COMPUTE DEPRESSION AND ANXIETY AMONG STUDENTS IN PAKISTAN, USING MACHINE LEARNING

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Abstract

The worldwide mechanical advancement in medical services digitizes the copious information, empowering the guide of the different types of human science all the more precisely than conventional estimating strategies. AI (ML) has been certified as a productive approach for dissecting the enormous measure of information in the medical services area. ML strategies are being used in emotional well-being to anticipate the probabilities of mental problems and, subsequently, execute potential treatment results.

In the speedy present-day world, mental medical problems like depression and anxiety have become exceptionally normal among the majority. In this paper, forecasts of depression and anxieties were made utilizing AI calculations. Depression and anxiety have become emergent hindrances in the lives of human beings. It not only disturbs their daily decorum but has also become a prominent cause for their downfall in health. All around the world people are getting affected by this mental disorder yet the majority of such cases lie between ages 18-25 making university-going students a prime target for such mental diseases.

Though the mental health of university students is known globally as a momentous public health matter. Academicals, social depression, and anxieties are playing quite a negative role in university student's life, especially in forms of mental illness like depression and anxiety. These mental health issues are becoming a major constraint on their studies and career. Hence, this research is being conducted to develop a technological solution for mentally distorted students.

This paper analyzes depression and anxiety amongst university students by effectively utilizing the k-nn algorithm (a conspicuous technique for detecting and analyzing mental depression and anxiety) and providing a technical solution for this mental hindrance. The experimental results show up to 76.5% accuracy in results after using k-nn without PCA while the accuracy was increased up to 76.6% when the results were generated with PCA.

Keywords: Depression, Anxiety, machine learning, classification, k-nn.

1. Introduction

Students are the greatest assets of society and thus special attention is paid when it comes to their health. On the other hand, depression is amongst the most pervasive mental problems, influencing a large number of individuals of any age all around the world. Most psychological issues show up by early adulthood, yet youthful grown-ups rarely get any help for their emotional well-being (Sarokhani et al, 2013). It has been observed that students are more prone to getting psychological illnesses such as depression and anxiety due to their hectic and strenuous environment along with a serious lack of consultation. Anxious students, in turn, were observed to have more difficulties during the learning and problem-solving techniques because of their unstable mental conditions. (Gazzaniga, 2003).

Students are considered a national asset for a country and special attention is paid when it comes to their mental or physical health. Traditional medical means have been beneficial in curing physical diseases while the question of improving their mental health lingers in the minds of medicinal experts. Therefore, the experts have implored the problem-solving techniques illustrated by AI engineers. AI methods have indicated viable in empowering the mechanized discovery and forecast of depression (Cohn et al. 2009; Yang, Fairbairn, and Cohn 2012; Nasir et al. 2016; Gong and Poellabauer 2017; Zhou et al. 2018; Shen et al. 2018; Ay et al. 2019). While a few conspicuous areas of society are prepared to accept the potential of AI, alert remaining parts pervasive in medication, including psychiatry, proven by ongoing features in the news media like "A.I. Can Be a Boon to Medicine That Could Easily Go Rogue" (Metz, 2019). Notwithstanding clear concerns, AI applications in medication are consistently expanding. As psychological wellness professionals, we need to acquaint ourselves with AI techniques, comprehend its current and future uses, and be set up to proficiently work with AI as it enters the clinical standard (Kim, 2019).

The application of AI techniques has proven to be profitable in the detection and cure of many mental diseases including mental pressure which is considered as the origin for anxiety leading to depression. Mental pressure has been seen as an easygoing element in the improvement of hypertension and cardiovascular ailments (Pickering, 2001). The pressure reaction is controlled by our impression of an occasion, change, or issue. Numerous techniques for distinguishing the reason behind these psychological issues have been presented by different analysts which indicate that academic and social pressure are playing an actively negative role in university student’s life, especially in forms of mental illness like depression and anxiety.

Recent research provided that anxiety and depression were calculated in high percentages amongst students. Arts students (Depression and anxiety 27.69%, Anxiety 73.84% and Depression 15.38%) have a low level of depression and anxiety, depression, and anxiety than science students have a high level of anxiety, and depression (Depression and anxiety 73.86%, Anxiety 96.14%, and Depression 88.46 %) (Wani, 2016). Thus, it has become a vital effort for scientists to calculate and analyze depression and anxiety levels amongst students to provide adequate solutions for such problems.

