MENTAL HEALTH PREDICTION USING A SUBJECTIVE WELL-BEING MODEL BASED ON THE PERCEIVED STRESS SCALE

(ÖZNEL İYİ OLUŞ MODELİNİ KULLANARAK STRESS ÖLÇEĞİNE DAYALI AKIL SAĞLIĞI TAHMİNİ)

by

B.S.

Thesis

Submitted in Partial Fulfillment

of the Requirements

for the Degree of

MASTER OF SCIENCE

in

LOGISTICS AND FINANCIAL MANAGEMENT

in the

GRADUATE SCHOOL OF SCIENCE AND ENGINEERING

of

GALATASARAY UNIVERSITY

Aug 2022

ACKNOWLEDGEMENTS

First of all, I would like to thank my supervisor for his support, understanding and the vision he gave us during this study.

I am also grateful to my dearest family for their infinite trust and support.

I would also like to thank my buddy for all support for years on this journey.

Last but not least, I would like to express my gratitude to my dear lecturers in İstanbul Kültür University – Industrial Engineering department.

Aug 2022

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LIST OF SYMBOLS

AI : Artificial Intelligence
DP : Deep Learning
ANN : Artificial Neural Network
ML : Machine Learning
SDT : Self Determination Theory
AWB : Affective Well-Being
CWB : Cognitive Well-Being
SWB : Subjective Well-Being
SWLS : Satisfaction With Life Scale
EWB : Eudamonic Well-Being
HWB : Hedonic Well-Being
PWB : Psychological Well-Being
PSQI : Pittsburgh Sleep Quality Index
QOL : Quality of Life
HRQOL : Health-Related Quality of Life

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ABSTRACT

It has been decided that one of the most significant facets of existence is well-being, as this is the greatest way to keep people healthy and productive. This has led to the conclusion that well-being is one of the most important parts of existence. Because there are a substantial number of different ways to define "well-being," there are also a significant number of different scales that can be used to assess it. The purpose of the well-being scale is to provide general information on the level of an individual's quality of life.

In this study, Subjective Well Being (SWB) characteristics are used in conjunction with machine learning classifiers to make predictions regarding levels of stress. In order to collect data from college students between the years of 2015 and 2019, sensors and self-reports were utilized, and approximately 700 students took part. To have a glance of understanding human nature and the requirements, it has has recently emerged as a popular topic of study among experts. Because of this, the combination of Artificial Intelligence (AI) and Psychology can appear to be straightforward; yet, in order to identify each of the aspects and their reflections in AI's research, the subject of psychology needs to be thoroughly researched. The purpose of this study is to provide individuals with a basic framework for understanding their physical and mental health situations by presenting and explaining in detail the findings of a psychological research.

A growing number of studies have been carried out to investigate the possibility of accurately predicting a person's level of happiness by making use of carefully constructed models. In order to build a Subjective Well-Being (SWB) model that has any chance of success, it is necessary to conduct research into the histories of the features. We have selected the variables from the literature on SWB that are appropriate for the real-world data instructions, and these variables come from the suitable categories. The purpose of

this work is to evaluate the model by providing it with SWB characteristics and then classifying the different levels of stress using machine learning methods in order to determine how well the model functions when applied to a real dataset. We have achieved significant metric scores, which may be taken into account for a particular task, despite the fact that it is a multiclass classification issue.

ÖZET

İnsanları sağlıklı ve üretken tutmanın en iyi yollarından biri olan varoluşun en önemli yönlerinden birinin mutlu olmak olduğu ortaya konmuştu. Bu, refahın varoluşun en önemli parçalarından biri olduğu sonucuna yol açmıştır. "İyi olma halini" tanımlamanın önemli sayıda farklı yolu olduğundan, onu değerlendirmek için kullanılabilecek önemli sayıda farklı ölçek de vardır. İyi oluş ölçeğinin amacı, bireyin yaşam kalitesi düzeyi hakkında genel bilgi vermektir.

Bu çalışmada, stres düzeylerine ilişkin tahminler yapmak için Öznel İyi Oluş (ÖİB) özellikleri makine öğrenimi sınıflandırıcıları ile birlikte kullanılmıştır. 2015-2019 yılları arasında üniversite öğrencilerinden veri toplamak için sensörler ve öz-raporlardan yararlanılmış ve yaklaşık 700 öğrenci katılmıştır. İnsan doğasını ve gereksinimlerini anlamak için bir bakış açısına sahip olmak, son zamanlarda uzmanlar arasında popüler bir çalışma konusu olarak ortaya çıkmıştır. Bu nedenle, Yapay Zeka (AI) ve Psikoloji kombinasyonu basit görünebilir; Yine de, Yapay Zeka araştırmalarındaki her bir yönü ve yansımalarını belirlemek için psikoloji konusunun kapsamlı bir şekilde araştırılması gerekiyor. . Bu çalışmanın amacı, psikolojik bir araştırmanın bulgularını ayrıntılı olarak sunarak ve açıklayarak bireylere fiziksel ve ruhsal sağlık durumlarını anlamaları için temel bir çerçeve sağlamaktır.

İyi tasarlanmış modeller kullanılarak refahın nasıl tahmin edilebileceğini belirlemek için birçok sayıda çalışma yapılmıştır. Uygulanabilir bir Öznel İyi Oluş (ÖİB) modeli oluşturmak için söz konusu değişkenlerin arka planını araştırmak gerekir. Öznel iyi oluş literatüründen uygun değişkenler seçilmiştir. Bununla birlikte gerçek hayatta toplanan veriler işlenerek modele uygun hale getirilmiştir. Bu çalışmanın amacı, psikolojik bakış açısıyla hazırlanan öznel iyi oluş modelini ÖİB değişkenleri ile besleyerek değerlendirmek ve ardından gerçek bir veri kümesinde ne kadar iyi performans

gösterdiğini görmektir. Bu süreçlerin gerçekleştirilmesinde makine öğrenimi yöntemlerini kullanarak stres seviyeleri kategorilere ayrılmıştır. Çok sınıflı bir sınıflandırma sorunu olmasına rağmen, belirli bir görev için dikkate alınabilecek önemli metrik puanlar elde edilmiştir.

1. INTRODUCTION

Nowadays it is hard not to hear Artificial Intelligence and its applications. Since digitalization brings many kinds of interaction together via social media people could be up to date about technology. However, understanding of AI differs from person to person due to perception of the definition. There are several agreed terms which most humankind can do such as learning, reasoning, understanding, grasping truths, seeing relationships, considering meanings, separating fact from belief. Although computers may do these activities based on the given code, firstly it has to be converted to software basis [0 1]. That's why a data shall be introduced with the Artificial Intelligence (AI) then algorithms provide to improve it.

On the other hand, it is not possible to use AI for every intelligence area of life for instance visual-spatial, bodily-kinesthetic, logical mathematical intelligence are suitable to moderate whereas creativity, linguistic, intrapersonal, interpersonal intelligence are low to moderate. As we can understand there are many artificial intelligence areas and to describe AI some of the definition enable us to understand, AI has anything to do with human intelligence. It is obvious that some of the application gives us the different view of AI, but they are still just a simulation. To map the AI four dimensions can be used such as acting humanly, rationally and thinking humanly, rationally.

As we can understand that AI has become critical for the societies because there have been many AI applications which help to human race. For instance, AI algorithms can detect anomalies in the data, and it is being used for the benefit of medical field. AI can identify the person who is going to have a heart attack for the near future. Therefore, there are dozens of devices which have a meaning with AI algorithms because the data which was collected could be used under the favor of AI.

2. PREPARATION FOR THE LITERATURE REVIEW

2.1 Artificial Intelligence

One of the important moments of AI started with Turing experiment which was done by Alan Turing (1950). The test was about distinguishing human intelligence from the artificial entity. According to experiment there are three empty room and human interrogator, a man and artificial entity and they are placed to each room and physical interaction is prohibited. If interrogator cannot separate artificial intelligence from the human intelligence Turing test is passed. Searle (1980) came out against to this idea and made an experiment called Chinese room experiment. This experiment stresses the idea of does artificial intelligence have an ability to understand Chinese. If we are able to convince the interrogator that inside a room who is giving answers is a human thus Turing test is passed. With all that debates bring out the terms which are strong AI and weak AI. Based on Searle's idea strong AI was not possible, but humankind make any program which is useful and have no understanding of the studied area. Beyond all these opinions computer scientist has reached their aim if the artificial entity is behaving intelligent.

