

**SUBJECTIVE WELL-BEING PREDICTION BY PERSONALITY TRAITS
AND SENSOR BASED DAILY ACTIVITY DATA**

**(KARAKTER ÖZELLİKLERİ VE SENSÖR TABANLI GÜNLÜK AKTİVİTE
VERİSİ KULLANILARAK ÖZNEL İYİ OLUŞ TAHMİNİ)**

by

Akif Can KILIÇ, 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

Supervisor: Assoc. Prof. S. Emre ALPTEKİN

Jun 2022

ACKNOWLEDGEMENTS

First of all, I would like to thank my supervisor Assoc. Prof. Dr. S. Emre Alptekin 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 Ahmet Karakuş 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.

June, 2022

Akif Can KILIÇ

TABLE OF CONTENTS

LIST OF SYMBOLS	v
LIST OF FIGURES	x
LIST OF TABLES	xi
ABSTRACT.....	xii
ÖZET	x
1. INTRODUCTION	10
2. LITERATURE REVIEW	13
2.1 Mobile Communication	15
2.2 Daily Activity.....	16
2.2.1 Physical Activity/Daily Step Count.....	16
2.2.2 Sleep Duration	17
2.3 Big Five Personality Traits.....	19
2.4 Health, Happiness, and Health Satisfaction Inventories	22
2.5 Machine Learning Models	24
2.5.1 Decision Tree.....	24
2.5.2 Logistic Regression	25
2.5.3 Naive Bayes.....	26
2.5.4 SVM	26
2.5.5 KNN	27
2.5.6 Ensemble	28
3. METHODOLOGY	29
3.1 Data Set	30
3.2 Data Preprocessing.....	31
3.3 Classifiers.....	33
3.4 Performance Measures	34
4. IMPLEMENTATION AND RESULTS	36

5. CONCLUSION	40
REFERENCES.....	2
BIOGRAPHICAL SKETCH.....	50
PUBLICATIONS	50



LIST OF SYMBOLS

AUC	: Area Under Curve
BAI	: Beck Anxiety Inventory
BDI	: Beck Depression Inventory
CMC	: Computer Mediated Communication
CPU	: Central Processing Unit
DRM	: Day Reconstruction Method
EMA	: Ecological Momentary Assessment
FP	: False Positive
FPR	: False Positive Rate
ICM	: Interpersonal Communication Motives
KNN	: K Nearest Neighbour
MATLAB	: Matrix Laboratory Software
PANAS	: Positive and Negative Affect Scale
RAM	: Random-access Memory
ROC	: Receiver Operating Characteristic
SMS	: Short Message Service
STAI	: State-Trait Anxiety Inventory
SVM	: Support Vector Machine
SWB	: Subjective Well Being
TP	: True Positive
TPR	: True Positive Rate

LIST OF FIGURES

Figure 1.1: Summary of the model.	12
Figure 2.1: Bidirectional relationship between sleep and SWB.	19
Figure 2.2: Generated SWB index.	24
Figure 2.3: Decision Tree example.	25
Figure 2.4: Logistic Regression graph.	26
Figure 2.5: SVM graph.	27
Figure 2.6: KNN graphical explanation.	28
Figure 3.1: Methodology process flow.	29
Figure 3.2: Histogram of students' Fitbit usage during the chosen period.	31
Figure 3.3: Data filtration results.	32
Figure 3.4: Cross validation.	34
Figure 3.5: ROC curve on left and AUC specified as grey on right.	35
Figure 4.1: Correlation heatmap.	36

LIST OF TABLES

Table 2.1: Literature review.....	14
Table 2.2: “The Big Five Personality Traits” and definitions.	20
Table 3.1: Examination of the data set by genders.	33
Table 3.2: Formulation for each performance metric..	34
Table 4.1: Classifiers, parameters and performance metrics.	37
Table 4.2: Computation time of classifiers.	39
Table 4.3: Confusion matrix for each model.	39

ABSTRACT

People enjoy different things in life. For example, while some people enjoy walking and socializing, others may get the same pleasure from sleeping. Enjoyment improves people's moods, and different metrics are used in psychology to measure that well-being level. One of the most widely used is the "subjective well-being" scale. The degree of this scale is measured by short questionnaires applied to individuals. In this study, subjective well-being was chosen as the target. We transformed the target to a binary scale (0-1), and the problem is considered as classification. In the model created, the individuals' subjective well-being was estimated by applying Decision Tree, Logistic Regression, Naïve Bayes, SVM, KNN and Ensemble classification methods. The person's daily physical activity, socialization, and big five personality traits were used as attributes. As a result of the models applied, we have achieved an accuracy between 64 and 80%. Unlike other studies, this study revealed a model that predicts 80% accuracy by composing sensor data with character traits. In this study, NetHealth dataset that collected from college students during consecutive periods was used.

ÖZET

İnsanlar hayatta farklı şeylerden keyif alırlar. Bazı insanlar yürümekten, sosyalleşmekten keyif alırken, bazıları aynı keyfi uyumaktan alabilir. Keyif almak insanların ruh halini iyileştirir ve ruhun iyilik seviyesini ölçmek için psikolojide farklı ölçütler kullanılır. En çok kullanılanlardan birisi “öznel iyi oluş” ölçeğidir. Bu ölçeğin derecesi kişilere uygulanan kısa anketlerle ölçülür. Bu çalışmada hedef olarak öznel iyi oluş seçilmiştir. Bu hedef 0-1 olarak ikiye ayrılmış ve problem classification’a çevrilmiştir. Oluşturulan modelde farklı classification yöntemleri uygulanarak kişilerin öznel iyi oluşu tahmin edilmeye çalışılmıştır ve tahmin edilirken kişinin günlük fiziksel aktivitesi, sosyalleşmesi, beş büyük karakter özelliği göz önüne alınmıştır. Uygulanan modeller sonucunda %64-80 arası accuracy’e ulaşılmıştır. Bu çalışma diğer çalışmalardan farklı olarak SWB’nin anket kullanmadan, sensör verisi ve karakter özellikleri kullanılarak %80 oranında doğru tahmin edilebildiğini ortaya koymuştur.