The present survey has clarified that although pressure corrupts execution in the majority of the cases, this connection isn't so basic (Tiwari, 2011). This paper centers on the utilization of the K-neatest neighbor (k-NN) classifier for the said reason.

A significant initial step is perceiving how much we are influenced by the worry in our lives and after that advance toward techniques to improve it. Depression and anxiety finder arranges a focus on an individual level from an ordinary one by gaining his/her physiological flag through fitting sensors, for example, Electrocardiogram (ECG), Galvanic Skin Response (GSR), and so on., Depression and anxiety shirking is outlandish yet preventive activities defeat the pressure (Bakker, 2012). Therefore, in this research, we have utilized computational measures to reduce the said mental problems by engaging students and providing them a platform that can aid in diverting their attention and effectively reduce anxiety and depression in its wake. This research utilizes advanced AI techniques in the form of a k-nn algorithm for the detection and prevention of anxiety and depression among students.

2. K-NN classifier

The K-nearest neighbor (k-NN) technique is a famous grouping strategy in information mining and measurements as a result of its basic execution and noteworthy arrangement execution. Customary k-NN strategizes the utilization of a fix k esteem for the calculation of best outcomes by testing every single accessible example. The essential reason for NN is characterized as pursues: given a lot of the preparation tests, what's more, a question, discover a point that is the nearest to the query and afterward appoint its class mark to the query.

The customary k-NN content arrangement calculation utilizes all preparation tests for characterization, so it has countless preparing tests and a high level of computation multifaceted nature, and additionally, it doesn't mirror the novel criticalness of various examples.

Later on a superior and progressively compelling methodology for analysis of the outcomes utilizing k-NN was presented. As per this, the k-NN calculation can be improved by utilizing the bunching strategy for gathering and handling the examples (Zhou Yong, 2009). This technique brought about compelling abatement in the quantity of preparing tests alongside diminishing the figuring multifaceted nature.

3. Method

3.1. Research Methodology

There are primarily four stages to achieve the outcomes. The procedure embraced in this exploration includes an Action Research (AR) case study based on psychopathic non-technological students.

3.2. General Method

To organize a depression and anxiety state, the following four steps are used: data annotation, feature extraction, feature selection, and classification. Depression and anxiety state and calm state are labeled by data annotation. The feature can be calculated by feature extraction that can well categorize states in a classification algorithm.

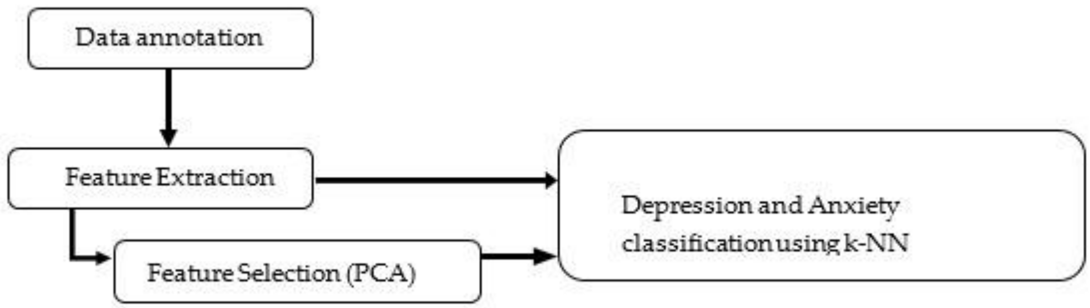


Figure 1. An overall process of stress classification

3.3. Dataset and Participant

Data from various universities all over Pakistan have been gathered and analyzed to generate promising results for this research. Almost 1366 healthy participants took part in this research through a questionnaire comprising of well-selected and precise questions. The students were asked to fill out the questionnaire keeping in mind their mental conditions one week before solving the questionnaire for most recent and valid data collection purposes.

3.3.1. Application and computing a K-nn model

The distance between the sample to be sorted and the training sample of the known category is calculated, and the k neighbors closest to the sample data to be sorted are found. The categories of the sample data to be classified are determined according to the category to which the neighbors belong.

i. **Calculate the distance:** Given the test object, calculate the distance from each object in the training set. ii. **Find neighbors:** delineation of the nearest k training objects, as the test object of the neighbors.

iii. **Classification:** According to the k Kordia attribution of the main categories, to test the object classification.