While theoretic discussions had been around AI had started with the idea of neurons in the brain. This approach was proposed by McCulloch and Pitts (1943). Based on the idea, artificial neurons have the binary variety which can be one or zero. The proposed model was developed by Donald Hebb (1949) with Hebbian learning for neural networks. Marvin Minsky and Dean Edmonds invented the first neural network computer named as SNARC. In the pursuit of this achievement and Turing's improvement of the Turing test, neural networks and artificial intelligence has become popular topic all around the world among the researchers. With all these developments, AI is started to be the new discipline which forms the artificial entity having ability to learn, react and make decisions on the given problem in the ambiguous environment.

Human logic models were the beginning outstanding models for the AI. Called the Logic Theorist program was working with the idea of mimicking human problem solving skills is developed by Allen Newell and Herbert Simon (1961) and it is accepted the first artificial entity. In 1961 General Problem Solver was programmed by Newell and Simon and the program was designed to solve simple problems such as Tower of Hanoi and the problem was about the sequencing the tower as demanded position.

In 1958, A hypothetical program was defined by McCarthy (1958) and the name was Advice Taker. Program was designed to give response to changing environment with no need of reprogramming.

‘’The main advantages we expect the advice taker to have is that its behavior will be improvable merely by making statements to it, telling it about its symbolic environment and what is wanted from it. To make these statements will require little if any knowledge of the program or the previous knowledge of the advice taker. One will be able to assume that the advice taker will have available to it a fairly wide class of immediate logical consequences of anything it is told and its previous knowledge. This property is expected to have much in common with what makes us describe certain humans as having common sense. We shall therefore say that a program has common sense if it automatically deduces for itself a sufficiently wide class of immediate consequences of anything it is told and what it already knows.’’

— McCarthy, 1958

AI researchers had gained success in the early stage of the AI history, and this makes them optimistic about AI’s future. Following is one of the well-known quote of the AI history:

‘’It is not my aim to surprise or shock you – but the simplest way I can summarize is to say that there are now in the world machines that think, that learn and that create. Moreover, their ability to do these things is going to increase rapidly until – in a visible future – the range of problems they can handle will be coextensive with the range to which the human mind has been applied.’’

— Simon, 1957

With that envelope researchers started to build knowledge based system which can be able to solve difficult problems. One of the triumphant knowledge based system were DENDRAL (Lindsay et al., 1980), a system for analyzing mass spectrograms in chemistry XCON (McDermott, 1982), a system for configuring VAX computers; and ACRONYM (Brooks, 1981), a vision support system.

Beyond the all this certain knowledge-based systems Neapolitan (1989) shows that there are numerous uncertain cases where ruled-based AI system is insufficient. In 1980s, researchers from different disciplines came together at the Workshop on Uncertainty in Artificial Intelligence conference to discuss what is the best approach for uncertain environments in artificial intelligence. With all these discussions one of the most important network had been found as an Bayesian Network which is used frequently now for many application of AI.

In the light of these developments the idea of using different approaches together is becoming popular and it is called swarm intelligence. As like many other species such as ants and their efficiency of doing tasks together more than doing individually. For instance, while any specie is more efficient at finding food, water when they are acting as a group. That's why the idea of using probabilistic and logical approaches jointly has solved lots of practical problems. As it is indicated above AI had started in the 1950s with the question of could we make computer thinking. Nowadays when we think of AI deep learning and machine learning comes up to mind as definitions. However early programs such as chess program has strict rules for every iteration that program takes, and they were not as qualified as machine learning approach. For the long time period scientist had believed that hardcoded rules and algorithms could be able to solve even complex problems. It was the sign of the symbolic AI which started in the 1950s and lasted late 1980s. Even though symbolic AI was able to solve complex problems with changing environments such as playing chess, latest improvements showed that symbolic AI was not enough to reach better solution when it comes to deal with speech recognition, image classification, fuzzy models and language processing. There was a new trending approach which has the better performance which was named machine learning. Machine learning concept came out with Lady Ada Lovelace and Charles Babbage who were the inventor of the analytical engine which was a mechanical computer. As it is understood from the name analytical engine it was using mechanical operations to automate certain computations from mathematical analysis. This invention was used by outstanding name of the AI who is Alan Turing in his "Computing Machinery and Intelligence, 1950" paper.

In this paper Alan Turing is introduced the Turing test which we mentioned above, and it support the idea of artificial intelligence. Alan Turing was mentioning about Lady Ada Lovelace and he was contemplating that could computer be able to learn? Then he concluded that they could. The question of could computers learn by just looking at the data without explicitly programming. This question provides to transit a new phase in the AI journey. In the sense of classical programming called symbolic AI there are rules and data which is passing through from the hardcoded structure and giving answers. On the contrary in the machine learning structure data and answers is inserted and the algorithm bring out the rules and those rules can be used for another data in order to compute new answer.

2.2 Machine Learning

Machine learning algorithms are fed by the data and answer then algorithm finds a proper way to produce general rules which you can apply for the new data. For instance, you would like to find family related photos in your gallery. To do that ML needs to see enough amount of your family related photos to be able to find the demanded target. Even though machine learning came into play in 1990s, it has rapidly earned reputation in the AI environment. Speaking of Machine learning, we shall mention relation with mathematical statistics. As it is mentioned above there are many ML algorithms which use Bayesian network and decision tree which are closely related with statistics. However, encountering with high volume data prevents you to use these statistics method. In the face of speech recognition and image classification there are millions of images which has enormous data volume, and it is impractical to use statistical methods. Instead of that making engineering tricks will help you to set better models.

We have seen the difference between symbolic AI programs and ML approaches. Now another term come up with ML which is deep learning. For better understanding of deep learning, we should go in detail in ML algorithms. As it is stated above for the ML approaches firstly input data is required and it should be suitable for each data set. For instance, if we are working with speech recognition the input data should be sounds of people, cars, parks. If it is about the image classification, we need to feed the dataset by pictures. Secondly examples of the output data is required in order to help the algorithms while it finds the relation between input and output data. Lastly, we shall have an understanding of how far we achieved. Afterwards a structure has been formed to see if the ML algorithm is learning effectively and this gives the user an insight what should be doing next. On the other hand, there is another problem for both ML and DL algorithms which is the representation of the input data. This representation provides you to cope with data more easily if it is in the right form.

Even though deep learning is subfield of AI, it has helped to solve many of the complex problems so the future of deep learning seems bright. However, the attitude towards the that kind of invention should be so careful because when we set our expectations too high it starts to be counterproductive for deep learning. As AI is a popular topic all over the world there are lots of myths and legends have been going around. As a result, people think of a human level advanced general intelligence entities which is so far from today. It is obvious that there are many examples such as autonomous driving, face recognition, natural language processing which makes people exaggerating the deep learning for the short term period. With these attitude societies expects more from the deep learning but it is not possible for all the times. When deep learning cannot deliver what was demanded from the all over the world research investments and the money which comes from the companies will decrease. This is one of the important point in the artificial intelligence history because this has occurred twice in the past. In 1960s the expectation from AI was so high and one of the well-known person Marvin Minsky foresee that in 1967 (Massaron, 2018), “Within a generation … the problem of creating ‘artificial intelligence’ will substantially be solved.” and three years later he made a more precise prediction with these words “In from three to eight years we will have a machine with the general intelligence of an average human being.”. It is not possible to claim something like even in the today’s environment. Afterwards artificial intelligence had failed because the expectation was too high to be met. Supports and investments decrease and first winter of AI started in 1970s. After the first winter stage in 1980s, new symbolic AI movement had started and it stimulates companies’ interest. In 1985 companies began to invest AI era once again with 1 million dollar each year. However, with the same sense expectations could not be met. When we reach early 1990s companies cut off their investment on AI and second winter AI began due to the unrealistic expectation which AI cannot be able to provide it.

As it is mentioned above short-term high expectations has negative effects but for the long-term expectations AI will be taking place almost all types of area in the world. From a to z AI approaches has begun to applying for every area like the internet joined our lives. People has not realized the joining of internet to life but now we cannot imagine living without internet. However, there is a long way down the road comparing to journey of the internet. AI has not been using in many areas too with advance usage. Machine learning algorithms is an effective way to detect anomalies in medical sector but when we think of using near human AI entities which helps to doctor to detect any kind of disease spontaneously seems far from now. That's why intervention of AI for the general use will be taking more time. However, there are plenty of small accessories which helps people with recommendation. AI has become good at recommending something which users try to find. Recommendation of products, music and such things on the internet has been a good helper for people. General use of AI will increasingly continue to be part of our lives. You may have an assistant or even a friend which plans your entire day and look after your family with broad range of support. As it is stated in this paper those vision is for the long term future of the AI otherwise if we imagine for the near future 3rd AI winter break may be occurring. As a conclusion it is not that far away from now having an advanced level of AI entities in our society and all over the world.