1. INTRODUCTION

If the well-being term is mentioned, a large part of the society considers economic welfare. Although economic well-being has an impact on the overall well-being of a person, studies have been conducted that indicate that economic income is not the only factor affecting a person's well-being apart from this (Diener & Seligman, 2004). For centuries, philosophers and scientists have debated about well-being and happiness, tried to understand their causes, worked on their measurability and discussed many theories. Achieving a certain level of life satisfaction, living healthy, feeling good spiritually are the main reasons behind the decisions and actions taken by every person, and it is believed that these will bring happiness. Happiness for humans is defined as a high level of life satisfaction, frequency of positive feelings, and infrequency of negative feelings (Diener, 1984). To understand the level of happiness, the question of "how are you?" seems to be sufficient, but studies have revealed that the answer to this question is actually in the structure of a multivariate equation (Ryan & Deci, 2001).

Activities done during the day contribute to happiness and positive feelings at different levels. A study conducted by Kahneman listed 16 actions performed during the day and it was revealed that all of them had different effects on positive feelings (Kahneman et al., 2004). In addition, it has been revealed that these variables that determine happiness can differ from person to person and that there is no single state of happiness for every person, and this different happiness concept is discussed as "subjective well-being" (Diener, 1984). In the following process, the relationship between subjective well-being and character traits was also questioned, and it was observed that the SWB level was also correlated with character traits (Hayes & Joseph, 2003). This shows that SWB, scientifically defined as happiness, has a relationship with daily activities and character traits (Shaw et al., 2002).

Today, technological devices equipped with sensors such as mobile phones and smartwatches, which allow the monitoring of daily activities, are actively used. These devices are also used in the field of data analysis since the data that can be collected with these devices is diverse, can be collected more frequently, and data collection is easier compared to the old methods (Can et al., 2019). There have been enough studies showing a relationship between daily activities and well-being (Csikszentmihalyi & Hunter, 2003).

In this study, the predictability of subjective well-being was investigated by using the communication activities over walking, sleeping, voice phone calls, text messages, social media platforms, and in addition, the character traits of the people collected with the help of such devices and repeated at certain periods during the day. The data set, which was created at the University of Notre Dame between 2015-2019 and contains information such as activity collected from Fitbit smart wristbands, communication from the phone, and psychological test results, was used as the data set (Purta et al., 2016). Since the scope of this study, which is called "The NetHealth data set", is very wide and includes evaluation results such as questionnaires and tests in many different contexts, a certain elimination process has been applied and this large spectrum has been narrowed. For example, since the State-Trait Anxiety Inventory (STAI), Beck Anxiety Inventory (BAI), Stress and Beck Depression Inventory (BDI) in the survey results section may show an inverse correlation with happiness and may create a positive association bias in the estimation since it contains similar questions with the happiness questionnaires, in the estimation process.

As can be seen in Figure 1.1, the person's average daily sleep duration and daily average number of steps were used to represent the person's daily physical activity; daily average call duration and daily average message character length were used to represent the person's daily mobile communication; Big Five Personality Traits applied to the individuals and results such as "Openness, Responsibility, Extraversion, Agreeableness, Emotional Balance" values were also used to estimate the SWB level. The SWB value was used as a binary scale that was created by summing up the scores of the "Happiness, Health, Health Satisfaction" questionnaires. To estimate a person's SWB

level, Mobile Communication, Physical Activity, and Big Five Personality Traits were used to predict.

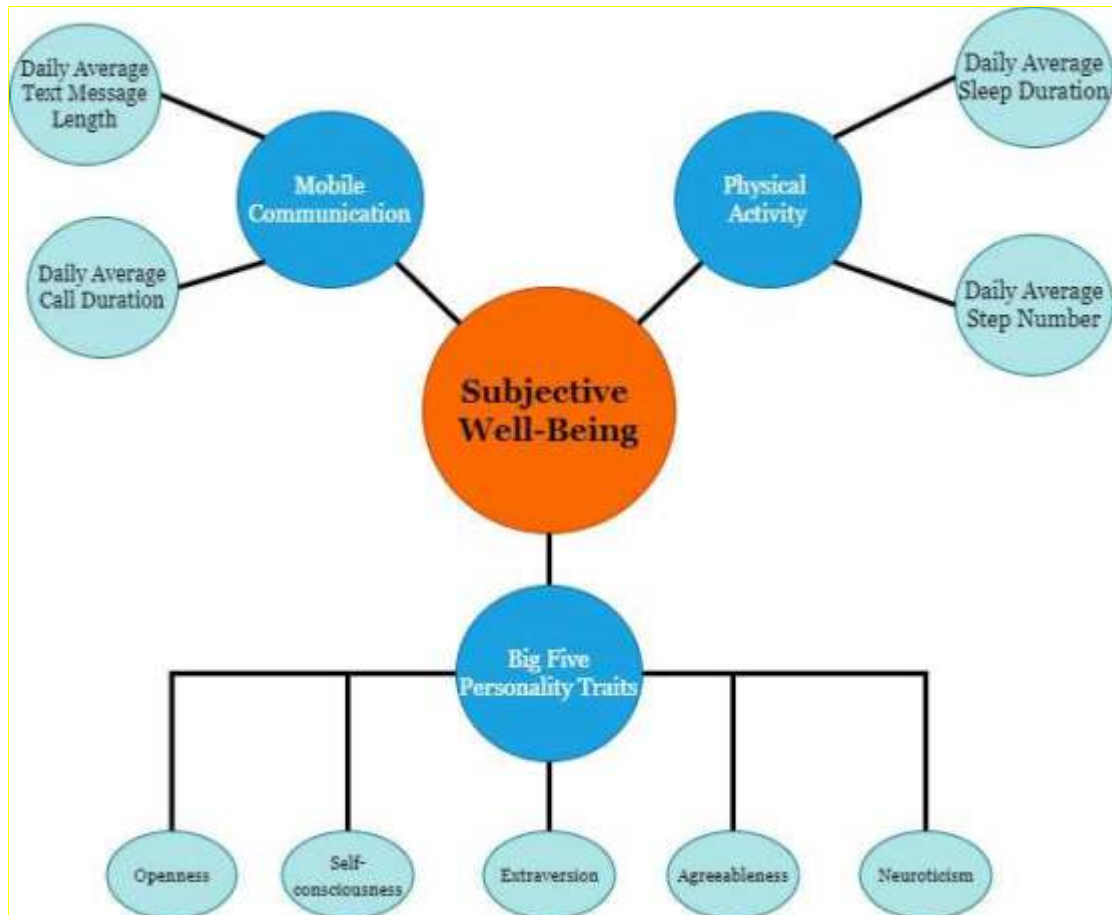


Figure 1.1: Summary of the model.