The non-parametric classifier used here is the K-Nearest Neighbor (KNN) (Palanisamy, 2009). KNN is applied for classifying the depression and anxiety levels which purely depends upon Euclidean distance between nearest-neighbor of training and testing feature vectors.

3.4. Feature Selection

Highlight choice is an approach to decrease a high-dimensional component space. It is conceivable to diminish the calculation time for the grouping through the element choice. In this paper, PCA (Principal Component Analysis) was utilized for expanding the exactness of the information.

PCA (Jolliffe, 2002) is regularly utilized to highlight dimensionality decrease. This strategy helps envision a high-dimensional element space that is interrelated by finding an important part (PC) that amplifies the fluctuation of the highlights. Along these lines, excess data from the first highlights space is dispensed with. In PCA, a change lattice is utilized to scale and pivot the first highlights space. It very well may be figured as a straight change by anticipating highlight vectors on changed subspace by

pertinent bearings. PCA sums up the component determination process for the entire arrangement of information. In this investigation, the Euclidean separation is utilized to discover the separation between two element vectors.
Condition (1) demonstrates the Euclidean separation recipe.

Feature selection is a way to reduce a high-dimensional feature space. It is possible to reduce the computation time for the classification through feature selection. In this paper, PCA (Principal Component Analysis) was used for increasing the accuracy of data. PCA (Jolliffe, 2002) is commonly used in feature dimensionality reduction. This method is useful for visualizing a high-dimensional feature space that is interrelated by finding a principal component (PC) that maximizes the variance of the features. In this way, redundant information from the original features space is eliminated. In PCA, a transformation matrix is used to scale and rotate the original features space. It can be formulated as a linear transformation by projecting feature vectors on transformed subspace by relevant directions. PCA generalizes the feature selection process for the whole set of input data.

In this study, the Euclidean distance is used to find the distance between two feature vectors.
Equation (1) shows the Euclidean distance formula:

$$d(X_i, X_j) = \sqrt{\sum_{i=1}^{n} (X_i, X_j)^2} \ldots\ldots\ldots\ldots\ldots\ldots (eq\ 1.)$$

Where x and y are two different feature vectors, and n is a number of features.

3.5. Classification Method

In this paper, *k*-nearest neighbors (*k*-NN) (Ackermann, 2016) are used for classification. The *k*-NN classifier is one of the most popular classification schemes due to its simplicity and computational efficiency. It classifies the corresponding classes by comparing the features from the feature extraction and feature selection process with the closest *k* learning data. To reduce the possibility of specific results for specific learning data, we use *k*-fold validation to separate training and test data (i.e., k = 3 in this study). Various k-nn techniques i.e., weighted k-nn, medium, cosine, coarse, and cubic k-nn were used to generate adequate results in this paper.

3.6. Measurements

We gathered the requirements through a medically approved survey questionnaire “The hospital anxiety and depression scale (HADS) from which we computed the level of anxiety and depression. The principal bit of the poll comprised of Anxiety questions (what they feel in the day by day life). The following arrangement of melancholy inquiries (what they feel while working with innovation).

4. Results and Discussions

The following are the experimental results for various k-nn methods used in this research i.e., weighted knn, medium, cosine, coarse, fine, and cubic k-nn.

4.1. Data Distribution Curve

The graphical method used to elaborate on the data distribution is known as the AUC-ROC curve. This curve is used to measure performance at various threshold settings. AUC represents a degree of separability while ROC symbolizes a probability curve.

TPR (True Positive Rate) / Recall /Sensitivity

TPR/Recall/Sensitivity = $\frac{\text{Number of True Positive}}{\text{Number of True Positive+Number ofFalse Negative}}$

Sensitivity

Sensitivity = $\frac{\text{TP}}{\text{TP+FN}}$

4.2. SPSS Validation

Furthermore, the results gathered using the questionnaire were validated using SPSS techniques. Factor analysis (under the data reduction menu) is used to calculate the internal validity of a questionnaire through SPSS. And hence evidence of validity (at least of the factorial variety) can be identified. Additionally, factor analyses with PC extraction are utilized to determine the number of factors.