AI has three prominence topic which are symbolic AI, machine learning and deep learning. There are lots of problems which can be solved by ML algorithms without using DL algorithms. Machine learning has well-structured algorithms such probabilistic modelling, kernel methods, decision trees, random forests, which are practical for many problems.

Probabilistic modelling is working with statistic principles to analyze the data and it has a wide range of usage even today's environment. Naive Bayes is one of the important algorithm which is a machine learning classifier and it calculates the probability of the classes. For example, think of a bank which has broad range of customer types and the bank would like to know which type of customers as a class has the highest risk for the given loan payment. With that knowledge the bank may be able to deliver the loan to the least risky customer class and naïve bayes algorithm can give you a clue about it. Another well-known algorithm which is the starter point of machine learning is logistic regression. As you may think from the name it is a regression algorithm, but it is not. It is logrec classifier which has a practical use for many data type so many researchers put their data in logistic regression to classify it in the first place.

The idea of neural networks is also important milestone for the machine learning history. Origin of the idea had started with the simple form in 1950s and it took approximately 40 years to reach remarkable form. This was happened with the backpropagation algorithm in 1980s. In (1989) Yan Lecunn combined convolutional neural network and backpropagation algorithm then he applied the algorithm in order to classify handwritten digits. In 1990s the network called Lenet was applied to USA Postal Service to make system which reads ZIP codes automatically.

Later neural network had lost its fame quickly after its success in 1990s. Then other one of the important ML algorithm kernel method is developed by Vladimir Vapnik and Corinna Cortes in the beginning of 1990s. Kernel methods are the group of the classification algorithms and one of the well-known kernel method is support vector machine. The main idea of how SVM work is based on the drawing a hyperplane as a good decision boundary which divides the data in two or more dimensions. In order to draw hyperplane SVM algorithm computes the distance of closest data points and it is trying to maximize them called maximizing the margin. However, Support vector machines are practical for the shallow learning models whereas it is not practical when we are dealing with the large data sets like image classification.

In 2000s interest for the decision trees had been increased because algorithm works with the ease of visualization and interpretation. Decision trees is a hierarchical structure which is divided by the probabilities of the data and data is fed by the suitable answer for each divided probabilities. In 2010s it was started to be preferred over the kernel models. Afterwards random forest has become popular and it was applied to broad range of the problems. Furthermore, random forest was one of the most used algorithm in the competition website which is Kaggle. Until 2014 random forest has protected its place but then gradient boosting machines took the lead. The gradient boosting algorithm focus on the weak point of the joint decision trees and improving weak point for previous decision tree models with each iteration.

In 2010s neural networks has regained its reputation by the work of small number of groups. In 2011 the first modern achievement has been reached by Dan Giresan who win the academic image classification competition with GPU-trained deep neural networks. Then in 2012, Geofrey Hinton's group attended the ImageNet challenge which was large scale image classification problem. Each year accuracy of the ImageNet challenge was increased and then challenge is evaluated as a solved problem because accuracy was 96.4% in 2015. In 2012 deep convolutional neural networks called convnets has found a great place among all these algorithms and it was using at perceptual tasks. On the other hand, convnets has started to be a good option for natural language processing and it is exchanged with SVM and decision tree algorithms. The accompanying classifiers diagram provides a visual overview of the algorithm's mathematical foundation.

2.3 Psychological Aspect for Subjective Well-Being (SWB)

In this part psychological findings are presented to have a clear understanding for Subjective Well-Being.

2.3.1 Psychological Needs

With that approach, a new area has become prominent among researchers, understanding human nature and its needs. That is why combining both psychology and AI can seem easy, but to define each of the elements and their reflections in AI's research, the field of psychology shall be strictly analyzed. As a good starting point, human emotions are investigated by Mcdougall (1908). In his introduction social psychology book, he indicated that all emotions could be distinguished, such as joyful and sorrowful emotions. One of the reasons behind the separation is that there has been a great variety of emotion types, and it is not simple work to be done. For instance, wonder and gratitude could be named joyful emotions, whereas fear and pity could be sorrowful emotions. Mcdougall stated the second point, which is that how to distinguish primary emotions from other emotions. Firstly, humankind's exhibited emotions should have common ground with the higher animals and their instinctive activities. Due to these similarities between humans and the higher animals, it is logical to stress that those emotions are the primary, simple emotions.

On the other hand, if it is impossible to detect these similarities, emotions could be described as complex emotions or genuine emotions. Moreover, the term sentiment refers to all the feelings and emotions, and it can be described as an affective aspect of mental processes. In AI, research sentiment analysis is one of the salient research areas, and psychological aspects help detect human needs.

As mentioned above, need concepts for human psychology are essential to draw a general map that gives a clue about human behavior. There are several strong examples of the need to belong in this research paper (Baumeister & Leary, 1995). For most of humankind, it is easy to form social bonds or attachments. Especially when it comes to sharing the same kind of experiences or things, forming social bonds, friendships can be so easy. Moreover, after having bonds or friendships with others, most people avoid losing it. According to the research paper, illnesses, mental problems, and eating disorders are common among people who have less social attachments than those with more social attachments. Another aspect is that when the person loses his/her bonds, friendships, or any other social attachments, he/she starts to attend more events to look for a new social attachment. Belonging to a group may provide to boost self-esteem (Turner, 1985). Another consequence of social attachment can be violence. Being a member of a group may be obliging the person to use violence, and thus the person can be accepted to the group by this kind of behavior.

Understanding human and human needs are sophisticated topics, yet their origins are not validated, even there are numerous examples. However, there are some sentiments which most people would like to obtain. Those are competence, relatedness, and autonomy, and it is called self-determination theory (Ryan and Deci, 2000). According to the theory, people shall have competence, relatedness, and autonomy jointly unless it is hard to maintain their well-being sufficiently. As you may notice, the term well-being and will be explained below later. SDT analysis the intrinsic motivations, which helps to enhance self-esteem, self-actualization and also to reduce anxiety and depression. Based on the book (Ryan and Deci,1985) following definitions will be mentioned so that competence could be described as the cumulative consequence of one's engagement with the set of surroundings and one's discovery, training, and harmony with the environment. The more the person experiences those explained steps, the more he/she become competent. Relatedness is a need to belong to others, and it is described above. Autonomy can be described as the experience of choice. The autonomy-centered person will try to organize himself/herself to be in search of self-determined aims. The choice concept does not have to be logical or on purpose, but the person should determine it. Those points have been explained to provide a general understanding of human needs because that information will be required to form a robust AI structure.

In this quoted research paper (K. M. Sheldon, 2001), ten human needs are contrasted in terms of the psychological fundamentals needs. For ease of understanding, we try to explain self-determination theory and three fundamental needs. In this research (K. M. Sheldon, 2001), competence, autonomy, relatedness, self-esteem, security, self-actualization-meaning, physical thriving, pleasure-stimulation, money-luxury, and popularity-influence has been rated by the audience. However firstly, researchers demand from the audience to consider satisfying events during the last month. Afterward, the audience scored every ten items with a scale from one to five. This research has been conducted in two different social structures and three different time frames to understand both the differences between cultures and time frames. Consequently, in American culture, compliance with the SDT competence, autonomy, and relatedness are the most satisfying events. However, self-esteem has the first rank in the queue as a psychological need. In South Korean culture, relatedness was one of the first needs in satisfying events compared to the US sample, and the first need was self-esteem. This research had shown that satisfying events could differ from culture to culture. In this thesis, since the aim is both forming an effective AI model with psychological perspective and application in different cultures in the light of these pieces of information, some of the needs can be used as features (inputs) of our model.

2.3.2 Affective and Cognitive Well-being

Since SWB is strongly related to affective and cognitive well-being their context shall be analyzed well. AWB contains positive and negative emotions and moods which are analyzed (by) their frequencies and intensities. In comparison to CWB, AWB is more about the individuals' emotional state, so personality characteristics and other things that are about the affective state of individual show stronger correlations on AWB than CWB (Steel, Schmidt, & Shultz, 2008). To be more prices on this topic, AWB and personality characteristics can conflict at some points, so the data should be analyzed to avoid this kind of situation statistically. CWB contains domain-specific evaluations, in other words, global assessment of individuals, which can be about job satisfaction, life satisfaction, and marital satisfaction, and so on. Surrounding habitats, for instance, salary, education level, body shape, have more substantial effects on CWB.

