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Speech under Stress: Analysis and Recognition using KNN

Bhawna Sharma[1]

bhawna190sharma@gmail.com

[1]Assistant Professor, Guru Nanak Khalsa College, Yamunanagar

ABSTRACT

This work examines how speech characteristics might be analyzed to tailor automated conversation recognition to illness diagnosis. Voice analysis, which is now performed by a skilled physician using techniques based on auditory analysis, enables the diagnosis of illnesses that impact the vocal apparatus. The suggested work offers a cutting-edge way to monitor a patient's pathology. It is stress-free to use, quick, and affordable for the physician, and safe for the patient. This technique practices a parametric methodology (jitter, shimmer, harmonic to sound, etc.) to assess the sick vocal sound. Additionally, the technique for this work rest on on the feature extraction of Mel Frequency Cepstral Coefficient (MFCC) and the feature matching of Dynamic Time Warping (DTW). This article provides a step-by-step breakdown of the speech analysis procedure used on anxious individuals. The degree of classification accuracy attained for each of the retrieved characteristics confirms that our method is effective in differentiating between stressed individuals. Thus, the speech analysis feature on the PRAAT platform has produced positive results and shown to be an effective tool for differentiating between those who are under stress and those who are not. Using MATLAB 2018b, the work displays several 2D and 3D displays of teaching and anticipated matters.

Keywords: Dynamic Time Warping, Mel Frequency Cepstral Coefficient, K nearest neighbor**,** Virtual Reality

1. INTRODUCTION

1.1 INTRODUCTION TO STRESS

Strain in the body or concentration can be triggered through a bodily, psychological, or expressive stressor. Strain is typical bodily responses to circumstances which create an individual feel scared or unbalanced [1]. The term was originally introduced by Hans Selye in 1936 to characterize "the non-specific response of the physique to somewhat request for transformation". The anxiety response, sometimes recognized as the "contest or flying or restriction" response, [2] is a quick, reflexive process that the body goes into high gear when a person perceives threat, real or imagined. Figure 1.1 demonstrates this procedure.

Figure 1.1: Fight or Flight Response

1.2 ROOT OF STRESS

Strain may be caused by a extensive variety of causes, from emotional (such as concern for your family or career) to physical (such as dread of anything unstable). Amongst the most characteristic reasons of strain are:

a) Survival Stress – Every person and every animal has a similar reaction to danger: the "fight or flight" reflex. The body instinctively releases more energy when a person fears that something or someone may physically harm them, increasing their chances of escaping the risky circumstance or surviving it altogether (flight). Stress related to survival is this.

b) Internal Stress – Some of the most important varieties of strain to realize and controller is internal tension. When someone stresses themselves out, it's called internal stress. This frequently occurs when someone puts himself in circumstances or worries about things they are powerless to control. Some people develop an obsession with the fast-paced, stressful lifestyle that comes with stress.

c) Environmental Stress - This is a reaction to stressful stimuli in their environment, such as commotion, loudness, and demands from family or the workplace. A person's strain level can be condensed through distinguishing certain conservational stressors and wisdom in what way to cope through them or evade them.

d) Fatigue and Overburden - Long-term accumulation of this sort of stress can have detrimental effects on the body. Working excessively or excessively firm at work, university, or household might be the cause of it. It may also result from a lack of knowledge about effective time management and scheduling rest and relaxation periods. Since many individuals believe they have no control over it, this might be one of the most difficult forms of stress to avoid [4].

1.3 STRESS AND ITS KINDS

Stress is characterized as a need for balance between the body and the mind, which may be managed by sitting management strategies and relaxation. There are several kinds of strain.

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a) Acute Stress – Acute stress is usually brought on by the daily stresses and responsibilities that each person faces. What truly makes our life exciting, joyful, and thrilling is acute strain.

1) **Emotional distress:** such as severe depressive episodes, agitation, anxiety, and fury.

2) Physical troubles: such as pain, upset stomach, headache, heart palpitations, dizziness, and shortness of breath, as well as bowel issues and hypertension [5].

b) Episodic Stress - Episodic stress is the term for acute stress that occurs too often. This kind of strain is typically observed in those who establish self-imposed, impractical, or idealistic burdens that become jumbled and cause excessive tension in the process of achieving them. People with "Type A" personalities, who are often extremely competitive, aggressive, demanding, and occasionally tense and confrontational are also known to experience episodic stress [6]. As a result, Type A personalities exhibit the signs of episodic stress [6].

1.4 SYMBOLS AND INDICATIONS OF STRESS BURDEN

Stress overload can manifest as nearly any number of indications and symptoms. Stress has a variety of effects on the mind, body, and behavior. Table 1.1 illustrates how various people feel stress. Excessive stress may harm a person's relationships at work, family, and school in addition to causing major mental and physical health issues [7].

Table1.1: Stress overloads signs and symptoms

Signs and symptoms of stress overload			
Cognitive symptoms	**Behaviourial symptoms**	**Physical symptoms**	**Emotional symptoms**
Memory problems	Eating more or less	Aches and pains	Moodiness
Inability to Concentrate	Sleeping more or less	Dysphonia(voice disorder)	Depression,general unhappiness
Poor judgement	Isolating yourself from others	Constipation,diarrhea	Irritation
Constant worrying	Using alcohol and cigarettes	Frequent cold	Feeling overwhelmed,
Seeing the negative	Nervous Habits	Chestpain,rapid heartbeat	Sense of loneliness

1.5 BLOOD PRESSURE

The heaviness of blood inside the veins is known as blood pressure. The cardiac muscle's contraction is the main source of it. A person's upper arm is often used to test blood pressure [8]. Blood pressure is measured in millimeters of mercury (mm Hg) and is expressed as the diastolic (lowest) and systolic (highest) pressures. Along with body temperature, heart rate, oxygen saturation, and respiration rate, it is one of the essential ciphers. An adult's usual relaxing blood pressure is about 120/80 mm Hg. Blood pressure changes according on the circumstance, level of exercise, and illness. The endocrine and neural systems keep it in harmony. Hypotension is the term for low blood pressure caused by a sickness, whereas hypertension is the term for continuously high blood pressure. The blood pressure is displayed below in figure 1.2.