4.3. Weighted K-nn Results

The Distance-weighted k-nn technique was first introduced by Dudani (S. A. 1976). In this type of k-nn algorithm farther neighbors are weighted less heavily than the closer ones. The weight w_i for the ith nearest neighbor of the query x ′ is defined as follow:

$$w_{i'} = \begin{cases} \dfrac{d(x',x_{kNN})-d(x',x_{iNN})}{d(x',x_{NN})-d(x',x_{iNN})} & \text{if } d(x',x_{kNN}) \neq d(x',x_{iNN}) \\ w_i' = 1 & \text{if } d(x', x_k^{NN}) = d(x', x_i^{NN}) \end{cases}$$

Then, the majority weighted voting makes the classification result query

$$y' = argmax \sum_{(x_{iNN},y_{iNN})\in T'} w^i \times \delta(y = y_i^{NN})$$

The furthest neighbor weights 0, the nearest neighbor gets a weight of 1 and the other neighbors' weights are scaled linearly to the interval in between. The accuracy rate without PCA with 14 selected features was 76.5% while the accuracy rate after PCA was 76.6%.

This is a perfect situation. At this point, the two bands don't overlap at all which indicates that the model has a perfect proportion of distinctness. It is flawlessly ready to recognize positive class and negative class. AUC is 0.7, which means there is a 70% chance that the model will be able to distinguish between positive class and negative class.

4.4. Medium K-nn Results

The accuracy rate without PCA with 13 selected features was 57.6% while the accuracy rate after PCA was 65.8%.

4.5. Fine k-nn Results

The accuracy rate without PCA with 13 selected features was 76.6% while the accuracy rate after PCA was 63.8%.

4.6. Cubic k-nn Results

The accuracy rate without PCA with 13 selected features was 58.1% while the accuracy rate after PCA was 63.9%.

4.7. Cosine K-nn Results

The accuracy rate without PCA with 13 selected features was 58.9% while the accuracy rate after PCA was 64.1%.

4.8. Coarse k-nn Results

The accuracy rate without PCA with 13 selected features was 58.6% while the accuracy rate after PCA was 65.6%.

4.9. SPSS Results

The results are divide into three categories depending upon the mental states of the students involved in the study. The three categories are distinctly defined as normal, borderline, and abnormal which each range from a healthy and stable to an upset mental state. The normal state describes the number of students with a comparatively optimistic and healthy mental state while Borderline indicates behaviors indicating effective liabilities. Lastly, the students falling under the category of abnormal symbolize an unhealthy and unstable mental condition verging through the risks of anxiety and depression.

Anxiety

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	normal	367	26.9	26.9	26.9
	borderline	419	30.7	30.7	57.5
	abnormal	580	42.5	42.5	100.0
	Total	1366	100.0	100.0	

Depression

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	normal	672	49.2	49.3	49.3
	borderline	392	28.7	28.7	78.0
	abnormal	300	22.0	22.0	100.0
	Total	1364	99.9	100.0	
Missing	System	2	.1		
Total		1366	100.0		

Descriptive Statistics

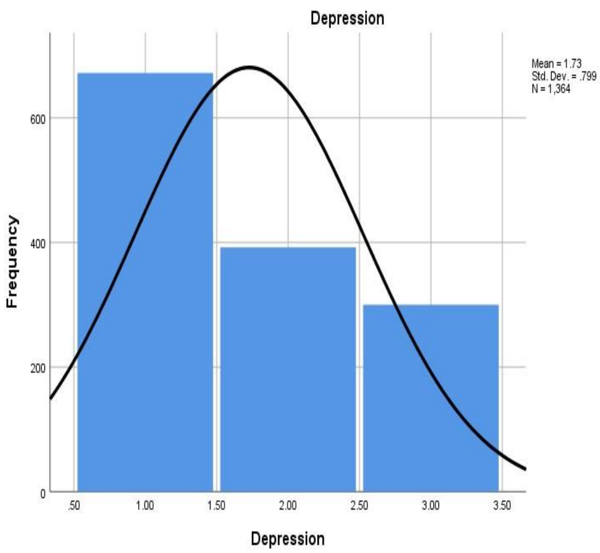
	N	Minimum	Maximum	Mean	Std. Deviation	Variance
AnxAvg	1366	.00	95.24	46.6081	16.95678	287.532
DepAvg	1364	.00	90.48	36.4370	17.01579	289.537
Valid N (listwise)	1364					