This study has shown us that personality traits, mobile communications, and daily physical activity levels collected by sensors play an important role in estimating SWB levels, or not.

2. LITERATURE REVIEW

For the detection of SWB, different methods have been used in the literature (Voukelatou et al., 2021). The most preferred of these methods is the self-report scales such as Positive and Negative Affect Scale (PANAS), which is a psychological scale to assess mood (Watson et al., 1988; Watson & Clark, 1999). In addition, large institutions, and organizations such as Gallup, British Household Panel and Eurobarometer measure people's happiness and well-being levels with their own scales. It has been proven in the literature that the results measured with these scales may vary by some factors. For example, asking political questions before the happiness scale affected the results (Deaton & Stone, 2016). It was revealed that the weather conditions at the time the scale was applied also influenced the results (Lucas & Lawless, 2013; Yap et al., 2017). To eliminate these effects, tests such as the Day Reconstruction Method (DRM) and Ecological Momentary Assessment (EMA) have emerged that require the person to answer day by day (Tay et al., 2014), but there are drawbacks in these methods since the application of these scales affects the person's normal daily activities or the inability to catch instantaneous mood changes (Kahneman et al., 2004). For this reason, unlike previous studies, the SWB target, which was created by using the "Happiness, Health, Health Satisfaction Inventory", was tried to be estimated using the personality traits of the participants, daily physical activity average and daily communication average. Thus, it has been researched whether it is possible to measure by interacting with the person less than the previous measurement methods. In this way, machine learning algorithms have been used to predict SWB of a person which algorithms will be explained in detail in the following subsections. Studies that predict other psychological treatments such as depression, stress, bipolar disorder given in the Table 2.1. The same models applied within that study.

Table 2.1: Similar studies in literature.

Study Reference	Study Type	Study Duration	Predictors	Participants	Results
(Sano & Picard, 2013)	Stress detection	5 days	Wearable sensors	18 subjects	Accuracy over .75 with SVM and KNN.
(Muaremi et al., 2013)	Stress detection	4 months	Wearable sensors	35 subjects	Accuracy .61 with multinomial logistic regression.
(Garcia-Ceja et al., 2015)	Stress detection	8 weeks	Wearable sensors	30 subjects	Accuracy .71 with Naive Bayes and Decision Trees.
(Carneiro et al., 2012)	Stress detection	short-term	Wearable/external sensors	19 subjects	.78 classification accuracy with J48 tree.
(Grünerbl et al., 2015)	Bipolar disorder detection	12 weeks	Wearable sensors	10 subjects	.76 recognition accuracy with Naive Bayes, .97 recall in state change detection.
(Maxhuni et al., 2016)	Bipolar disorder detection	12 weeks	Wearable sensors	10 subjects	.85 classification accuracy with Bagging.
(Reece & Danford, 2017)	Depression detection	short-term	Instagram photos	166 subjects	70% correctly identified of all depressed cases with Random Forest.
(Kılıç, 2022)	SWB detection	1 year	Wearable sensors + Big Five Personality Traits	191 subjects	80% correctly identified of all high SWB out of all high SWBs with KNN. (recall)

2.1 Mobile Communication

The use of mobile phones has become very common today and communication activities such as phone calls, messaging through applications on the phone, or directly over the operator have become an important part of our daily social life. As an important indicator of this, the number of mobile line subscriptions around the world can be used. According to 2019 global report published by International Telecommunication Union, the number of mobile line subscriptions has exceeded 8 billion in the world. As a result of this stat, usage has passed the 7 billion thresholds, which is the world population, in 2019 also shows how important the role of mobile devices is in communication.

Social relations were divided into mediated and non-mediated social relations on a sociological basis, unmediated relations were considered as the primary and most important relationship type, and mediated relations were evaluated as secondary relations. Contrary to this standard sociological inference, accepting mediated communication as secondary relation is criticized by some sociologists in the context of "connection, interaction and emerging forms of social relations" (Cerulo and Ruane, 1998). Additionally, some other sociologists who support this idea have classified this area as computer-mediated communication (CMC) and stated that devices such as phone calls and SMS are frequently used to communicate with people feel close to. It has been revealed that it is used to fill the gaps, which strengthens the social ties more (Wellman et al., 1988).

Another study conducted in 2010 among 232 university students investigated the motivation of phone calls and SMS usage. This research used the Interpersonal Communication Motives (ICM) scale (Rubin et al., 1988) to understand the reasons for people's use of communication devices, and the respondents were presented with options such as "inclusion, control, affection, pleasure, relaxation, escape". When the results are examined, it has been revealed that the three major motivations for both phone call and SMS communication are "affection, escape and inclusion" (Jin and Park, 2010). Another study revealed that mobile phone use has a positive effect on emotion

control and that phone use to regulate negative emotions has a positive correlation with SWB ($\rho = 0.18$, $p < 0.01$) (Hoffner & Lee, 2015).

Many studies have been conducted on the effect of communication on SWB, and these studies have shown that social isolation negatively affects mental health (Appau et al., 2019). Again, some studies show that not only personality traits or financial situation but also social institutions are important in determining SWB; determined that weak social relations also play an important role in decreasing the level of happiness (Bartolini et al., 2013). It can be deduced that communication-based on social relations has gained a new and different dimension with the evolution of mobile devices from technological devices to social devices (Srivastava, 2005).

Based on all these reasons, "average time spoken by phone during the day" and "average character length of SMS sent during the day" in the NetHealth data set are used under the mobile communication part. The average daily call duration can be an incoming or outgoing call, FaceTime or Skype call on the line. The data received under the SMS heading consists of Apple's messaging application iMessage and normal SMS data.

2.2 Daily Activity

Daily activities are basically divided into two main topics according to the data used as physical activity/daily step count and sleep duration.