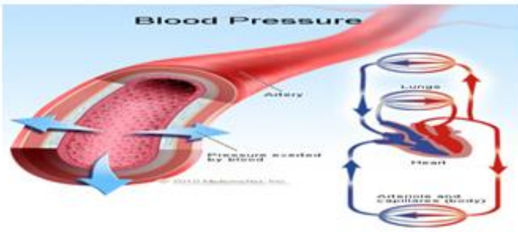

Figure 1.2: Blood pressure

1.6 HYPERTENSION (High Blood Pressure)

A frequent ailment known as hypertension, or high blood pressure, occurs when there is sufficient blood pressure on the walls of one's arteries. The volumes of blood the heart drives and the grade of artery confrontation to blood movement both upsets blood pressure. The greater the blood pressure, the additional blood the heart drives and the smaller the veins. In addition to injuries, hypertension can cause a number of diseases, comprising heart letdown, stroke, heart attack, and kidney letdown. In the American Academy of Neurology publication, UC Davis researchers found that middle-aged high blood pressure may increase the likelihood of cognitive deterioration in later life [9].

2. RELATED WORK

N. P. Dhole et al. spoke about a method for identifying speaking in the English language. Anxiety revealing, which gives present insight into an individual's mental state, is essential. The author took into account the MFCC Voice characteristics, which are altered by stress. Experimentation was carried out on first-year scholars in the age range of 18 to 20 to investigate the impact of exam stress on speech output. They were handed an assignment along with instructions that their presentation in the viva on that assignment will determine their concluding inner scores for the test. Students were under stress, as evidenced by the experiment and test results analysis, which led to a notable shift in MFCC [1].

S. V. Bakhtiyari determines the connection between the work environment and different individual factors and employees' stress levels. The goal of the study was to determine how different factors affect an employee's level of stress. It existed discovered that the phase collection affects both the strain level and the requirement for

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employee analysis. According to the report, the majority of workers frequently experience stress as a result of their workload. The author made an effort to ascertain the connection between stress and credentials as well as potential strategies for stress management. In order to do an excellent study and recommend to the company certain strategies for reducing stress in the workplace, the data for analysis was gathered from various employee levels [2].

U. Devi talked about that the dynamic social environment and shifting demands of modern lifestyles have made stress a prominent issue. Even though stress causes the death of brain cells, strain is an adaptive reaction to an outside circumstance that can cause changes in behavior, mental health, and physical health. A healthy dose of stress may actually kindle imagination, awaken dormant skills, and create a love for one's profession. Every occupation has some level of job stress. Due to their intense focus on goals and pressure to meet deadlines, IT workers experience significant levels of stress. When stress is recognized and well managed, it may actually help someone be creative and useful. The author's main goal was to examine the stress levels of IT workers and offer coping mechanisms. The author conducted a study with 200 IT workers from IT firms in and around Hyderabad. Strain controlling packages, bodily events incorporated into job designs, lifecycle flair change packages, identifying stressors and activates, supportive workplace cultures, strain therapy packages, and divine packages are a few of the strain coping strategies examined in this study [3].

S. C. Haines spoke about the pressures that modern culture places on law enforcement personnel. This study looked at a few different stresses and the potential consequences they could have on police officers and their families. This study looked at the potential harm that police officer work-related stress can do to an officer's family. For this study, professional papers, magazine articles, and online resources were the main sources of information. Numerous factors contribute to the stress experienced by police officers, such as shift work that takes away from spell expended with their relatives, associated cops, and the general public. Numerous additional issues, such as poor income, irregular sleep habits, and conflicts with friends and family, all contribute to the stress experienced by police officers. The author found that officers were better able to control their stress when they had received the appropriate training and understood the impacts of stress. Officers were able to maintain a greater level of morale as a result of this stress management, since they brought less tension with them to their families. In order to prevent officer stress and provide education and training, police departments must assume greater accountability. In addition, the agency must offer private therapy to officers whose health is being adversely affected by work-related stress [4].

M. Kotteshwari et al. Discussed how performance is inversely correlated with occupational stress. Put otherwise, when stress levels are higher, so should the performance. Stress at work may come from a variety of causes. A challenging administrator, insufferable colleagues, wayward scholars, furious customers, hazardous states, prolonged exchanges, and a limitless assignment are a few examples. Over the past century, there have been significant changes to the nature of labor, and these changes are happening at a breakneck pace. As things change, stress will inevitably arise. Stress at work may be harmful to one's physical health. India's business process outsourcing (BPO) sector has long been known for its long hours, boring work, poor perceived value, and demoralizing efficiency, all of which contribute to a high turnover rate. The aim of this study was to ascertain whether demographic and job-related factors are connected to BPO employees' levels of employee satisfaction. This study has attempted to identify the elements of job stress that impact employees' performance [5].

