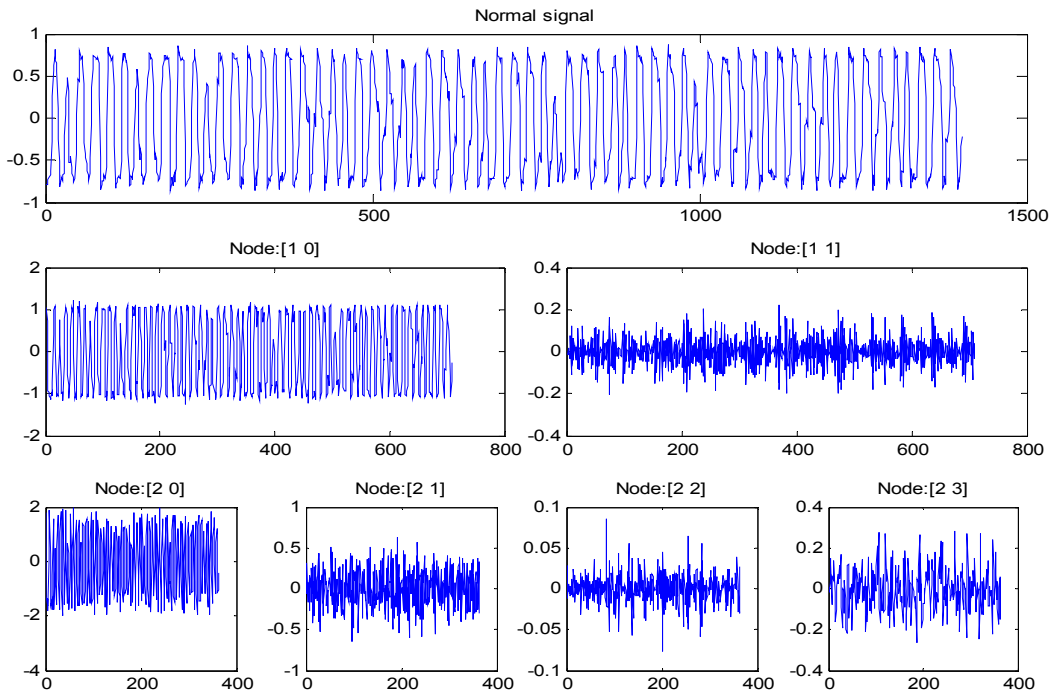

Figure-3(a). Two level WP decomposition of the /ah/ sound signal for normal class with "db10" wavelet.