2.2.1 Physical Activity/Daily Step Count

Every movement performed by the skeletal system and skeletal muscles in the body and causing the body's energy expenditure is called physical activity, and physical activities in daily life can be used for work, occupational, domestic, or sports purposes, etc. Walking activity, on the other hand, can be a part of sports or daily routine (Caspersen et al., 1985). Walking activity can be directly related to the number of steps a person takes during the day. This number of steps varies according to two main situations; the first of these is a compulsory walk, which is carried out to reach a different location

from one place, or a walk for leisure/leisure activities, sports, etc. purposes which are done for oneself.

The first case includes the distance traveled to work, school, at work, or for work, while the other case is arbitrary. Although these two states appear to be separate and have different external triggers, basically there is an intrinsic positive benefit to being on the go and is itself a valuable activity (Mokhtarian et al., 2001). In addition, it has been found that physical activities performed regularly for a certain period reduce the tendency for depression (North et al., 1990) and anxiety (Petrusello et al., 1991). If a person who walks regularly sees results such as increasing the walking distance and walking longer distances after a certain period, it will also increase the person's sense of control and have a positive effect on general well-being (Spirduso, 1995). In addition, it was stated that if the physical activity lasted less than 10 weeks, the effect on SWB and mental well-being would be less compared to longer activities (McAuley & Rudolph, 1995).

In our study, one of the features used for SWB estimation, the "average number of daily steps of the individual", was calculated over the average of the daily step number in the data set over a one-year interval, and the consistency with the results obtained from previous studies was also taken into consideration in this section. These data gathered from FitBit wristbands.

2.2.2 Sleep Duration

Sleep is one of the most basic activities of human life. Although it may seem like a complex phenomenon when taken alone, it is a subject that is studied by scientists who have specialized in many different fields, related to many physiological and mental situations in human life, and collaborated with different disciplines. There are also journals such as "Journal of Clinical Sleep Medicine" and "Sleep" that only publish scientific publications on sleep. The relationship between sleep and quality of life, happiness, health, and risk of death has often been the subject of scientific research. Sleep deprivation or insomnia is a subject that has attracted the attention of scientists in the field of health. A simple search of the Web of Science using the words "sleep

deprivation” has 1,054 results in 2019 and 1,189 results in 2020; when a Google Scholar search is performed with the same method, 24,000 results are produced in 2020 alone.

Insomnia and the inability of the body to get enough sleep have a serious negative effect on mood, cognitive performance, and motor skills. Although five hours of sleep a day is sufficient acceptance and perception of good to sleep less in society, it has been revealed that the cognitive, mental, and motor skills of a person who sleeps less than five hours a day are lower than someone who does not sleep for forty-five hours (Pilcher & Huffcutt, 1996). There are also studies showing that insomnia reduces emotional well-being. For example, an individual who sleeps between 4 and 6 hours for 14 consecutive days, i.e., with increasing cumulative wakefulness, has been found to have significantly reduced cognitive performance on all tasks (Van Dongen et al., 2003). In addition, a study discussing the relationship between obesity and insomnia revealed that while insomnia also affects mental health, it causes stress and depression, while triggering chronic sleep disorders (Dauvilliers et al., 2005; Kryger, 2010).

As a result of these and similar studies, it can be concluded that sleep duration has both direct and indirect effects on SWB (Greene et al., 2019). Besides, some studies show that there is a bidirectional relationship between sleep and SWB, as can be seen in Figure 2.1, and that both can affect each other. Hence, an increase in SWB for another reason would trigger a better quality of sleep (Steptoe et al., 2007; Birchler-Pedross et al., 2009; Lau et al., 2015; Ong et al., 2017). In addition, if it is accepted that sleep is a period that body's systems that have a direct effect on physical health, such as metabolism, hormones, immunity, and inflammatory functions, enter into the process of renewal and restoration, it can be said that it has a direct effect on being healthy and feeling healthy (Knutson, 2010; Faraut, 2012).

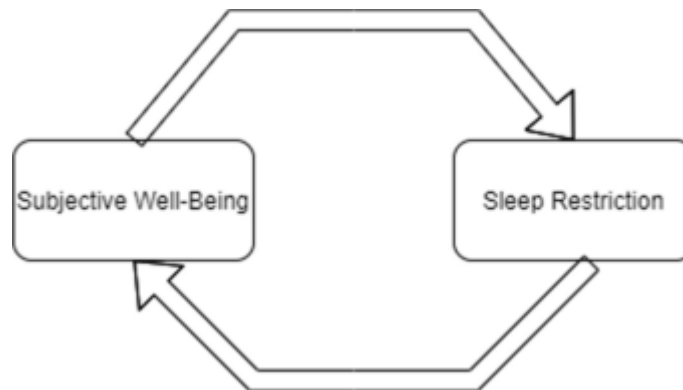


Figure 2.1: Bidirectional relationship between sleep and SWB.

For these reasons, in this study, the daily sleep time data in the NetHealth dataset collected via Fit Bit smart wristbands were used to calculate average daily sleep time. Average daily sleep time was accepted as a predictor of individuals SWB.

2.3 Big Five Personality Traits

If a person thinks of people around, the first thing that will be noticed is how different people are from each other. While one person may enjoy an activity, another may hate the same activity. While some people enjoy an active life, others get the same pleasure from spending time at home. Some people may like silence, while others like noisy environments. Gordon Allport, in his work in 1937, tried to generalize these differences of people, named as personality traits, collected and summarized these views and founded personality psychology and put forward the view that to understand people, first of all, it is necessary to analyze and understand their personality traits (Allport, 1937).