H. Lu et al. outlined the potential long-term harm that stress may have to a person's physical and mental health. One of the several physiological alterations brought on by stress is a shift in the way speech is produced. People carry microphones around with them all the time and these microphones allow for the continuous, non-invasive monitoring of stress in real-world scenarios. The author of this study proposed stress sense, a smartphone app that discreetly uses human speech to identify stress. The author looked at ways to modify universal stress models to meet different speakers and situations. Through model adaption, the author showed how the Stress Sense classifier can reliably recognize stress in a variety of auditory settings across numerous individuals. In indoor and outdoor settings, Stress Sense delivers 81% and 76% accuracy, respectively. The author demonstrated that Stress Sense could be installed and used in real-time on regular Android phones. To assume speech constructed strain discovery and model adaption utilizing smartphones in various real-world informal scenarios the author looks into the initial system [6].

J. H. L Hansen et al. Spoke nearly stress-induced speech acknowledgment, modeling, and analysis. The author began by defining stress and discussing how it affects the mechanism that produces speech. The author examined how people perceive stress differently in order to better understand the indicators connected to stress perception. After taking into account the stress domains and regions for speech analysis under stress, the author turned their attention to creating algorithms that might be used to categorize, estimate, or differentiate between various stress circumstances. The author provided strategies for mitigating the impact of stress on speaking acknowledgment and social-PC communication schemes in his conclusion [7].

N. Mbitiru et al. voice stress analysis is carried out by assessing variations in the physiological micro tremor found in speaking. The author talked about the Empirical Mode Decomposition in this study. The examination of the physical palmtop vibration involved a comparison between the standard Fast Fourier Transform and Empirical Mode Decomposition. The outcomes demonstrated that EMD was a more appropriate method for identifying vocal stress [8].

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Agarwalla and Sarma extracted pertinent data samples from huge data space utilizing Feed-Forward (FF) networks and Deep Neural Network (DNN) methodologies, and then castoff them for instinctive communication empathy by means of easygoing work out systems for Assamese communication with dialectal adjustments [10].

Kimani & Bickmore VR has also been used to enhance interpersonal and public speaking abilities. The immersive experience that virtual reality (VR) environments offer their users is an advantage as it allows them to learn in a manner that is similar to learning in real life [12].

Kamiloğlu et al. Pitch consists of elements that are associated with speech rhythm and tone. The F0 contour and other statistical traits that are produced by the F0's fluctuation over time can also be utilized as features. [13]

Arushi et al. offer a conceptual framework for the creation of a computational algorithmic model for stress detection based on speech analysis that may be included into a virtual reality or other multimedia application [15].

3. PROPOSED WORK

The principal objectives of these endeavors are the exploration of dysphonia in persons with hypertension and anxiety, as well as the identification of anxious individuals by speech signal analysis and extracted topographies.

First, a voice database of healthy, anxious, and hypertensive individuals is created. After that, this database is examined, and several characteristics from the patient recordings, such as pitch, standard deviation, HNR, DVB, and jitter shimmer, are retrieved. Next, for classification, the KNN classifier is employed. The KNN classifier will distinguish between hypertensive and normal individuals as well as among stressed and normal people. Classifier accuracy is verified at the conclusion.

4. RESULTS AND ANALYSIS

From PRAAT, several voice characteristics are retrieved. Next, MATLAB simulates the K-means method and displays the results in cluster form. The following sections, which further separate the result section, are discussed below:

4.1 STRESSED VERSUS NORMAL WOMAN SAMPLES

The teaching (normal) and forecast (strained) women are displayed in Table 4.1 as follows:

Table 4.1: Teaching and Forecast Subjects

	Max. Pitch (Hz)	Min. Pitch (Hz)	Mean (Hz)	S.D (Hz)	Jitter(%)	Shimmer (%)	DVB(%)	HNR (%)
Training Subjects	474.081	85.766	210.316	44.63	1.841	8.194	46.578	13.999
	467.092	154.45	213.309	50.159	1.564	7.113	56.875	13.824
	457.464	75.923	266.693	36.075	1.741	7.168	49.365	14.817
	328.971	175.747	234.93	48.448	1.729	7.925	47.954	13.705
	435.574	213.533	282.823	40.637	1	8.148	29.975	12.32
	474.71	196.766	275.359	69.655	1.169	8.532	36.098	12.197
	483.693	183.531	248.827	44.889	1.742	8.749	19.031	12.12
Prediction Subjects	262.933	178.642	230.955	22.573	3.276	16.002	49.986	6.217
	251.51	189.061	237.48	8.673	4.999	18.714	39.05	6.559
	270.962	200.945	234.793	12.029	3.523	15.223	37.279	8.787
	274.883	119.638	229.558	18.085	3.737	16.406	19.391	9.289
	257.549	177.546	212.535	12.731	3.567	14.998	36.17	9.542
	267.243	94.743	204.369	28.907	3.416	12.351	31.983	9.599
	435.574	213.533	282.823	40.637	1	8.148	29.975	12.32

Table 4.1 makes it evident that the initial seven women are considered for teaching purpose, and the subsequent seven are considered for predictable purpose. Figure 4.1 displays the training and anticipated subjects. The training subjects are indicated by blue circles in figure 4.1, whereas the anticipated subjects are depicted by cyan circles.