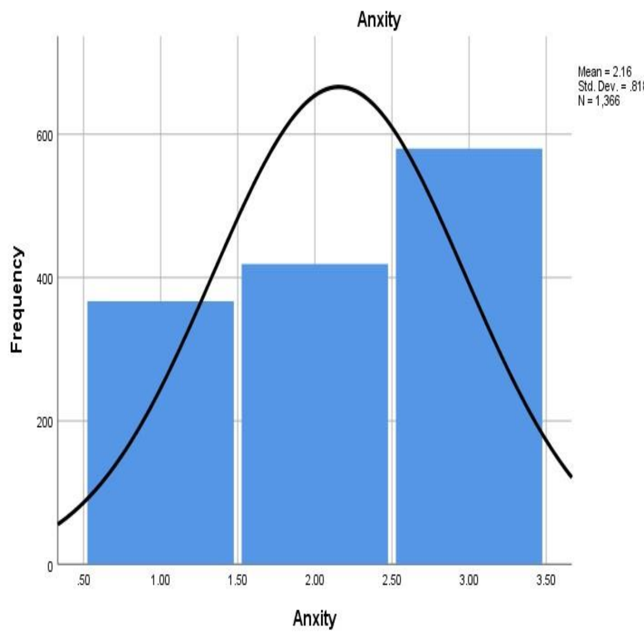
Statistics

		AnxAvg	DepAvg	Anxity
N	Valid	1366	1364	1366

Missing	0	2	0
Mode	52.38	38.10	3.00
Std. Deviation	16.95678	17.01579	.81819
Variance	287.532	289.537	.669

Histogram





5. Comparison Results

Table 1 shows the different results computed through various methods of k-nn i.e. cubic, cosine, fine, medium, weighted and coarse k-nn.

Table 1. Comparison results for different methods of k-nn

Name	PCA	K	Accu%	Dist. Matric	Dist. Weight	Roc Male	Roc Female	Male positive	Male Negative	Female Positive	Female negative	AUC
Medium	NO	37	59.4	Euclidean	Equal	0.48,0.67	0.33,062	477(60%)	240(40%)	335(58%)	314(42%)	0.62
Medium	Yes	37	57.6	Euclidean	Equal	0.49,0.64	0.36,0.51	456(59%)	261(41%)	331(56%)	318(44%)	0.60
Medium	Yes	7	65.8	Euclidean	Equal	0.36,0.67	0.33,0.64	481(68%)	236(32%)	418(64%)	231(36%)	0.71
Medium	No	7	64.1	-	-	0.38,0.66	0.34,0.62	475(66%)	242(34%)	401(62%)	248(38%)	0.70
Weighted	NO	37	76.5	-	Sq. inverse	0.24,0.77	0.23,0.76	553(78%)	164(22%)	492(75	157(25%)	0.88
	Yes	37	76.6	-	-	0.24,0.78	0.22,0.76	557(78%	160(22	490(75	159(25%)	0.88
	Yes	7	76.6	-	-	0.26,0.79	0.21,0.74	564(77	153(23	482(76	167(24%)	0.87
	No	7	76.1	-	-	0.25,0.77	0.23,0.75	552(77	165(23	487(75)	162(25	0.87
Cubic	NO	37	58.5	Minkowski	Equal	0.49,0.65	0.35,0.51	467(60	250(40	332(57	317(43)	0.61
	YES	37	58.1	-	-	0.47,0.62	0.38,0.53	448(60	269(40	346(56	303(44)	0.61
	Yes	7	66.5	-	-	0.35,0.68	0.32,0.65	488(68	229(32	421(65	228(35	0.71
	No	7	63.9	-	-	0.39,0.66	0.34,0.61	476(65	241(35	397(62	252(38	0.69
Cosine	No	37	58.1	Cosine	Equal	0.47,0.63	0.37,0.53	450(60	267(40	343(56	306(44	0.61
	Yes	37	58.9	-	-	0.49,0.66	0.34,0.51	472(60	245(40	333(58	316(42	0.61
	Yes	7	64.9	-	-	0.36,0.66	0.34,0.64	473(67	244(37	414(63	235(37	0.70
	No	7	64.1	-	-	0.35,0.63	0.37,0.65	454(67	263(33	421(62	228(38	0.70
Coares	No	37	59.2	Euclidean	Equal	0.47,0.65	0.35,0.53	465(60	252(40	343(58	306(42	0.61
	Yes	37	58.6			0.48,0.64	0.36,0.52	461(60	256(40	339(57	310(43	0.61
	Yes	7	64.6	-	-	0.37,0.66	0.34,0.63	471(66	246(34	411(63	238(37	0.70
	No	7	65.6	-	-	0.36,0.67	0.33,0.64	480(67	237(33	416(64	233(36	0.70
Fine	No	1	76.8	Euclidean	Equal	0.24,0.78	0.22,0.76	558(78	159(22	491(76	158(24	0.77
	Yes	1	76.6	-	-	0.23,0.76	0.24,0.77	547(78	170(22	499(75	150(25	0.77
	Yes	7	64.8	-	-	0.37,0.66	0.34,0.63	473(67	244(33	412(63	237(37	0.70
	No	7	63.8	-	-	0.38,0.65	0.35,0.62	469(66	248(34	403(62	246(38	0.70
	No	37	59.7	-	-	0.48,0.67	0.33,0.62	478(61	239(31	337(59	312(41	0.62
	Yes	37	57.4	-	-	0.49,0.63	0.37,0.51	455(59	262(41	329(56	320(44	0.60