Personality traits reveal the basic dimensions in which people differ from each other. Although there are a limited number of dimensions, each individual could find a place for themselves within the scale. The levels on each dimension can be low, medium, or high (Matthews et al., 2003). A lot of comments have been made by psychologists about what these dimensions are, and they have divided personality diversity into hundreds of subcategories, and as the diversity of these traits increases, it has become more difficult to follow and interpret. Allport and Odbert examined personality traits lexically and encountered about 18,000 different personality type characterizations, which they called

the lexical approach (1936). Later, it was noticed that this approach could not continue with so many character classes, and "Factor Analysis", which is a statistical tool, was used and personality traits were classified under five main features covering the majority. For example, since people who describe themselves as 'friendly' also describe themselves as 'extroverts', a more specific trait such as 'friendliness' is measured by 'sociability' (Allport & Odbert, 1936). By using this method, personality traits were made to be examined under five main domains, and they were named the "Big Five Personality Traits" or the "Five Factor Model" and became the most widely accepted personality trait classification in psychology (McCrae & Costa, 1987; Goldberg, 1990; McCrae & John, 1992). The five major personality traits and their definitions are shown in Table 2.2.

Table 2.2: “The Big Five Personality Traits” and definitions.

Openness	A tendency to appreciate new and unusual ideas, feelings, adventures, and to be open to, fantasize about and wonder about various experiences.
Self-consciousness	Being careful, keeping the promises made on time; a tendency to obey rules, and being hard-working.
Extraversion	The tendency to be talkative, sociable, enjoying spending time with others, seeking the partnership and encouragement of others, and being dominant in social environments.
Agreeableness	The tendency to seek and adapt to the consensus of the community rather than to apply one's ideas and views.
Neuroticism	Often experiencing negative emotions such as anger, anxiety, anger, sadness; a tendency to be sensitive in social relationships.

In the data set we used, five major character traits of the participants were calculated using the 44-item inventory developed by John, Donahue, and Kentle in 1991. In this inventory, each question has a score in terms of character traits, and the points to measure dimensions are calculated according to the 5-point Likert Scale (1-Strongly

Disagree, 5-Strongly Agree). Each question affects the score of a different character trait. For example response to the item "I see myself as an introvert" Extraversion, response to the item "I see myself as a creative person" Openness to Experience, response to the item "I see myself as relaxed and able to cope with stress" Neuroticism, response to the item "I will do a job well enough" Self-consciousness, and the answer to the item "I see myself as someone who tends to find fault with others" affects the Agreeableness score.

There are two different views in psychology on the effect of these personality traits on human life. The first of these is temperament and the second is the tool view (McCrae & Costa, 1991). While the temperamental view argues that the five major personality traits are directly related to the human temperament and that this also affects SWB as a result of the temperament, the instrumental view argues that the personality traits affect the decisions and the environment of the person and have an effect on the SWB through them. The basis of the temperament view is that personality traits change the emotional activity and cognitive functioning of emotional information from external stimuli, which in turn will affect SWB (Diener et al., 2003).

Another study found that extroverts distract from rewarding stimuli more slowly than introverts (Derryberry & Reed, 1994). This increases extroverts' enjoyment of temperamentally positive stimuli and they become prone to experience positive effects that lead to higher satisfaction (Rusting & Larsen, 1997; Uziel, 2006). Thus, the happiness level of the person will increase, which will increase the SWB. On the other hand, the tool view revealed that extroverts will also increase their SWB level to higher levels compared to introverts, as extroverts adopt more diverse and adaptive methods of gaining social support and coping with negative factors (McCrae & Costa, 1986). Also, it is shown that the relationship between personality traits, especially Extraversion and Neuroticism, and SWB is stronger (Diener et al., 2003).

Based on these studies, personality traits were used in attributes as a factor affecting SWB. The 44-items Big Five Personality Inventory measured students' character traits in the NetHealth dataset. In this study, "Extraversion, Agreeableness,

Conscientiousness, Neuroticism and Openness" results at the beginning of the 12 months were used as the attributes.

2.4 Health, Happiness, and Health Satisfaction Inventories

The state of health of a person can be measured in two ways. The first of these is health assessments made with self-assessment questionnaires, and the other is objective physical health measures. Health self-assessment is an evaluation of one's condition by considering social, mental, and physical aspects. Health self-assessment is more associated with SWB than with objective physical health measures. According to studies, when this question is asked to people, the person gives the good-bad answer, thinks in the context of the illness and the bad experiences indirectly caused by the illness, and answers as a result of a multidimensional mental evaluation from multiple sources, including many psychological and social components (Manderbacka, 1998; Diener et al., 2003). So, health-related self-assessment questionnaires are not only related to physical health status but also related to mental and psychosocial elements and contain messages related to these (Krause & Jay, 1994; Benyamini & Idler, 1999; Benyamini et al., 1999; Ferraro & Farmer, 1999; McHorney, 2000; Mavaddat et al., 2011). For this reason, it has been stated that it covers concepts such as "life satisfaction" or "happiness", and it has been defined as the emotional reactions of individuals, their satisfaction in health, finance, social relations, etc., and their judgments that determine life satisfaction (Diener et al., 1999; Diener & Chan, 2011).

This led to the questioning of whether there is a relationship between health self-evaluation reports and SWB. In a meta-analysis, it was revealed that there is a correlation of over 30% (Okun et al., 1984). A study with older participants also revealed that health self-assessments were a strong predictor of SWB (Veenhoven, 2012). Another approach that supports this view is that the states that want to increase the happiness and welfare of the societies first adopt the policy of improving social health services (Diener, 1984; Ngamaba et al., 2017).

Happiness is another important factor in the relationship of health self-assessment to SWB. When people are asked what they want in life, the answer is "happiness". Even if

happiness is not answered directly, the answers given are indirectly related to internal and external factors that affect happiness. In a detailed study about SWB (Diener, 1984), the terms "high life satisfaction, frequent positive emotions, and rare negative emotions" were used a lot when describing SWB. So SWB is a label used for different forms of happiness. It has also been proven that people's self-evaluation reports are relatively valid for the happiness scale (Diener et al., 2013).

The last indicator we use to create the SWB that we set the target in this study is called the Health Satisfaction Inventory (Body Image). The concept of body image has been defined as a complex psychological structure influenced by multiple factors (Cash & Pruzinsky, 1990). Negative body image perception/dissatisfaction is also considered a psychological problem; it has negative consequences for physical and mental health (Stice & Shaw, 2002; Grave et al., 2008; Wilson et al., 2013; Bucchianeri & Neumark-Sztainer, 2014; Becker et al., 2017). Examples of these problems are eating disorders, anorexia, and a tendency to depression (Thompson & Stice, 2001; Stice & Shaw, 2002; Bucchianer et al., 2013). There are opinions that such situations will affect human well-being and happiness (Halliwell, 2015; Swami et al., 2017). In addition to these views, many studies have also revealed an inverse correlation between body dissatisfaction and well-being (Swami et al., 2017; Avalos et al., 2005; Frederick et al., 2016; Gongora, 2014; Swami et al., 2015; Tylka & Kroon Van Diest, 2013).