Furthermore, life incidents surrounding the individuals, such as birth, death, retirement, marriage, and so on, have more potent effects on CWB than AWB (Maike Luhmann, Louise C. Hawkley, 2012). Due to the structural difference between AWB and CWB, time frame distinction should be arranged independently and accordingly. For instance, if a person is being exposed to a specific life event and the life incident's lasting effect could vary from event to event (Luhmann, M., Hofmann, 2012). There are numerous life events such as death, winning the lottery, being fired or hired that have remarkable lasting effects on SWB. While forming our mathematical model, time frame differences shall be considered because AWB and CWB can influence SWB jointly.

One of the well-known AWB scales is Positive Affect Negative Affect Scale (PANAS) and Job-related Affective Well-being Scale (JAWS), and Affect Intensity Measure (AIM). PANAS has 20 items in two parts, one part has positive definitions, and the other part has negative definitions on how the person is feeling over the specified period (Watson, Clark, & Tellegen, 1988). Another AWB scale is connected with the intensity of the positive or negative feelings. The scale of PANAS aims to measure the frequency of the sentiment, whereas the scale of AIM targets to measure the intensity of the sentiment. In other words, it measures how the sentiment is affecting intense individuals. Since one of the aims of this research paper is to form a time series problem and contain personalization tools such as AIM, which is exclusive to the individual. Several research papers investigate the individual's reaction to daily events such as reading or seeing a bad news on a newspaper and asking an individual how intense he/she is being influenced by that newspaper (Ed Diener, Randy J. Larsen, 1986).

As it is reviewed above, AWB scales, and it is one part of SWB called affective well-being. The other part is more about the cognitive side of our well-being. Since it is a subjective inference, it mainly includes life events such as graduation from university and having or losing a job, and so on. One of the critical CWB scales is the Satisfaction With Life Scale (SWLS), and it has five general questions which determine one's life with global judgments such as "In most ways, my life is close to my ideal." Besides, SWLS has a 1-7 scale on the subject's answer, and it is a representation of the individual's perception. To know the SWLS and correlation between other CWB scales, researchers have compared SWLS with other scales such as Cantril Ladder, Fordyce 1, Campbell, Bradburn-PAS (Ed Diener, Robert A. Emmons, Randy J. Larsen & Sharon Griffin, 1985). Consequently, it has been shown that SWLS has a strong correlation with other scales. In this thesis, one of our focal points is choosing one or two CWB scales that are reliable and validated.

2.3.3 Hedonic and Eudaimonic Well-being

There are many types of well-being definitions, and we could not say that they are incorrect, but there are many incomplete aspects to each definition. When it comes to the evaluation of life from the aspect of hedonic or eudaimonic enjoyment, hedonic enjoyment could be described as whenever the person is feeling pleasant, joyful without having any conceptual restriction. Since there are numerous types of needs such as psychological, social, intellectual, physical, and so on, hedonic enjoyment can be coming up with any of these needs (Alan S. Waterman, 1993). To make it clear, there are two main perspectives to characterize well-being (Ryan & Deci, 2001). The first perspective stresses an individual's assessment of their life both affectively and cognitively. It could be referred to as hedonic well-being (HWB), and it is composed of (a) frequent pleasurable sentiments, (b) infrequent unpleasurable sentiments, (c) and the person is satisfied with a comprehensive assessment of his/her life (E. Diener, S. Oishi, & L. Tay, 2018). This model of HBW may also be referred to as subjective well-being (Diener, 1984) because it is based on an individual's evaluation of how good their life is going, and a detailed explanation will be done under the topic which is Types of Well-Being.

The second perspective contains several concepts, which are referred to as eudaimonic well-being (EWB). EBW focuses on the needs and qualities required for an individual's psychological growth and improvement. As it is mentioned above, according to self-determination theory (SDT), the satisfaction of those kinds of needs allows an individual to reach their full potential (Ryan, R. M., & Deci, E. L., 2001). The argument of Psychological Well-Being (Ryff, 1989) can be an example of the EBW path (E. Diener, S. Oishi, & L. Tay, 2018). Psychological Well-Being will be explained in section 2.7 (Types of Well-Being). Furthermore, it has six core features of individuals performing well in their life: Self-Acceptance, Environmental Mastery, Positive Relations, Purpose in Life, Personal Growth, Autonomy. An individual who is dealing with an activity will have followed experiences of EWB such as (a) uncommonly dense engagement in an undertaking, (b) a sense of an exclusive fit or being under an activity which is not usual daily tasks, (c) a sense of densely being alive, (d) a sense of being complete while dealing with an activity, (e) an idea that this what the individual was meant to do (Waterman, 1990a).

As it is reviewed above, both HWB and EWB, in this research paper, our aim is to set an artificial intelligence model fed by the inputs such as CWB and AWB scales (questionnaires) and some other field of questionnaires. As it is seen that detection of the EWB is not that easy task comparing to HWB because the experiences of EWB is mainly about the intrinsic motivation of individual (Ryan and Deci, 1985). When you speak of collecting datum with sensors and questionnaires (scales), interpreting signs of HWB is more accessible than the sign of EWB. Thereby, we generally would like to focus on HWB, in other words, subjective well-being (SWB).

2.3.4 Types of Well-Being

There is a significant number of well-being definitions; thereby, there are also many scales that measure well-being. The well-being scale aims to give general information about one's quality of life level.

SWB is being divided into three characteristic features (Diener, E., 1984). The first feature is the practical understanding of life; in other words, it is a subjective perspective based on the gained experience of a person (A. Campbell, 1976). There is a specified normal for each individual that the person itself is setting. The people can evaluate the quality of life of themselves, so it is not imposed by any other external sources (Ed Diener, 1985). The key phrase here is that the person's judgment, so individuals' opinions at determined points can differ from person to person. At the same time, some of the individuals may place greater weight on financial topics, whereas some of the individuals may be placing more weight on social relations in terms of satisfaction of life. Secondly, in SWB, there are also positive measures, so the aim is not only to search for the lack of opposing elements.

Nonetheless, it is not possible to understand the connection between them yet. Thirdly, in SWB measures, there are both cognitive and affective well-being components in other saying cognitive component includes global judgments of one's life and satisfaction with specific life domains (job satisfaction) (Diener, 2000), so those measures give a general evaluation of one's life. It is mentioned those measures above.

In this paper, the aim is the detection of SBW for individuals. For that goal, people's lives should be followed for a long time (A. Emmons, 1985). Since individuals' cognitive and affective well-being are being tracked with sensors and mobile phones' help accordingly, it provides ease of accessibility. However, there are numerous problems for the collection of data, and those problems will be analyzed later. In the early past research, there are a significant number of investigations about ones' day-to-day affective states. In one of them, individuals show two-dimensional difference independently: (1) named average hedonic level which is dwelled by the person and it is a number of both positive and negative affect and (2) the number of variabilities which individual presents in their affection (Wessman, A. E., & Ricks, D. F., 1966). In this research, a wide range of data will be collected to determine how long a person is being exposured to a specific condition and the effects of this exposure in terms of negative and positive affect. Afterward, it turns out that affective well-being can be separated in two components which are positive and negative affect frequency and intensity. Intensity and frequency are independent components, and they have distinctive features which belong to them. A person who experiences more positive incidents but with low intensity can generally result in lousy well-being (A. Emmons, 1985).

Another prominent well-being is Psychological Well-Being (PWB). As we have noted above, PWB is an example of EWB tradition, and it is different from the HBW approach. Since the Greek word eudaimonia can be translated as happiness but Aristotle defines it as the realization of one's true potential (Waterman, 1984), which is more than happiness. It is evident that in order to understand positive psychological functioning, happiness is not the only sign of it in previous empirical studies. Another point is that, like SBW, PWB has a solid theoretical background, and the components of PWB were improved for other purposes, then it became prominent for positive functioning (Ryff, 1989). As we can understand from this perspective, components of PWB helps to realize one's true potential, and now each core feature of PWB will be explained briefly. Self-Acceptance is one of the primary criteria for both mental health and self-actualization, and Life span theory stresses acceptance of the present and past life of a person (Reference). The second component is that Positive Relations with others; we have noted above how important is having a social connection. Again in this approach, the ability to love has a decisive role in positive psychological functioning. The third component is that autonomy. As it is reviewed above, autonomy is a crucial part of the Self-Determination Theory (SDT), and the person evaluates himself/herself with his/her internal standards. When we speak of self-actualization, one of the most important aspects is that autonomy gives the person freedom against the norms of life (Ryff, 1989). The fourth component is Environmental Mastery, the capability to manage a person's own life and the surrounding world predominantly (Ryff, 1995). On the above, we have reviewed one of the critical components of SDT, which is competence. Furthermore, competence and environmental mastery show some similarities because an individual who is advance in both competence and environmental mastery will try to improve their surrounding world for a better outcome. The Fifth component is that Personal Growth, the feeling of progressing growth and development personally. The sixth component is that purpose in life, such a belief that an individual has a purpose in life and life is meaningful for him/her.