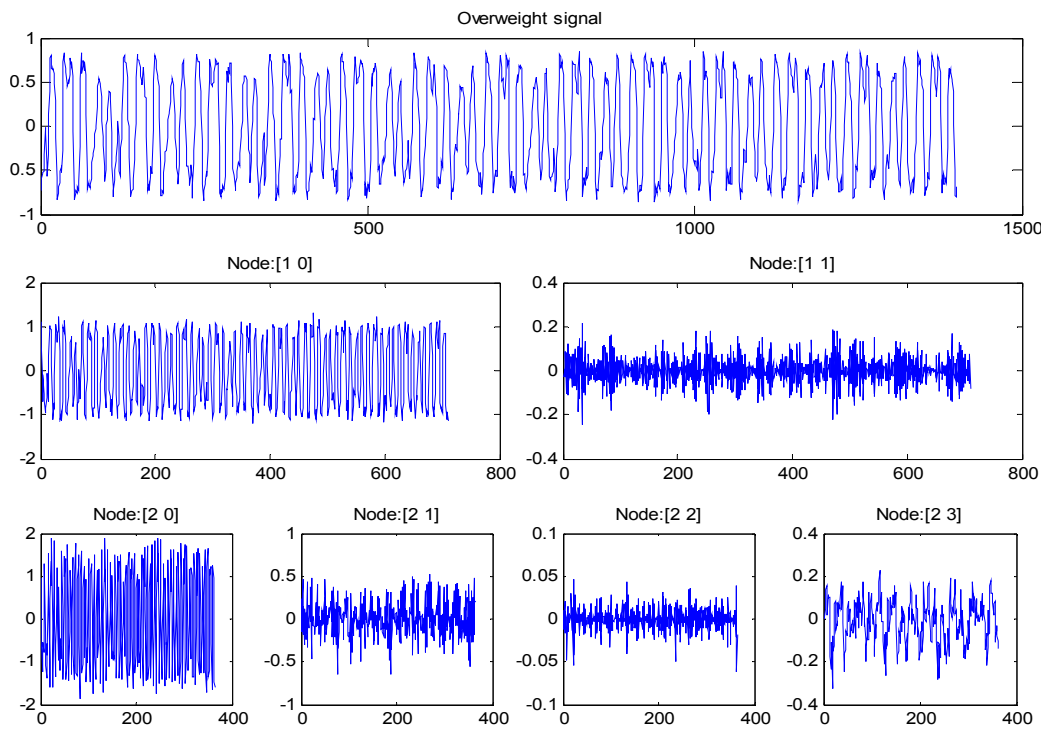

Figure-3(b). Two level WP decomposition of the /ah/ sound signal for overweight class with "db10" wavelet.

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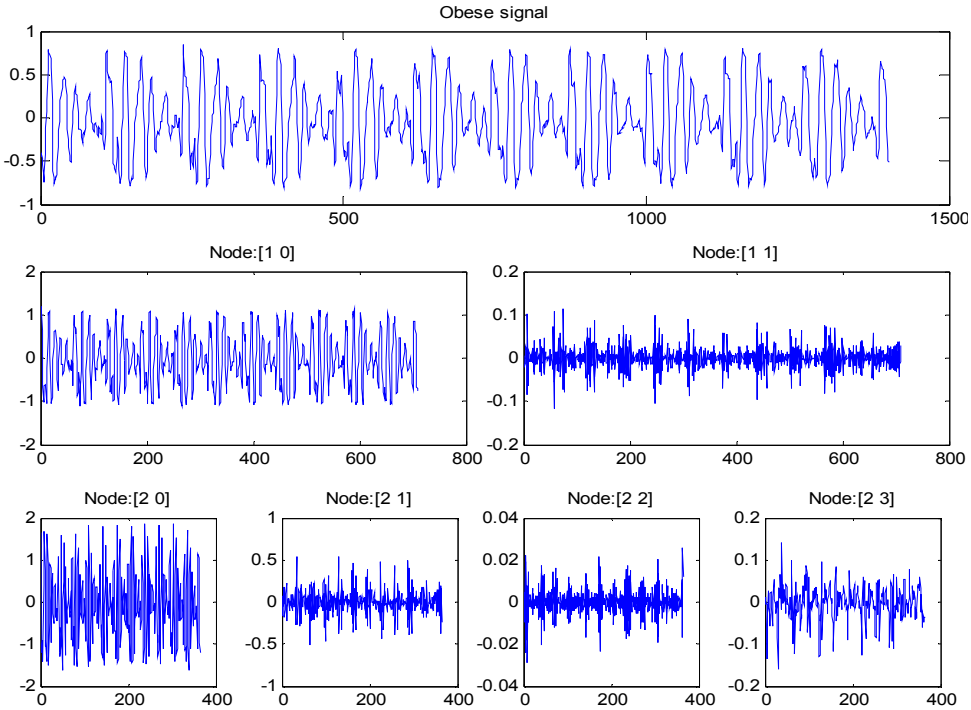

Figure-3(c). Two level WP decomposition of the /ah/ sound signal for obese class with "db10" wavelet.

CLASSIFICATION

Probabilistic neural network

The artificial neural network is one of the modern tools which are used to study the trend and the behavior of some phenomenon and to point out the issues that are being examined through the experiments carried out in different fields. The aim of our current study is to examine the impact of PNN structure on the BMI status' classification which has to deal with some medical issues such as the weight gaining. PNN can be split into four segments such as the inputs, pattern, summation and the output segment (Specht, 1990). The PNN can compute nonlinear decision boundaries by substituting the sigmoid activation function used in neural networks with an exponential purpose and a fast training process, orders of magnitude faster than back propagation which will allow inherently parallel structure, that guaranteed to converge to an optimal classifier as the size of the illustrative training set increases, a local minima issues can be avoided and at the same training samples can be supplementary or removed without extensive retraining. All these segments are highly linked and connected with each other. The pattern segment is stimulated through an exponential function rather than sigmoidal one. The segment related to pattern is responsible for the measurement of the space which separates the input vector and the training input vector. The summation segment gathers all the outputs which are dedicated to contribute and results in an output known as a vector of probabilities. These probabilities use the binary principle, the segments responsible for outputs display 1 for the concerned segment and 0 otherwise by implementing a full transfer function. The net is an efficient means that is utilized for the purpose of classification when a pattern of each of the two segments when it is introduced to it. On the other hand, PNN can be of great help whenever it is put through a myriad of examples. Varying smoothing parameter (SP) has a power on the nonlinearity of the assessment's interval of the net. The notion of decision boundary attain a hyper plane for bigger SP and for the small SP it round up the decision surface of the classifier.