The Health, Happiness, and Body Image questionnaires mentioned in this section were applied to the participants separately in the NetHealth dataset. Considering that SWB has a multi-factorial structure, according to this literature review we have done, an SWB index has been created that can be measured and estimated by melting these three factors, which are interconnected and affect each other, and which are indicated in Figure 2.2 in a single pot.

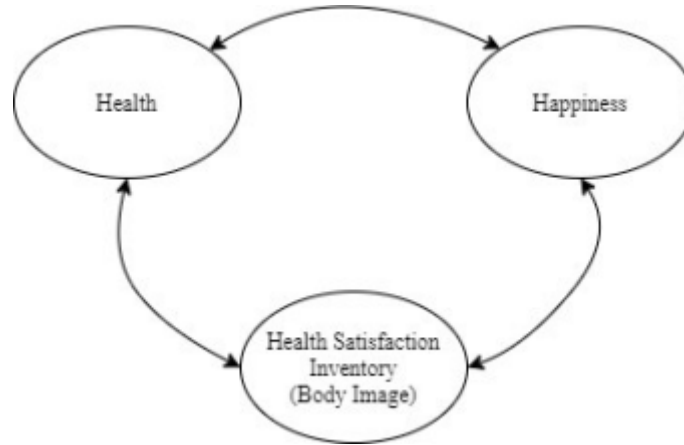


Figure 2.2: Generated SWB index.

2.5 Machine Learning Models

Machine learning is a part of artificial learning that aim to make computers learn from past and obtain accurate predictions about future (Michalski et al., 1983). Idea of using brain cells as a model for computer algorithms was born in 1940s by a published paper of Warren McCulloch and Walter Pitts (1947). Alan Turing came up with the question “Can machines think?” (1950) and carried that topic to one further step. It was followed by chess playing programs (Samuel, 1952), artificial neural networks modeled by human neurons (Rosenblatt, 1958) and statistics also included to that topic and new models were developed by using that concept (Paluszek et al., 2017). So, in this study machine learning models used to estimate target on the training data, and tested on unseen examples (Mitchell, 1997). In this section, the most common machine learning models used to predict psychological phenomena’s, namely Decision Trees (Murthy, 1998), Logistic Regression (Long, 1997), Naive Bayes (Domingos and Pazzani, 1997), SVM (Burges, 1998), KNN (Fix and Hodges, 1951), Ensemble (Freund and Saphire, 1996; Shapire, 1999), will be briefly described.

2.5.1 Decision Tree

Decision trees are classification trees that order entities based on attribute values (Swain and Hauska, 1977). Each branch indicates a value that a node might take, and each node shows an attribute to be categorized. Each entity categorized and ordered depending on their factor values by starting at the root mode. Fundamental benefit of decision trees,

and hierarchical approaches in general, is that they breakdown the problem into the subproblems. Hence, it becomes easier to solve. The process continues until all training data has been divided into subsets (Safavian and Ladgrebe, 1991). A sample tree is given in the Figure 2.3 (Gençalp, 2020).

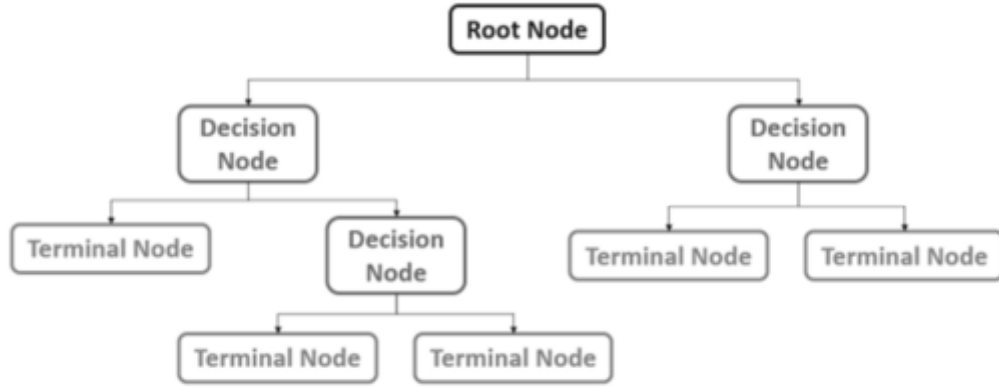


Figure 2.3: Decision Tree example.

2.5.2 Logistic Regression

Logistic regression is applicable when target is specified as binary and there exists two different classes (Dumitrescu et al., 2022). The relation between input and output is not linear, and logistic function is used as classifier. The function is given below in the equation 1 (Hosmer et al., 2013):

$$p_i = f(y|x) = \frac{1}{1 + \exp\{-(\beta_0 + \beta_1 x_i)\}} \quad (1)$$

where p_i is the probability of success and in the condition satisfied in figure below:
 $P(y_i = 1) = p_i$ and $P(y_i = 0) = q_i = 1 - p_i, 0 \leq p_i \leq 1$. A graphical representation of logistic regression is given in Figure 2.4.