2.3.5 Introduction to Subjective Well-Being

In order to keep people healthy and productive, well-being has been rated one of the most crucial aspects of existence (Das et all.,2020).

Subjective Well-Being (SWB) is one type of well-being, and it has three distinct characteristics (Diener, E., 1984). The first characteristic is a practical grasp of life; in other words, it is a subjective viewpoint based on a person's acquired experience (A. Campbell, 1976). Individuals can determine their own quality of life, which is not influenced by external factors (Ed Diener, 1985). Second, positive metrics are included in SWB, thus the goal is not solely to find negative factors. Finally, there are both cognitive and affective well-being elements in SWB measurements. Deci and Ryan (2006). In more depth, the cognitive component includes overall life evaluations and contentment with specific life domains, whereas affective well-being is an individual's mood (job satisfaction) (Diener, 2000). As a result, the SWB's structure has yet to be identified, however it can be seen in Figure 2.1 below (Busseri, Sadava, 2011).

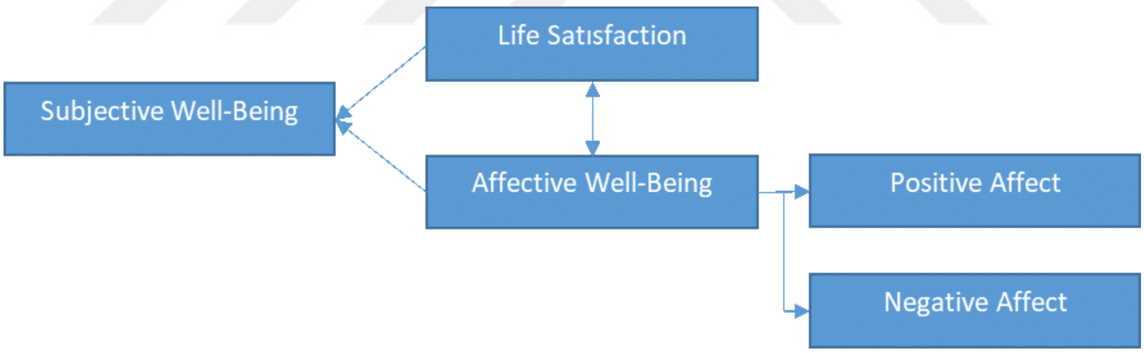

Figure 2.1: Structure of Subjective Well-Being (SWB)

The goal of this research is to test the model by feeding SWB features into the heuristic model and identifying stress levels using machine learning algorithms. The level/severity/degree of SWB is influenced by a variety of features/variables/items/inputs/determinants (Feist, Bodner, Jacobs, Miles, & Tan, 1995). It has been suggested that social support and work stressor are essential factors in SWB (Scheck C., Kinicki, A., Davy J., 1997). Positive and negative stresses are those variables, and they have a direct impact on SWB. Stressors, like SWB, are perceived items

(Lazarus, DeLongis, Folkman, & Gruen, 1985), and they are so predictable that they vary from person to person. Law students' subjective well-being suffers as a result of their high stress levels (Bergin, Kenneth, 2015). Furthermore, long-term stress exposure can be harmful to a person's mental health, physical health, and SWB (Gatchel & Kishino, 2012; Diener et al., 1999). The following research shows the link between stress, mental health, and happiness (Cleland et all 2016; Schneider et all, 2020). Stress among students is frequent in universities (Misra & Castillo, 2004; Sax, 1997), and stress has been linked to a variety of undesirable outcomes, including suicidal ideation, smoking, and alcohol addiction (Hudd et al., 2000). Stress may increase the risk of developing the following health problems: mental illnesses (such as depression and anxiety), addiction, hypertension, and heart attack risk (2). Stress is not as unpleasant as worry or depression, according to neuroscience. Acute or moderate stress can also benefit people's health by boosting their immune and cardiovascular systems (Dolcos et all, 2018).

In Figure 2.2 depicts a stress process model that aids in understanding the relationship between stress and SWB (Pearlin , 1999). Primary and secondary stresses, resources, status, and outcomes are among the words used in the model (Pearlin, 1999; Pearlin, 1989; Pearlin, Menaghan, Lieberman, & Mullan, 1981). Primary stressors are categorized into objective and subjective stressors based on this theoretical concept. Subjective stressors, on the other hand, are people's assessments of objective stressors, which might be interpreted positively or negatively. It has a therapeutic impact on negative stressors and SWB, according to the word resource (Folkman, 2013; Lazarus & Folkman, 1984). Resources will assist people in coping with stress and increasing their SWB (Rueger, Malecki, & Demaray, 2010). Controllability and predictability of the stressor, as well as social support, are the major drivers for the development of stress reactions while an individual is responding to a perceived or actual stressor (Salvador, 2005). (Koolhaas et al., 2011).

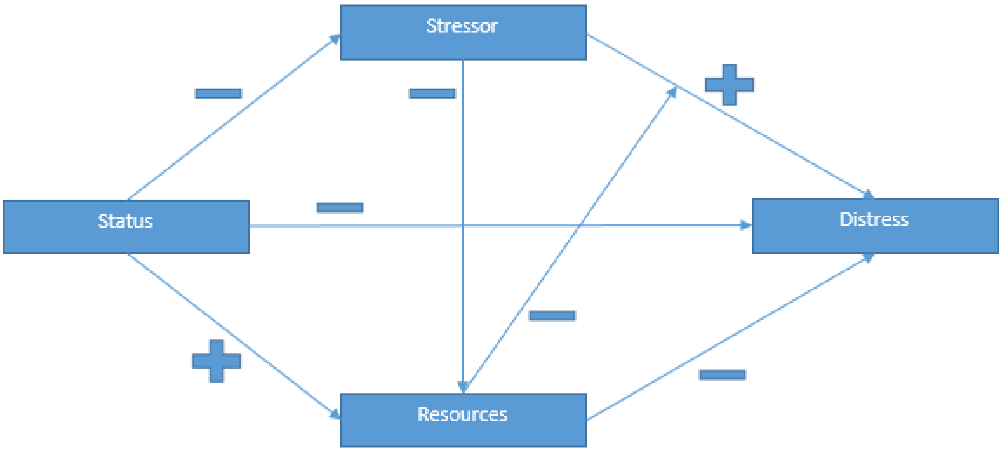

Figure 2.2: Process of Stress

Before diving into the linked work, the paper is organized into six sections, beginning with an introduction. The backdrop of the heuristic model is discussed in section two, with reference to each of the selected SWB determinants, and a generic schematic of the heuristic model is drawn. Perceived stress scale is explained under section 2. The dataset is summarized in section 3 to describe the type of preprocessing used to deal with the data and the model's inputs and outputs were displayed. Section 4 lists the many types of machine learning algorithms and their performance measures. The performance of measures and insights into the machine learning algorithm are reported in section 5. Finally, in section 6, we summarized our findings.

3. PROPOSED METHODOLOGY

A growing number of studies have been conducted on predicting happiness using well-designed models (Striegel et al., 2021; Robles-Granda et al., 2021). Backgrounds of determinants are explored independently from Nethealth studies in order to create a strong SWB model. We chose the appropriate factors from the Subjective Well-Being (SWB) literature that are appropriate for the Nethealth data. In other words, if the selected SWB determinant in the Nethealth project has a limited number of patterns, we do not include it in the heuristic model. Since the SWB determinants have been divided into three groups, some of the determinants may heuristically fall into other groups.
Physical Well-being, Affective Well-being, and Cognitive Well-being are the three SWB factors that we divide into three components. The selection of SWB determinants (features) is detailed in the next section. We also analyzed the data from statistic perspective followingly.

3.1 Dataset Analysis

3.1.1 Dataset Description

SWB characteristics are employed in this paper to predict stress levels using machine learning classifiers. From 2015 to 2019, sensors and self-reports were utilized to collect data from college students, with roughly 700 students participating ("Data Collection" NetHealth, http://sites.nd.edu/nethealth/data-collection/). The initiative is known as the Nethealth Study, and the scope of the data collected is as follows. The initiative is referred to as NetHealth Study, and the scope of the collected data includes the information presented in Table 3.1.

Table 3.1: Nethealth Dataset Brief Descriptions

Codebooks	Details
Basic Survey Codebook	(Big 5 Personality traits), (Rosenberg Self-Esteem Scale), (Trust), (self-reports for anxiety, depression, stress), (demographics)
Network Survey Codebook	(Self-report filled by the participants and contains wide range information about the network of the individuals)
Communication Events Codebook	(Communication types for each individual such as WhatsApp, Sms etc.)
Fitbit Sleep and activity	(Steps, Bed time duration, Floor, Mean heart rate, Calories burned etc.)