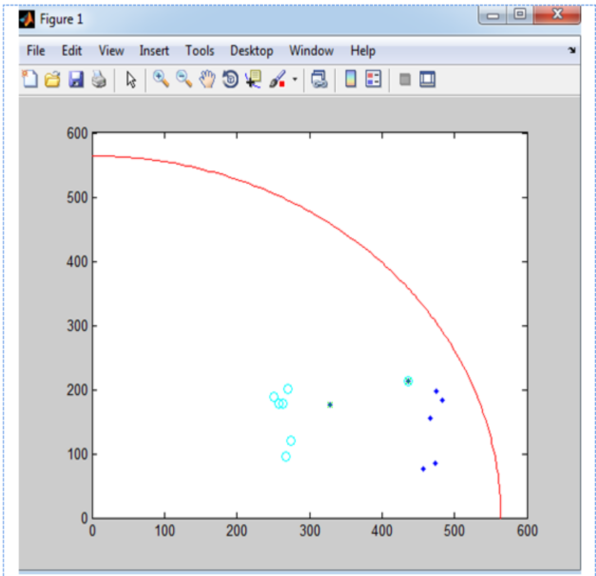

Figure 4.1: Advice of teaching and forecast subjects

Females that are under stress can be distinguished from normal using the K-means classification. Several clusters are generated after the training and anticipated subjects are subjected to the K-means method, as seen in table 4.2.

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Table 4.2: Groups of teaching and forecast subjects (women)

	Max. Pitch (Hz)	Min. Pitch (Hz)	Mean (Hz)	S.D (Hz)	Jitter (%)	Shimmer (%)	DVB (%)	HNR (%)	Clusters
Training Subjects	474.1	85.8	210.3	44.63	1.8	8.2	46.6	13.9	1
	467.1	154.5	213.3	50.2	1.6	7.11	56.9	13.8	2
	457.5	75.9	266.7	36.1	1.7	7.2	49.4	14.8	3
	328.9	175.8	234.9	48.5	1.7	7.9	47.9	13.7	4
	435.6	213.5	282.8	40.6	1	8.2	29.9	12.3	5
	474.7	196.8	275.4	69.7	1.2	8.5	36.1	12.2	6
	483.7	183.5	248.8	44.9	1.7	8.8	19.0	12.1	7
Prediction Subjects	262.9	178.6	230.9	22.6	3.3	16.0	49.9	6.2	4
	251.5	189.1	237.48	8.7	4.9	18.7	39.0	6.6	4
	270.9	200.9	234.8	12.1	3.5	15.2	37.3	8.8	4
	274.9	119.6	229.6	18.1	3.7	16.4	19.4	9.3	4
	257.6	177.6	212.5	12.7	3.6	14.9	36.2	9.5	4
	267.3	94.7	204.4	28.9	3.4	12.4	31.9	9.6	4
	435.6	213.5	282.8	40.6	1	8.2	29.9	12.3	5

The training and projected dataset clusters (females) are displayed in figure 4.2.

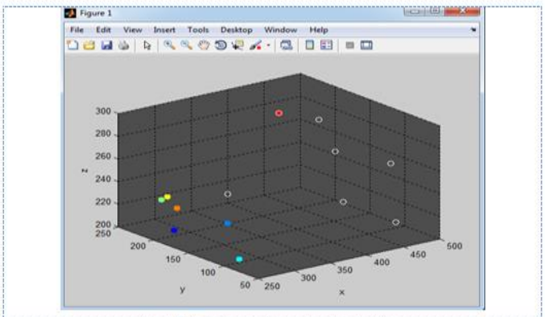

Fig. 4.2: Clustering of training and predicted subjects.

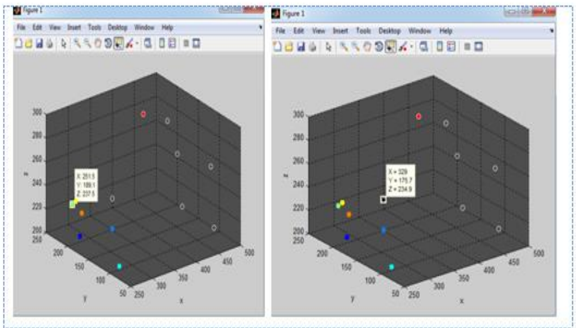

Figure 4.3: Coordinates of subjects

The KNN classification is explained in detail in figure 4.3. Figure 4.2 displays the third patient from the Prediction dataset as a yellow circle, whereas the second patient from the same dataset is represented by a green circle. It is evident that the fourth patient in the training dataset is situated in close proximity to the second and third patients in the predicted dataset after the clusters have been given coordinates.

4.2 STRESSED VERSUS NORMAL MAN SAMPLES

The training (normal) and anticipated (stressed) men are displayed in table 4.3 as follows.

Table 4.3: Teaching and Forecast Subjects

	Max. Pitch (Hz)	Min. Pitch (Hz)	Mean Pitch (Hz)	S.D (Hz)	Jitter (%)	Shimmer (%)	DVB (%)	HNR (%)
Training subjects	175.929	93.968	128.583	14.142	2.746	10.652	55.794	11.482
	147.223	83.181	122.114	13.704	2.713	10.436	47.345	10.222
	157.279	93.47	128.918	12.217	2.587	10.813	51.14	8.77
	163.701	93.389	134.77	17.694	2.576	10.676	43.058	10.493
	154.355	75.007	123.44	18.438	2.12	10.51	48.29	7.454
	226.44	134.074	184.635	22.255	1.932	9.915	48.771	12.273
	237.717	72.043	151.38	32.212	2.12	10.357	40.443	7.354
Predicted Subjects	261.183	70.764	129.091	39.657	4.39	14.292	65.776	5.922
	163.951	67.742	120.624	19.189	2.671	10.791	44.857	9.603
	258.838	66.729	111.979	42.232	3.699	15.699	32.816	6.98
	203.627	75.094	203.627	24.327	3.011	18.878	9.197	6.27
	175.394	67.803	133.472	19.84	5.046	16.854	23.999	4.954
	210.423	70.79	157.798	26.319	6.572	19.942	37.21	4.537
	210.151	279.17	141.981	37.217	2.094	12.47	53.183	9.298

Table 4.3 makes it evident that the initial seven women are considered for teaching purpose, while the subsequent seven are considered for predictable purpose. Figure 4.4 displays the training and anticipated subjects. The training subjects are indicated by blue circles in figure 4.4, whereas the anticipated subjects are depicted by cyan circles.