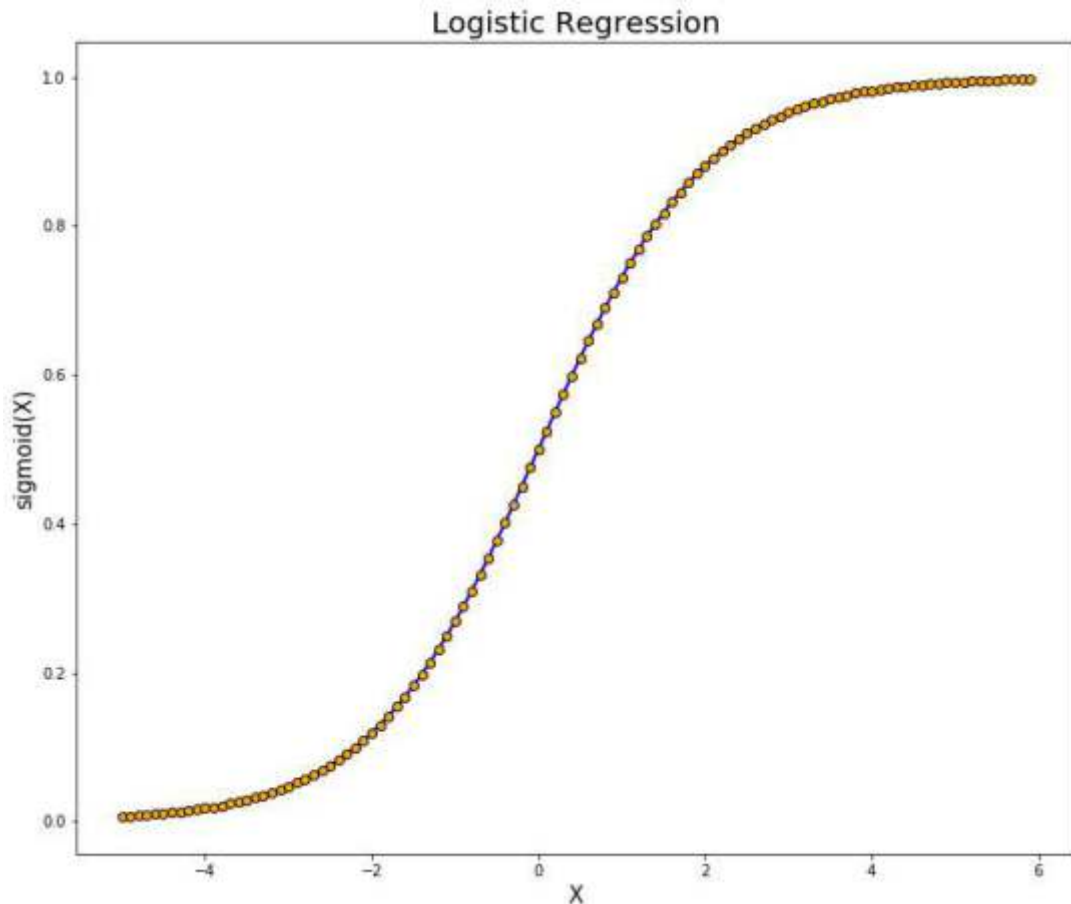


Figure 2.4: Logistic Regression graph.

2.5.3 Naive Bayes

Naive Bayes is the most basic form of the Bayesian network algorithms (Leung, 2007). It depends on the idea assuming that features are not dependent to given class, that is $P(X|C) = \prod_{i=1}^n P(X_i|C)$, where $X = (X_1, \dots, X_n)$ is a feature vector and C is a class (Rish, 2001). It is successful in practice and competing well with more sophisticated techniques. The algorithm assumes every attribute is independent, given the state of class attribute.

2.5.4 SVM

The SVM is a method learns by example to assigned labels of entities. It specifies a margin, and either side of a hyperplane denotes different classes (Boser et al., 1992). Theory is based on Vapnik-Chervonenkis theory (1982) and after training a sets of labeled data for each class, algorithm categorize new sample. The Figure 2.5 (Soares et

al., 2017) shows the idea that divide the by a linear hyperplane. The hyperplane type could be change according to the dataset with non-linear kernels.

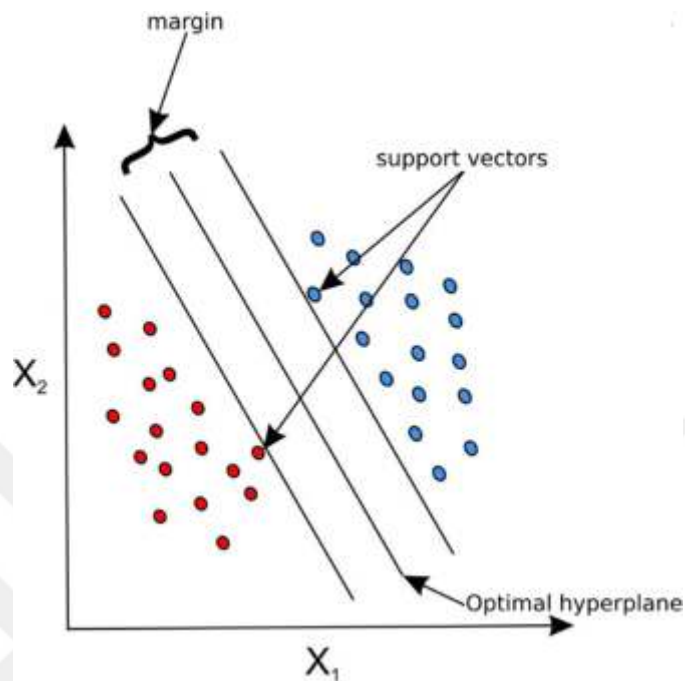


Figure 2.5: SVM graph.

2.5.5 KNN

Supervised learning algorithms are generally called as lazy-learning algorithms (Mitchell, 1997) because they delay application until categorization of all instances completed. One of these instance-based methods is KNN approach that depend the idea that similar instances usually be found in close to the others with similar attributes. The value of the label determined by looking at the class of its nearest neighbors (Piegl and Tiller, 2002). K specifies the k nearest neighbors' labels and the prediction can change according to k parameter. In the Figure 2.6 (Nechuta et al., 2011) below, a sample for algorithm is shown.

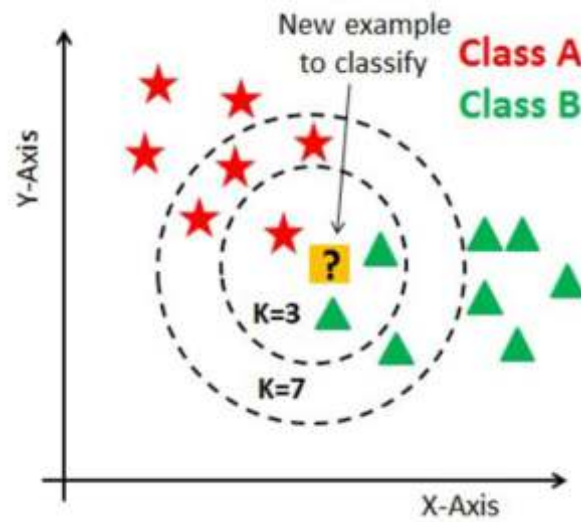


Figure 2.6: KNN graphical explanation.