3.1.2 Missing Data

In this study, we used information from individuals from semesters 1, 2, 4, 6, and 8, which included 15 attributes (determinants), 3 goals (outputs), and a total of 605. Table 3.2 shows the issue with using self-reports from each semester: some reports, such as Big Five and self-esteem, were not gathered for each semester. Except for the Big Five personality traits, required determinants and targets are discovered in semester 4. As a result of the minor mean level shift in personality traits over four years (Specht et al., 2011), Big Five scores from semester 2 are used. Because the time between semesters 2 and 4 is less than a year, this method is recommended. As a result, we only use semester 1 for general demographic data that was obtained once, and the total number of samples after combining semesters 4, 6, and 8 is 605.

Table 3.2: Data Selection from Related Semesters

	# of individuals	---	---	212	253	140

SWB Determinants and Target	Semesters	W1	W2	W4	W6	W8
Cognitive Well-Being	Religion	X				
	Parent's Income	X				
	Network's Income	X				
	Social Relations			X	X	X
Affective Well-Being	Big Five		X		X	X
	Self-Esteem			X	X	X
Physical Well-Being	Physical Activity			X	X	X
	Average Sleeping Time			X	X	X
Target	PSS			X	X	X

Researchers are ready to lower the amount of missing data because, as previously noted, missing data is critical for longitudinal studies. To do so, Nethealth researchers look into the relationship between the percentage of people who are compliant and other metrics. Fitbit characteristics were found to be the most important since healthier people wear them and are more likely to stick to the Nethealth schedule, resulting in a higher compliance rate (Faust, Purta, Hachen, Striegel, Poellabauer, Lizardo, Chawla, 2017; Faust, Pazmino, Holland, Lizardo, Hachen, and Chawla, 2019). The following 3.3 table shows the compliance rates for the semesters that we used in our model.

Table 3.3: Compliant Rate of Selected Semesters

Semesters	Compliant Rate Average %

W2	86,63
W4	90,02
W6	88,50
W8	87,11

3.1.3 Determinant Analysis

The determinants of SWB are statistically examined. The following findings were discovered: (a) the data is tiny; (b) there are outliers; and (c) the data has ordinal and nominal parameters, allowing both parametric and non-parametric methodologies to be used. Pearson correlation looks for linear connection, while spearman correlation looks for monotonic relationships. Below are some correlation tables.

There are 15 features and detecting a liner link between the targets and features is difficult. Because not all features are linearly and monotonically associated, some of them may have polynomial or other types of correlations. The following correlation values differ in terms of spearman and Pearson correlation for each determinant. Furthermore, not all p values for each target are statistically significant. Table 3.4 displays spearman and Pearson correlation values, and it is clear that they vary across the various factors.

Table 3.4: Correlation and P Value Scores for Each Determinants

	Correlation Type	**Pearson**	**Spearman**	**P Value**
DETERMINANTS	Target	PSS	PSS	PSS
	Physical activity	-0,16	-0,15	0,29
	TrustFrequency	-0,03	-0,02	*0,03*
	Average sleep	-0,25	-0,25	*0,07*
	Parents_income	-0,01	-0,02	0,40

	Networks Parents_income	-0,04	-0,03	0,67
	Religion	0,07	0,10	0,58
	SelfEsteem	-0,59	-0,59	*0,00*
	Extraversion	-0,20	-0,18	*0,03*
	Agreeableness	-0,27	-0,27	0,66
	Conscientiousness	-0,34	-0,33	0,82
	Neuroticism	0,57	0,56	*0,00*
	Openness	-0,08	-0,06	*0,03*

3.2 Physical Well-being

Physical activity, sleep, and sound lifestyle choices all help to improve overall health (Vagetti et al., 2014). Data is collected via sensors and self-reports in the NetHealth project, and our goal is to reduce the self-reports to for developing a robust heuristic SWB model that can be used to different cultures. Under the PWB section, sleep, walking (steps), and mean heart rate are selected.

3.2.1 Sleep

Sleep deprivation reduces reaction speeds, alters mood, and increases perceptual and cognitive dysfunction, according to study (Krueger, 1989). In comparison to cognitive well-being, affective well-being has a smaller impact on cognitive performance (Pilcher & Huffcutt, 1996). There is a strong link between sleep and mood (Stoica, 2015).
Some sleep questionnaires include questions like "Do you have problems falling asleep at night?" that can be used to measure sleep component measurement methodologies. "Do you wake up in the middle of the night after you've gone to sleep?" (DMS) is one of the most strongly associated dimensions with SWB, and it has also been discovered that

DIS is linked to depression and stress (Yokoyama et al., 2007). In addition, the Pittsburgh Sleep Quality Index (PSQI) was used in this study (Li et al., 2015). It's a well-known self-reported questionnaire that assesses overall sleep quality as well as disturbances between set times. Sleep Quality, Sleep Latency, Sleep Duration, Sleep Efficiency, Sleep Disturbances, Sleep Drug Use, and Daytime Impairments are all components of PSQI (Reynolds et al., 1989). We used the average sleeping time collected from self-report as average sleep time per day in numerical representation.

3.2.2 Physical Activity

The data for this study (Faust et al., 2018) was acquired through Nethealth between 2016 and 2019. Participants with positive physical activity (PA) trends have better self-image, self-esteem, and health, according to studies. Participants with negative PA trends, on the other hand, have a higher risk of anxiety and sadness. A different phrase is employed in another study (P. Gothe, 2019): quality of life (QOL). Positive and negative life perspectives make up QOL (WHOQOL,1998). In the 1980s, a new word was coined: health-related quality of life (HRQoL) (P. Gothe, 2019). The findings reveal that low physical activity has a consistent and independent negative influence on QOL and HRQoL, and that these effects are bidirectional. As a result, PA has been linked to reduced stress and increased well-being, and it may be a useful SWB component, thus we chose the activity level of individuals from self-reports.

3.3 Cognitive Well-being

CWB includes life events that occur around individuals, such as birth, death, retirement, and marriage, and these life events have a stronger impact on CWB than AWB (Maike Luhmann, Louise C. Hawkley, 2012; Luhmann et al., 2012). As previously stated, SWB has two aspects: 1) AWB is concerned with an individual's mood, which might change on a daily basis, and 2) CWB is concerned with external circumstances (money, job position, or recent life events) (Luhmann et al., 2012). As a result, we've heuristically chosen the external circumstances: 1) the size of the message and duration of the call for each individual with whom they engage on a regular basis, 2) social relations, 3) religion, and 4) their parents' and networks' income levels.

3.3.1 Social Relations

SWB benefits from strong social relationships (Myers, 2000; Steverink et all, 2001; Windle, Woods, 2004). Parents who are supported through their social network, for example, demonstrate better adaptations following catastrophic circumstances (McIntosh et all, 1993). Loneliness is defined as having negative feelings about missing relationships. It affects people of all ages, and it is one of the most important measures of social welfare (Gierveld, Tilburg, 2006). As a result, having a social network can cause negative or positive sensations depending on whether or not an intimate relationship is present in a person's life (Dykstra and De Jong Gierveld 2004; Wenger et al. 1996). That's why we created a new scale based on the network's degree of closeness as well as how frequently they meet with their networks.

3.3.2 Religion

It is reported over 100 studies that religion and mental health are positively correlated (Koenig and Larson, 2001). One study show that religion and depression is negatively associated and it is found that overall influence of the religion increases when the individual encounters distress through life stress (Smith, McCullough & Poll, 2003). Religion enable person to have trust in God and it is related with greater happiness and lower levels of depression for Jewish participants (Rosmarin et all, 2009). Another study points that religiousness predicts better health among elderly Japanese participants (Krause et all, 1999). In another study it is presented that religiousness predicted SWB among Christian participant in Hong Kong (Ng & Fisher, 2016). In another study, specific religions are investigated such as Buddhism, Christianity, Hinduism and Islam, and it was found that religiousness is positively associated with positive feelings (Diener & Clifton, 2002).

3.3.3 Individual Parent’s and Network’s Income Level

SWB is influenced at the national and cultural levels, and it is believed that nations with higher purchasing power have higher levels of well-being (Diener, 2000; Myers, 2000). Income may have functional aspects (Tay et al., 2018), and the functional aspect of income may support individuals in two ways: a) as a resource for protection against adverse life events (hospital fees, essential expenditures, etc.), and b) to meet the person's needs through the purchase of goods and services (Diener et al., 2013; Tay &Diener, 2011). One's income can be determined by one's own consumption preferences in their living situation, therefore individuals who live in neighborhoods with both poor and high income groups may experience bad effects on their SWB (Luttmer, 2005).