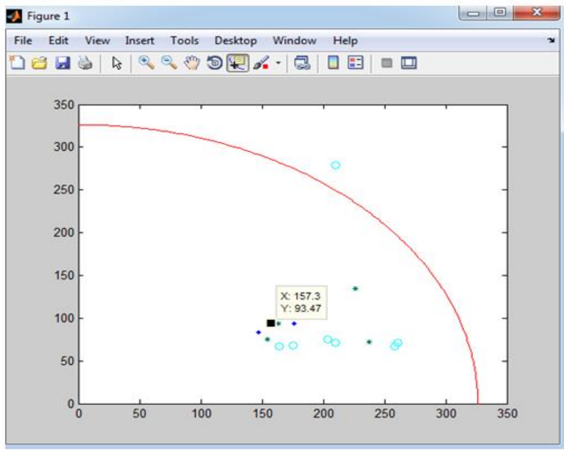

Figure 4.4: Suggestion of teaching and forecast subjects

Males who are stressed out and those who are not are distinguished using the K-means categorization. Several clusters are generated after the training and anticipated subjects are subjected to the K-means method, as seen in table 4.4.

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Table 4.4: Groups of teaching and forecast subject (men)

	Max. Pitch (Hz)	Min Pitch (Hz)	Mean Pitch (Hz)	S.D (Hz)	Jitter (%)	Shimmer (%)	DVB (%)	HNR (%)	Clusters
Training Subjects (Normal)	175.929	93.968	128.583	14.142	2.746	10.652	55.794	11.482	1
	147.223	83.181	122.114	13.704	2.713	10.436	47.345	10.222	2
	157.279	93.47	128.918	12.217	2.587	10.813	51.14	8.77	3
	163.701	93.389	134.77	17.694	2.576	10.676	43.058	10.493	4
	154.355	75.007	123.44	18.438	2.12	10.51	48.29	7.454	5
	226.44	134.074	184.635	22.255	1.932	9.915	48.771	12.273	6
	237.717	72.043	151.38	32.212	2.12	10.357	40.443	7.354	7
Predicted subjects	261.183	70.764	129.091	39.657	4.39	14.292	65.776	5.922	7
	163.951	67.742	120.624	19.189	2.671	10.791	44.857	9.603	5
	258.838	66.729	111.979	42.232	3.699	15.699	32.816	6.98	7
	203.627	75.094	203.627	24.327	3.011	18.878	9.197	6.27	7
	175.394	67.803	133.472	19.84	5.046	16.854	23.999	4.954	4
	210.423	70.79	157.798	26.319	6.572	19.942	37.21	4.537	7
	210.151	279.17	141.981	37.217	2.094	12.47	53.183	9.298	6

The teaching and forecast dataset groups are displayed in figure 4.5.

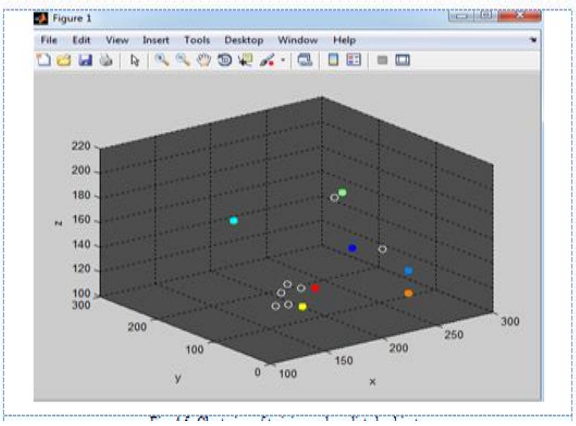

Figure 4.5: Grouping of teaching and forecast subjects

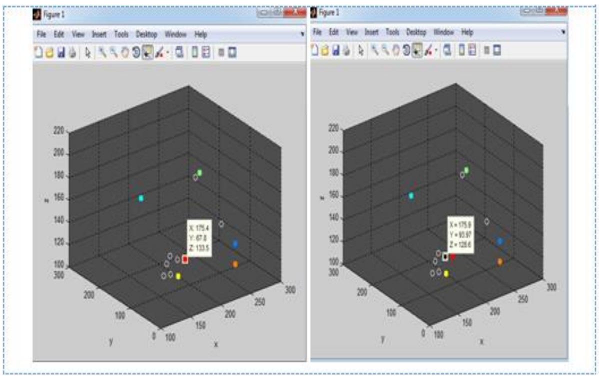

Figure 4.6: Matches of subjects

The KNN classification is explained in detail in Figure 4.6. Figure 4.5 displays the fifth patient from the Predicted dataset as a red circle. It is evident from the clusters' assigned coordinates that, as shown in figure 4.6, the first patient of the teaching dataset is located adjacent to the fifth patient of the forecast dataset.