6. Conclusion

This paper elaborates on the use of analysis methods to compute and analyze the mental depression and anxiety levels in human beings. A few useful features were selected carefully from the collected samples through PCA-based selection methods. Then the classification was carried out with the virtue of the *k*-NN algorithm by using the reduced feature subsets through PCA. Finally, the classification accuracy was measured. The final percentage accuracy by using k-nn with PCA was 76.6% as it was reduced to 76.5% without PCA.

7. Appendix

This research adopted a methodology that is based on an Action Research case study grounded on psychopathic technological students. We developed a plan for conducting the survey. Firstly, we contacted the HOD of the computer department and asked to approve the survey for different classes at the campus.

After getting approval, we randomly selected the classes and sections to get filled the survey forms. Forms were distributed amongst the students and taken back. When we distributed the survey forms in the classes, the instructor was present all the time. All member students were recognized with similar attitudes of directions and were expressed that their inclusion in this area of information gathering was willful and their personality would be kept unidentified. Every benefactor did with a self-report overview.

Age:______ Place of Birth:______________________ Gender:________

D	A		D	A	
		I feel tense or 'wound up':			**I feel as if I am slowed down:**
	3	Most of the time	3		Nearly all the time
	2	A lot of the time	2		Very often
	1	From time to time, occasionally	1		Sometimes
	0	Not at all	0		Not at all
		I still enjoy the things I used to enjoy:			**I get a sort of frightened feeling like 'butterflies' in the stomach:**
0		Definitely as much		0	Not at all
1		Not quite so much		1	Occasionally
2		Only a little		2	Quite Often
3		Hardly at all		3	Very Often
		I get a sort of frightened feeling as if something awful is about to happen:			**I have lost interest in my appearance:**
	3	Very definitely and quite badly	3		Definitely
	2	Yes, but not too badly	2		I don't take as much care as I should
	1	A little, but it doesn't worry me	1		I may not take quite as much care
	0	Not at all	0		I take just as much care as ever
		I can laugh and see the funny side of things:			**I feel restless as I have to be on the move:**
0		As much as I always could		3	Very much indeed
1		Not quite so much now		2	Quite a lot
2		Definitely not so much now		1	Not very much
3		Not at all		0	Not at all
		Worrying thoughts go through my mind:			**I look forward with enjoyment to things:**
	3	A great deal of the time	0		As much as I ever did
	2	A lot of the time	1		Rather less than I used to
	1	From time to time, but not too often	2		Definitely less than I used to
	0	Only occasionally	3		Hardly at all
		I feel cheerful:			**I get sudden feelings of panic:**
3		Not at all		3	Very often indeed
2		Not often		2	Quite often
1		Sometimes		1	Not very often
0		Most of the time		0	Not at all
		I can sit at ease and feel relaxed:			**I can enjoy a good book or radio or TV program:**
	0	Definitely	0		Often
	1	Usually	1		Sometimes
	2	Not Often	2		Not often
	3	Not at all	3		Very seldom

Figure 2. Questionnaire

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