3.4 Affective Well-being

AWB Because AWB is more concerned with an individual's emotional state, personality traits and other factors (such as self-esteem) that are concerned with an individual's affective state have a larger link with AWB than CWB (Steel, Schmidt, & Shultz, 2008). Due to genetic causes, the AWB dimension (positive and negative affect) may be linked to self-esteem and personality traits (Big Five) (Lyubomirsky, King, & Diener, 2005; Steel, Schmidt, & Shultz, 2008; Zanon et al., 2013). We discussed the Big Five and self-esteem as SWB determinants in the AWB section.

3.4.1 Big Five

Many psychologists agree that there are five aspects to personality: extraversion, neuroticism, openness, agreeableness, and conscientiousness (McCrae & John,1992). The table below is a brief summary of the Big Five Personality Traits. You can get a quick overview of the Big Five Personality Traits from Table 3.5.

Table 3.5: Description of Personality Traits (John, Srivastava, 1999)

Traits	**Low**	**High**
Extraversion	Shy	Active
Neuroticism	Stable	Moody
Openness	Commonplace	Imaginative
Agreeableness	Cold	Soft hearted
Conscientiousness	Careless	Organized

One of the strongest predictors of SWB is personality (individual differences) (Lucas, R. E., 2018). Many studies have been undertaken in order to explain some of the aspects of the Big Five. Extroverts are more receptive to rewards, according to Lucas et al. (1998), since they find social interactions more enjoyable and gratifying. Openness, conscientiousness, and agreeableness, in addition to extraversion and neuroticism, exhibited high relationships with SWB. Steel and his colleagues (2008). All of the qualities are linked to positive and negative affect, with Extraversion being the most essential attribute for positive affect and Neuroticism being strongly linked to bad affect (Steel et al., 2008; Russel, 2001). The big five were chosen because there is a link between Big five and AWB, and we know that AWB is an important component of SWB.

3.4.2 Self-Esteem

Self-esteem is a general appraisal of one's value, and those with high self-esteem may believe they are capable and deserving of great outcomes (Margolis, S., & Lyubomirsky, S., 2018). There is a considerable positive association between self-esteem and well-being, according to many academics (Lyubomirsky, Tkach, & DiMatteo, 2006; Paradise & Kernis, 2002). Researchers discovered a favorable association between self-esteem and life happiness in one study that included 31 countries (Diener & Diener, 2009). Individualistic Americans (Oyserman et al., 2002) show a poorer association between self-esteem and life happiness than countries with collectivistic beliefs (Margolis, S., & Lyubomirsky, S., 2018). According to a meta-analysis of 77 research, there is a strong negative association between self-esteem and depression and anxiety; consequently, self-esteem predicted a reduction in depression (Sowislo & Orth, 2013). Furthermore, neuroscientific findings show that the hippocampus has the potential to protect an individual from psychological suffering, and that self-esteem is linked to the hippocampus (Pruessner et al., 2005). As a result, because self-esteem is strongly linked to SWB and also plays a role in psychological discomfort (Robins et al., 2001), we've included it in our heuristic SWB model.

3.5 Target (Perceived Stress Scale (PSS))

The Perceived Stress Scale (PSS) was used as a target in this study, and the SWB determinants were used to predict PSS.

We'd like to emphasize the reasons why PSS was picked as a target before detailing its structure and specifics. We studied practical SWB determinants that are compatible with obtained data in our study, and we chose PSS as our major aim (output) since it was the closest scale to measure subjective well-being among the scales collected. As previously stated, there are two explanations for this target preference. SWB involves both cognitive and affective elements. The first is that 1) the literature shows a substantial negative relationship between the Satisfaction with Life Scale (SWLS) and the Perceived Stress Scale (PSS) (Yew et al., 2015; Park, Colvin, 2019). SWLS is a subjective well-being (SWB) cognitive assessment (Aslan et al, 2020). The second reason is that 2) Positive affect (PA) and negative affect (NA) are two terms for affective well-being, and PSS has a strong link to both (Civitci, 2015).

PSS can be used as a four-item or fourteen-item scale with high reliability and validity (Cohen et al, 1983). The ten-item PSS, on the other hand, outperformed both the fourteen-item PSS and the four-item scale, and PSS is mostly used with college students (Lee, 2012). There are also numerous studies that examine the validity and reliability of national PSS-10 versions (Bastianon et all, 2020; Taylor, 2014; Berjot et all, 2012; Khalili et all, 2017).

Although the PSS-10 is not a scale of psychological symptomatology, it may aid researchers in detecting early indicators of various clinical psychiatric problems among students or in controlled settings such as universities and workplaces (Cohen et al., 1983). As a result, the participants in the Nethealth Project completed the ten-item PSS scale. The literature supports the two-factor structure of the 10-item scale PSS, which is superior to both 4 and 14 item PSS.

4. MODEL DESIGN

4.1 Feature Design

Preprocessing is essential in the Nethealth project because some dataset formats must be converted to the suitable format. The data preprocessing is briefly detailed in the following sections.

4.1.1 Cognitive Well-Being

4.1.1.1 Global Judgements of Life Satisfaction

1. The fundamental survey categorizes religion; therefore, it is transformed into numerical numbers.
2. The fundamental survey categorizes parental income, which is then transformed into numerical figures.
3. In the network survey, network income is categorically shared and turned into numerical numbers. Individuals' networks are shown with alterids in the Network survey. The basic survey then matches these alterids with egoids.

4.1.1.2 Satisfaction with Specific Life Domains

4. Social Relations:
    a. Network's Trust Level and Meeting Frequency: In the network survey, each person ranks the amount of trust in their network and describes the frequency with which they meet. They're both in category format, and they're both translated to numerical numbers. Finally, both are multiplied to create a single scale.

4.1.2 Affective Well-Being

1. Big Five Researchers calculated each personality trait's score using a 44-question personality questionnaire. These are the results of the basic survey.
2. Researchers calculated the self-esteem score using a 10-question self-esteem questionnaire. This is the result of the basic survey.

4.1.3 Physical Well-Being

1. Sleeping: The Pittsburgh Sleep Quality Index (PSQI) item 4's average bedtime is based on self-reports. There is no requirement to adapt this SWB functionality.
2. Numeric displays of individual activity levels are used. There is no requirement to adapt this SWB functionality.

Table 4.1: Data Conversion Processes for Swb Determinants

SWB Determinants	**Semesters**	Raw Data Format	Converted into
Cognitive Well-Being	Religion	Groups in text	Numerical Groups
	Parent's Income	Groups in text	Numerical Groups
	Network's Income	Groups in text	Average of Numerical Groups
	Social Relations	Groups in text	Numerical Groups
Affective Well-Being	Big Five	Numeric	---
	Self-Esteem	Numeric	---
Physical Well-Being	Avg. Sleeping Time	Numeric	---
	Phsyical Activity	Numeric	---

4.2 Design of the Target

PSS consists of ten questions that are presented in text style within the basic survey. Numerical values are assigned to categorical text. Table 4.2 presents a numerical representation of the categorized text.

Table 4.2: Data Conversion Processes for Targets

Targets	Raw Data Format	Converted into
PSS	Groups in text	Numerical Groups

4.3 Class Thresholds

Based on their quartile ratings, targets are classified into three classes (0, 1, 2). Below Table 4.3 is the quartile scores and Fig. 4.1 class distributions.

Table 4.3: Quartile Scores for Perceived Stress Scale

Count	605,00
Mean	15,89
Standar Deviation	6,49
Minimum	0,00
25%	12,00
50%	16,00
75%	20,00
Maximum	36,00
Scale Range	0 to 40

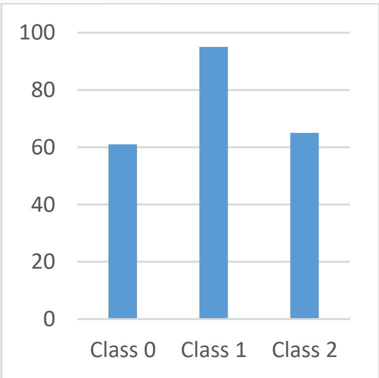

Figure 4.1: Class Distribution for PSS

5. METHODOLOGY FOR PREDICTION

The goal of this study is to use SWB determinants to differentiate three kinds of experienced stress: perceived self-efficacy, perceived self-helplessness, and perceived self-helplessness. Classes have been chosen consecutively from C0 to C2 because they can be recognized subjectively or objectively (Wilson, Wiebe, & Hwa, 2006). (low, moderate, high).