4.3 HYPERTENSIVE VERSUS NORMAL WOMAN SAMPLES

The teaching (normal) and expected (hypertensive) women are displayed in table 4.5 as follows:

Table 4.5: Teaching and Forecast Subjects

	Max. Pitch (Hz)	Min. Pitch (Hz)	Mean Pitch (Hz)	S.D (Hz)	Jitter (%)	Shimmer (%)	DVB (%)	HNR (%)
Training Subjects	474.081	85.766	210.316	44.63	1.841	8.194	46.578	13.999
	467.092	154.45	213.309	50.159	1.564	7.113	56.875	13.824
	457.464	75.923	266.693	36.075	1.741	7.168	49.365	14.817
	328.971	175.747	234.93	48.448	1.729	7.925	47.954	13.705
	435.574	213.533	282.823	40.637	1	8.148	29.975	12.32
	474.71	196.766	275.359	69.655	1.169	8.532	36.098	12.197
	483.693	183.531	248.827	44.889	1.742	8.749	19.031	12.12
Predicted Subjects	202.21	94.014	148.112	25.929	2.412	11.354	40.942	10.585
	259.621	110.62	185.12	14.786	3.74	14.143	36.112	11.523
	230.019	98.65	164.335	16.15	3.15	12.14	49.987	15.923
	190.62	158.2	174.41	20.574	2.276	10.012	46.225	9.523
	289.142	178.546	233.844	45.96	1.596	15.441	44.912	14.051
	229.32	101.21	165.265	21.51	1.221	12.621	38.14	13.217
	265.41	190.945	228.178	18.049	3.614	16.142	35.189	8.059

Table 4.5 makes it evident that the initial seven women are considered for teaching subjects, while the subsequent seven are considered for estimated subjects. Figure 4.7 displays the teaching and expected subjects. The training subjects are indicated by blue circles in figure 4.7, whereas the anticipated subjects are depicted by cyan circles.

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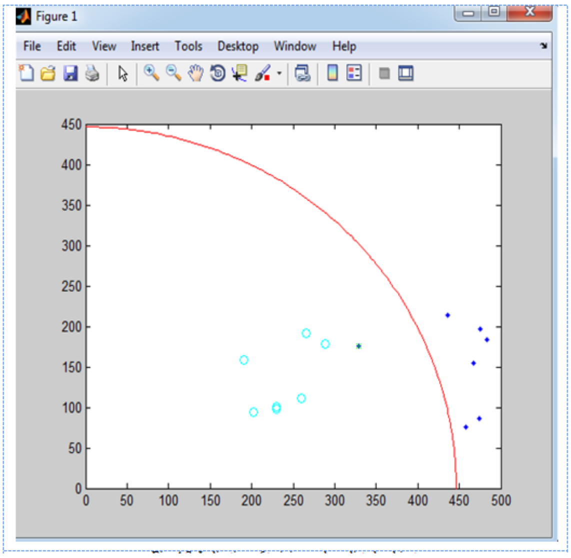

. **Figure 4.7: Suggestion of teaching and expected subjects**

Females with normal blood pressure and hypertensive ones are distinguished using the K-means classification. Several clusters are generated after the training and anticipated subjects are subjected to the K-means method, as seen in table 4.6.

Table 4.6: Groups of teaching and forecast subjects (women)

	Max. Pitch (Hz)	Min. Pitch (Hz)	Mean Pitch (Hz)	S.D (Hz)	Jitter (%)	Shimmer (%)	DVB (%)	HNR (%)	Clusters
Training Subjects	474.081	85.766	210.316	44.63	1.841	8.194	46.578	13.999	1
	467.092	154.45	213.309	50.159	1.564	7.113	56.875	13.824	2
	457.464	75.923	266.693	36.075	1.741	7.168	49.365	14.817	3
	328.971	175.747	234.93	48.448	1.729	7.925	47.954	13.705	4
	435.574	213.533	282.823	40.637	1	8.148	29.975	12.32	5
	474.71	196.766	275.359	69.655	1.169	8.532	36.098	12.197	6
	483.693	183.531	248.827	44.889	1.742	8.749	19.031	12.12	7
Predicted Subjects	202.21	94.014	148.112	25.929	2.412	11.354	40.942	10.585	4
	259.621	110.62	185.12	14.786	3.74	14.143	36.112	11.523	4
	230.019	98.65	164.335	16.15	3.15	12.14	49.987	15.923	4
	190.62	158.2	174.41	20.574	2.276	10.012	46.225	9.523	4
	289.142	178.546	233.844	45.96	1.596	15.441	44.912	14.051	4
	229.32	101.21	165.265	21.51	1.221	12.621	38.14	13.217	4
	265.41	190.945	228.178	18.049	3.614	16.142	35.189	8.059	4

The training and anticipated dataset clusters are displayed in figure 4.8:

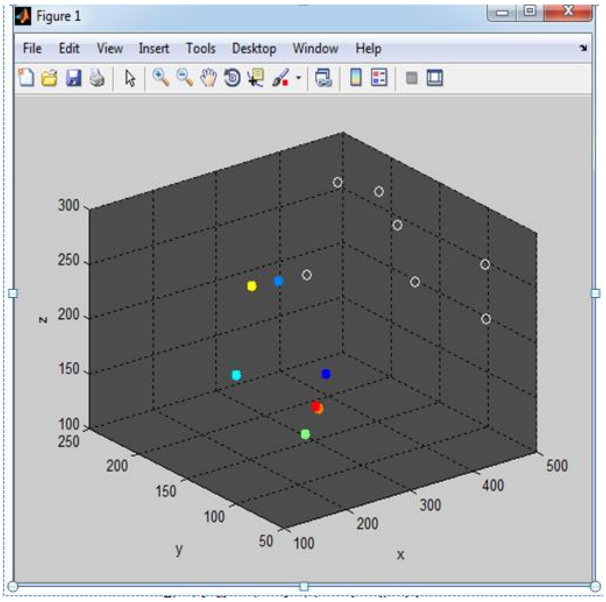

Figure 4.8: Grouping of teaching and forecast dataset

4.4 HYPERTENSIVE VERSUS NORMAL MEN SAMPLES

The teaching (normal) and predicted (hypertensive) men are displayed in table 4.7 as follows:

Table 4.7: Teaching and Forecast Subjects

	Max. Pitch (Hz)	Min. Pitch (Hz)	Mean Pitch(Hz)	S.D (Hz)	Jitter (%)	Shimmer (%)	DVB (%)	HNR (%)
Training Subjects	175.929	93.968	128.583	14.142	2.746	10.652	55.794	11.482
	147.223	83.181	122.114	13.704	2.713	10.436	47.345	10.222
	157.279	93.47	128.918	12.217	2.587	10.813	51.14	8.77
	163.701	93.389	134.77	17.694	2.576	10.676	43.058	10.493
	154.355	75.007	123.44	18.438	2.12	10.51	48.29	7.454
	226.44	134.074	184.635	22.255	1.932	9.915	48.771	12.273
	237.717	72.043	151.38	32.212	2.12	10.357	40.443	7.354
Predicted Subjects	190.162	60.17	125.166	25.07	3.94	18.47	10.176	4.298
	170.627	68.21	119.418	19.12	4.011	12.19	44.12	9.274
	260.119	75.07	167.594	26.36	3.036	19.69	32.776	8.661
	288.621	90.129	189.375	18.19	3.39	10.79	49.21	6.814
	201.112	72.15	136.631	17.22	6.671	19.22	38.09	4.365
	186.221	85.04	135.63	26.31	4.6	14.65	66.12	6.913
	220.92	65.91	143.415	20.11	5.11	10.09	25.08	9.551

Table 4.7 makes it evident which seven guys are considered training subjects and the remaining seven are considered anticipated subjects. Figure 4.9 displays the training and anticipated subjects. The training subjects are indicated by blue circles in figure 4.9, whereas the anticipated subjects are depicted by cyan circles.

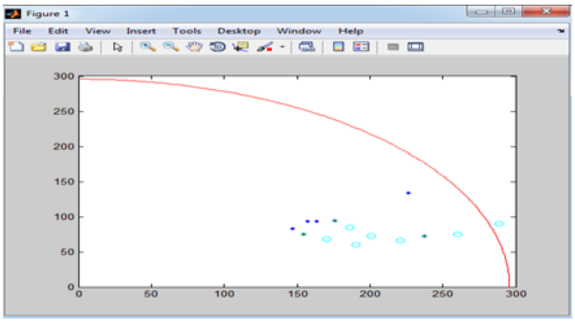

Figure 4.9: Suggestion of teaching and forecast subjects (men)

Male hypertensive and normal subjects are distinguished using the K-means classification. Several clusters are generated after the training and anticipated subjects are subjected to the K-means method, as seen in table 4.8.

Table 4.8: Groups of teaching and forecast subjects (men)

Training Subjects	Max. Pitch (Hz)	Min. Pitch (Hz)	Mean Pitch (Hz)	S.D (Hz)	Jitter (%)	Shimmer (%)	DVB (%)	HNR (%)	clusters
	175.929	93.968	128.583	14.142	2.746	10.652	55.794	11.482	1
	147.223	83.181	122.114	13.704	2.713	10.436	47.345	10.222	2
	157.279	93.47	128.918	12.217	2.587	10.813	51.14	8.77	3
	163.701	93.389	134.77	17.694	2.576	10.676	43.058	10.493	4
	154.355	75.007	123.44	18.438	2.12	10.51	48.29	7.454	5
	226.44	134.074	184.635	22.255	1.932	9.915	48.771	12.273	6
	237.717	72.043	151.38	32.212	2.12	10.357	40.443	7.354	7
Predicted Subjects	190.162	60.17	125.166	25.07	3.94	18.47	10.176	4.298	5
	170.627	68.21	119.418	19.12	4.011	12.19	44.12	9.274	5
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	186.221	85.04	135.63	26.31	4.6	14.65	66.12	6.913	5
	220.92	65.91	143.415	20.11	5.11	10.09	25.08	9.551	7

The Figure 4.10 displays the groups of teaching and forecast datasets (men).

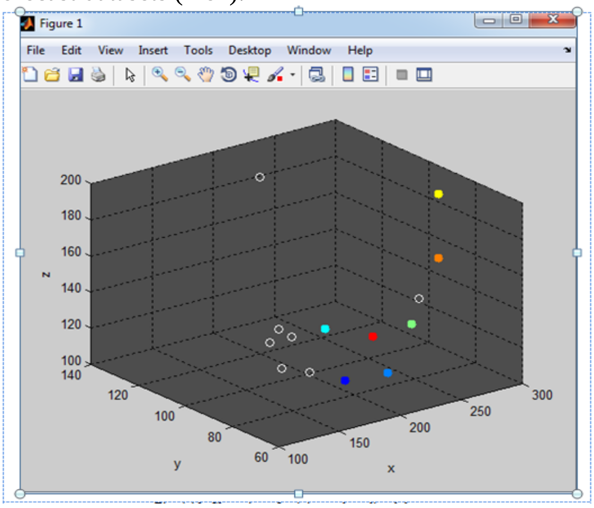

Figure 4.10: Grouping of teaching and forecast dataset

4.5 CLASSIFIER PERFORMANCE

To evaluate the classifier's performance, two metrics—accuracy and precision—are taken into account. The measurements true positive, true negative, false positive, and false negative are used to derive these metrics. The proportion of positive forecasts that is true.