RESULTS AND DISCUSSIONS

In The /ah/ sound signals are exposed to acoustic feature extraction utilizing WPT with energy and entropy features. With the database presented above, 10-fold- cross validation schemes are utilized to show the consistency of the classification results of BMI status. In the 10-fold cross validation scheme, the training is repeated 10 times and the suggested feature vectors are split haphazardly into 10 sets. The PNN is applied for classifying the BMI status. To get maximum accuracy, Smoothing parameter (SP) value was varying in PNN. Classification results of PNN for different wavelet families are showed in Table-2. Average and standard deviation of the categorization accuracies of different types of BMI status are displayed in a Table. The standard deviation of the classification obviously illustrates the reliability of the classifier results.

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Table-2 shows the results of PNN classifier for Daubechies orders "db4", "db6", "db10", and "db20" with entropy and energy features. From Table-2, the maximum classification accuracy was gotten at the fifth level of WPD. The best average classification accuracy using the PNN classifier for normal class is found to be 87.55% with less standard deviation of 1.33 for 'db10' and 'db20'. The lowest classification accuracy is 73.70% with the standard deviation of 1.33 for 'db20' using the PNN classifier for overweight class. The best overall accuracy was 80.83% for energy feature and 84.73% for entropy feature. The number of features at the fifth level of decomposition was 32. All the features were utilized to provide better representation of /ah/ sound signal. For "Daubechies orders "db4", "db6", "db10", "db20 entropy features implement better than energy features.

At the fifth level of decomposition, both the features equally perform well for "db4", "db6", "db10", and "db20".

In this paper, it can be observed from the above discussion that the highest of classification accuracy can be gotten irrespective of the different order of Daubechies wavelets. At the fifth level of wavelet decomposition, the maximum classification accuracy of 87.55% for "db10" and "db20" was gotten and it displays that the Suggested features and classification algorithm offers a good classification compared with previous research (73.8% (Lee, Ku, *et al.*, 2013)).

Table-2. BMI status classification results using PNN at every level of WP decomposition for diffident Daubechies orders "db4", "db6", "db10", "db20".

Daubechies orders	Classes	Energy features	Entropy features	Energy + Entropy features
db4	Normal	82.35±1.23	83.91±1.10	84±0.75
	overweight	73.97± 1.64	82.71± 1.49	78.14±1.19
	obese	78.25± 1.31	81.02±1.24	84.10±1.35
	Overall accuracy	78.19± 1.00	82.55± 0.70	82.08±0.60
db6	Normal	82.13±1.19	82.17± 1.14	85.33±0.99
	overweight	74.90± 1.13	77.48± 1.48	80.79±1.20
	obese	81.02± 1.16	82.92± 1.23	85.64±1.22
	Overall accuracy	79.35±0.66	80.86± 0.79	83.92±0.67
db10	Normal	84.97± 1.16	82.57±0.85	87.55±1.33
	overweight	74.76±1.36	83.77± 2.14	79.47±1.48
	obese	82.76± 1.02	83.28±1.03	85.64±0.93
	Overall accuracy	80.83± 0.73	83.21±0.83	84.22±0.73
db20	Normal	81.64±1.11	84.28± 1.17	87.55±1.12
	overweight	73.70±1.33	85.14±1.31	81.45±1.63
	obese	83.58± 0.80	84.78± 1.00	84.61±1.01
	Overall accuracy	79.64±0.63	84.73± 0.63	84.54±0.80

CONCLUSIONS

This paper presents the analysis of speech signals (/ah/ sounds) based on the Wavelet Packet Transform with energy and entropy features and PNN classifier. The /ah/ sound signals were decomposed into five levels. By using wavelet packet coefficients at every level, entropy and energy features were extracted. The impact of the proposed features was examined at each level of decomposition of /ah/ sound signals. At the fifth level of decomposition, maximum classification accuracy of 87% was acquired. The classification results indicate that the proposed approach has abilities to evaluation the BMI Status with accuracy of > 87%. To evaluate our method more studies will be implemented with larger databases.

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