Because of the inherent nature of the PSS dataset, the number of classes is not spread evenly. As a result, it's a multi-classification problem, and the output must be classified into one of the non-overlapping classes (Marina Sokolova, 2009). Due to the class imbalance ratio (IR), standard classifiers are unable to distinguish small from large classes (N.V. Chawla et all, 2004; N. Japkowicz, S. Stephen,2002). Next, in order to function well on the test dataset, the training dataset should have a larger sample size (Wasikowski, Chen, 2010). There have been a slew of ways offered to improve the performance of associated measures for multiclass classification. These approaches can be split into three categories. 2. Algorithmic level, 1. Data level 3. Cost-conscious (Fernández and colleagues, 2013).

5.1 Evaluation Metrics

Overall accuracy as a metric may be useful for binary classification, but due to the varying misclassification costs, it is advisable to combine it with other metrics for multiclass classification (Zong et all, 2013). The confusion matrix was used to get some of the evaluation metrics) (Fawcett, 2006; Kubat et all, 1998; Sun et all, 2009; Sokolova, Lapalme, 2009):

Precision $=\frac{TP}{(TP+FP)}$: Out of all the estimates, how many are correct?.

Recall $= \frac{TP}{(TP+FN)}$: How many of the true positive classes are correctly classified?.

F1 score = $2 \times \frac{(Precision \times Recall)}{(Precision + Recall)}$ Precision and recall are used to calculate the harmonic mean.

G-mean = $\sqrt{(True\ Positive\ Rate \times\ True\ Negative\ Rate)}$: dealing with a wide range of performance classes.

ROC AUC analysis: A probabilistic score is represented by the True positive rate on the y-axis and the False positive rate on the x-axis. When the genuine positive rate rises, the graph moves closer to the left corner. The area under the curve (AUC) is a single classification metric.

Accuracy = $\frac{TP+TN}{(TP+FP+TN+FN)}$: Overall efficiency of a classifier.

6. EXPERIMENT AND RESULTS

The results were calculated on a Jupyter notebook with an i7vpro processor, and table 6.1 provides specifics on the data's technical aspects..

Table 6.1: Technical Preferences

Technical Aspects (Brief Description)	
Laptop processor	i7vpro
Interface	Jupyter notebook
Missing values	are dropped with Dropnan fucntion
Outliers	After application 617 rows reduced to 605 rows
Standardization	Applied
Train test ratio	70% Train, 30% Test
5 fold stratified cross validation	Applied
Applied Machine Learning Algorithms without parameter setting	
Adaboost, (Base Estimator= Decisiontree)	
Support Vector Machine	
Decisiontree	
Kneighbors	
Logisticregression	
Random Forest	

6.1 Results

Finally, performance measurements for our heuristic model for the PSS are shown in the tables below.

The heuristic SWB model was used to predict PSS classes (0, 1, 2) in this investigation. Despite the fact that it is a multiclass classification problem, we have achieved significant metric scores, which can be considered for a particular challenge. In the dataset description section, we looked at the determinants of the heuristic SWB model and discovered significant p values and correlation scores between SWB determinants and PSS. In addition to these findings, all PSS metric scores at each class level show at least 50% for a certain machine learning algorithm (low, moderate, high).

In this research, we have employed SWB determinants as model inputs and heuristically predicted PSS. Given that it is a multiclassification task, achieving high metric scores is challenging. Significant relationships between PSS and Satisfaction with Life Scales (SWLS), Positive Affect, and Negative Affect may account for high metric scores. Positive & Negative affect relates to the affective aspect, whilst SWLS pertains to the cognitive aspect. Our model has three heuristic aspects, namely cognitive, affective, and physical well-being, but our target (PSS) does not directly measure the physical well-being component. However, as noted in II.A (particular indication), physical activity and sleep have significant effects on cognitive and emotional well-being.

As previously stated, the cost of misclassification varies depending on the problem. For example, PSS has three classes, with class 2 having a larger cost of misclassification than classes 0 and 1. The rationale for this is because class 2 (high stress) refers to people who have a high degree of stress, which could be an early marker of psychiatric symptomatology. As we all know, mental health costs are a significant financial burden for countries (Christensen et all, 2020). As a result, misclassifying class 2 could result in increased mental health spending. The metric scores and top classifiers can be seen in Tables 6.2 and 6.3)

Table 6.2: Metric Scores for Each Machine Learning Algorithms

	DecisionTree				
Metrics	**Recall**	**Precision**	**F1**	**ACC**	**ROCAUC**
Class 0	0,52	0,47	0,49	0,74	0,66
Class 1	0,49	0,51	0,50	0,55	0,54
Class 2	0,52	0,53	0,52	0,73	0,66
Average	0,51	0,51	0,51	0,67	0,62
	Ada Boost				
Metrics	**Recall**	**Precision**	**F1**	**ACC**	**ROCAUC**
Class 0	0,54	0,48	0,50	0,74	0,67
Class 1	0,49	0,53	0,51	0,56	0,56
Class 2	0,52	0,52	0,52	0,72	0,66
Average	0,52	0,51	0,51	0,67	0,63
	RandomForest				
Metrics	**Recall**	**Precision**	**F1**	**ACC**	**ROCAUC**
Class 0	0,54	0,64	0,59	0,81	0,84
Class 1	0,70	0,58	0,63	0,63	0,65
Class 2	0,56	0,69	0,62	0,80	0,83
Average	0,60	0,64	0,61	0,75	0,77
	Support Vector				
Metrics	**Recall**	**Precision**	**F1**	**ACC**	**ROCAUC**
Class 0	0,47	0,66	0,55	0,81	0,84
Class 1	0,73	0,56	0,63	0,61	0,66
Class 2	0,49	0,66	0,57	0,78	0,84
Average	0,56	0,63	0,58	0,73	0,78

Best machine learning algorithms are presented for each classes. (Ada:Adaboost, Dt:Decision Tree , Rf: Random Forest, Svm: Support vector machine).

Table 6.3: Best Ml Algorithms at Class Level

Metrics	**Recall**	**Precision**	**F1**	**ACC**	**ROCAUC**
Class 0	Ada, Rf, Dt	Rf, SVM	Rf	Rf	Rf
Class 1	Svm	Rf	Rf	Rf	Rf
Class 2	Rf	Rf	Rf	Rf	Svm, Rf
Average	Rf	Rf	Rf	Rf	Rf

7. CONCLUSION

In this study heuristic Subjective Well-Being model is built and heuristic model is being fed by the sensor's and self-report's data. In order to evaluate our model, Nethealth data set has been used which includes wide range of information about student's life for eight semesters. To the best of our knowledge, this paper is the first study that analyses Perceived Stress Scale (PSS) and predicts the stress with the help of machine learning classifiers from Subjective Well-Being (SWB) point of view. We present prominent metrics which can be preferred for the appropriate goals. Our model with four machine learning classifiers predicts the PSS levels with considerable metric scores in general for each class so this model can be used for in the wild applications robustly.

In this work, PSS predictions were made utilizing SWB predictors as model inputs. First, we eliminate any potential outliers, then we normalize the data, and finally, we employ stratified cross validation, which enables us to obtain samples that are evenly distributed over the train-test population. This is a multiclassification problem, and it is challenging to anticipate each class's metric values. There are well-designed research addressing binary classification issues, particularly psychological evaluations. The accuracy and precision and memory scores of these investigations are approximately 80% and 70%, respectively (Striegel et al., 2021; Yarkoni, 2017; Rosenbusch, et al, 2021). Using the random forest ensemble machine learning technique, we were able to attain an accuracy score of 76% in addition to precision and recall scores of roughly 60%.

7.1 Threats to Validity

This model may fail due to a lack of thorough SWB definition (Diener et al., 2018), although these investigations are assisting in the development of accurate SWB definition. With the use of the literature survey for subjective well-being, practical treatments may be able to improve an individual's stress level. Individuals could be notified if they are deficient in particular SWB determinants.

7.2 Limitation

Because time-based data is not adequately displayed in the Nethealth data collection, we chose a static model. Furthermore, certain data is not published publicly, such as content from Twitter and Facebook, and this type of data can be utilized to predict Big Five scores, self-esteem, and other self-reports without having to fill out surveys, saving time.

7.3 Future Works

In comparison to static models, dynamic models in the time domain may give a better answer for predicting stress, well-being, and mental health. First, provide a stronger framework for SWB determinants and targets, which will aid in providing a comprehensive view. Second, using a time-based model could provide additional information about people's health on an hourly basis. Finally, working with a dataset that includes phone apps like Twitter, Facebook, and Instagram may allow for the discovery of some interesting connections between self-reports (big five personality traits) and app usage (Peltonen et al, 2020).

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