Table 4.8: Defining Classifier Performance Measures

Measure	Formula	Meaning
Accuracy	(TP + TN) / (TP + TN + FP + FN)	The percentage of predictions that are correct.
Precision	TP / (TP + FP)	The percentage of positive predictions that are correct.

Table 4.9: Classifier Accuracy and Precision

Classifier	Accuracy	Precesion
K-means	98.2143%	80.3571%

CONCLUSION AND FUTURE SCOPE

The work's overarching goal is to investigate stress via patient testimony. The PRAAT program proved to be helpful in achieving this. Furthermore, it is noted that the feature retrieved values of hypertension and stress share a number of commonalities. This means that people with hypertension are also victims of stress. The majority of this work has been applied to PRAAT, a virtual computer-operated phonetics program. The understanding of voice analysis in general and the practical uses of voice analysis tools in everyday life has improved because to this effort. In order to simplify the voice signal and extract desired characteristics, voice analysis entails transforming the spoken signal into a collection of parameters. The PRAAT operates on the undersized interval frame investigation approach, which makes it easier to comprehend, compare, modify, and resynthesize tasks by enabling the grasping of these unique time-varying speech properties. Therefore, speech pathologists and other medical practitioners may utilize the PRAAT tool Voice to analyze, assess, and diagnose the patient's voice signal quality based on quantifiable aspects. MATLAB software also implements the K-means classification technique for clustering. Due to its many uses in the engineering and medical sciences, voice analysis has become a prominent field of research. The twenty-first century's technological advancements have given researchers access to incredibly fast and adaptable digital processors, enabling them to explore the enormous range of factors related to human voice. The Voice Analysis method has produced improved and beneficial results. The outcome further confirmed that the Voice Analysis technique worked in real-world settings. In this study, stress was identified as a cause of hypertension and stress was detected using human voice samples. But stress also contributes to a host of other illnesses, including obesity, diabetes, gastrointestinal issues, and heart disease. Thus, speech will also be able to be used in the future to identify these illnesses. As a result, the start of the third century has created new opportunities for voice diagnostic system development. It appears that biological technology is already in the process of evolving, and the manner it is advancing humanity appears to be highly hopeful for next generations.

REFERENCES

1. Neha P. Dhole and Dr. Ajay A. Gurjar, “Detection of Speech under Stress”, International Journal of Engineering and Innovative Technology (IJEIT), Vol. 2, Issue 10, 2013
2. Syed Valiullah Bakhtiyari, “Research paper on factors influencing on stress and its management with reference to employees of idea cellular”, EXCEL International Journal of Multidisciplinary Management Studies, Vol. 4, 2014
3. Uma Devi .T , “A Study on Stress Management and Coping Strategies With Reference to IT Companies”, Journal of Information Technology and Economic Development, Vol. 2, 2011
4. Sergeant Corey Haines, “Police Stress and the Effects on the Family”, An applied research project submitted to the Department of Interdisciplinary Technology as part of the School of Police Staff and Command Program, 2003
5. M. Kotteeswari, and Dr. S. Tameem Sharief, “Job Stress and Its Impact on Employees Performance: A study with reference to employees working in BPOS”, Vol. 5, Issue 2, 2014
6. Hong Lu, Mashfiqui Rabbi Cornell, and Gokul T. Chittaranjan, ”Stress Sense: Detecting Stress in Unconstrained Acoustic Environments using Smart phones”, 2012
7. John H.L Hansen, and Sanjay Patil, “Speech under Stress: Analysis, Modeling and Recognition”, Vol. 43, pp. 108-137, 2007
8. Nyaga Mbitiru, Peter Tay, James Z. Zhang, and Robert D. Adams, “Analysis of Stress in Speech Using Empirical Mode Decomposition”, Proceedings of the IAJC-IJME International Conference ISBN, 2008

[9] Palo, H., Mohanty, M. N., & Chandra, M., "Design of neural network model for emotional speech recognition", In Artificial intelligence and evolutionary algorithms in engineering systems, (pp. 291-300), Springer, 2015

[10] Agarwalla, S., & Sarma, K. K., "Machine learning based sample extraction for automatic speech recognition using dialectal Assamese speech", Neural Networks, 78, 97-111, 2016

[11] Teoh, A. N., & Hilmert, C., "Social support as a comfort or an encouragement: A systematic review on the contrasting effects of social support on cardiovascular reactivity", British Journal of Health Psychology, 23(4), 1040-1065, https://doi.org/10.1111/bjhp.12337, 2018

[12] Kimani, E., & Bickmore, T., "Addressing Public Speaking Anxiety in Real-time Using a Virtual Public Speaking Coach and Physiological Sensors", Proceedings of the 19th ACM International Conference on Intelligent Virtual Agents, Paris, France. https://doi-org.elibrary.jcu.edu.au/10.1145/3308532.3329409, 2019

[13] Kamiloğlu, R. G., Fischer, A. H., & Sauter, D. A., "Good vibrations: A review of vocal expressions of positive emotions", Psychologic Bulletin & Review, 27(2), 237-265. https://doi.org/10.3758/s13423-019-01701-x, 2020

[14] American Psychological Association, Anxiety. In APA Dictionary retrieved 7/2/2022, from https://dictionary.apa.org/anxiety, 2022a

[15] Arushi, Roberto Dillon, "Detecting Public Speaking Stress via Real-time Voice Analysis in Virtual Reality: A Review", https: // www. researchgate. net/ publication/372923716, 2023