2.5.6 Ensemble

Ensemble algorithms play an important role in the pattern recognition problems. Multiple individual classifiers form an ensemble classifier. Bagging and boosting are effective approaches to create an upper form. The performance is effected by the individual performance of each member. AdaBoost is one of the famous member that generates a powerful by combining several weak classifiers (Schapire and Singer, 1999).

3. METHODOLOGY

The aim of this chapter is to prepare a dataset to apply a machine-learning model that will be used to predict SWB. First of all, a time period within the dataset was selected. After that, attributes that could be used as mobile communication, physical activity, and the big five personality traits are specified. Then, dataset cleaned from noise and outliers, and proposed algorithms for predicting SWB were applied. Finally, tests and results of the algorithm will be presented. The flow chart of the methodology is shown in Figure 3.1.



Figure 3.1: Methodology process flow.

3.1 Data Set

The NetHealth dataset used in the study is the product of a project funded by the National Health, Lung and Blood Institute of the National Institutes of Health and conducted by the University of Notre Dame, Center for Network Science and Data. Approximately 700 undergraduate students participated in the project, but the number of participants decreased over time due to the difficulty of ensuring participant continuity in such continuous studies. A wide variety of data were collected from the participating students, including “social networking, physical activity, and sleep data by Fitbit devices, as well as physical and mental health questionnaires, socio-psychological conditions, habits, various self-evaluation reports, demographic, and personal backgrounds. This data has been grouped by the NetHealth (<http://sites.nd.edu/nethealth/>) working group as follows:

- Communication Data
- Basic Survey Data
- Network Survey Data
- Fitbit Data (Daily Activity and Sleep Data)
- Courses and Grades Data

These collected data are linked by a code called “egoid”, which is given to each participant to hide any personal information.

This model used 'call time' and 'message length' collected by the mobile devices, 'sleep time, number of steps' collected via Fitbit devices, and 'Big Five Personality Traits' gathered through psychological inventories. There are eight different waves within the data set. The wave selection depends to the maximizing entity number within that study. Hence, the data used in that study belongs to the wave covers 12 months between July 2015 and August 2016. Mobile Communication, Physical Activity and Big Five Personality Traits collected in this wave. In this study, they were examined respect to their relations with SWB in the literature.

3.2 Data Preprocessing

As mentioned before, the NetHealth dataset was used in the study. The period between 2015-2016 was chosen as the date range, and approximately 52 weeks in total were covered. Data filtering started from the FitBit sensor data because the sensor data is less than the survey data and creates a bottleneck. A total of 596 unique FitBit participants were identified during this date range. In this section, it was determined that the number of days that all 596 participants actively used FitBit during the year varied. In Figure 3.2, the histogram of those who used Fitbit watches for 1 year is given.

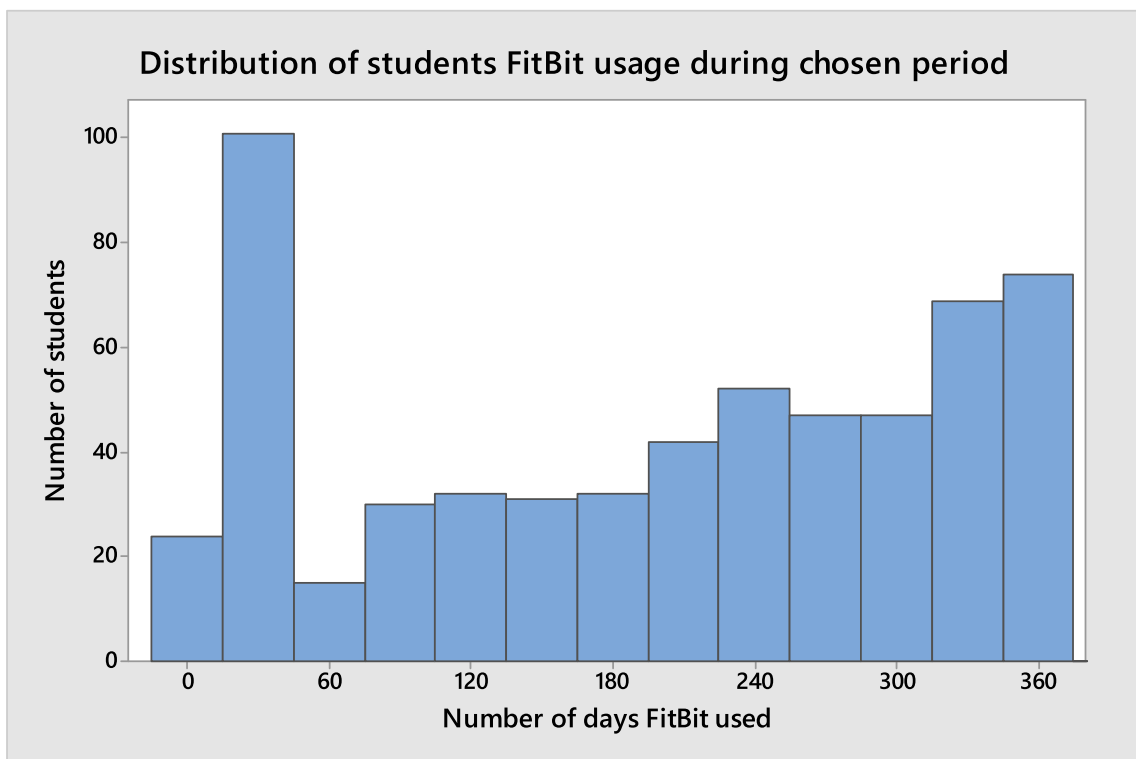


Figure 3.2: Histogram of students' Fitbit usage during the chosen period.

When users who participated in the Big Five Personality Traits survey and users with FitBit data were filtered, the data size decreased to 472 users. Another bottleneck noticed at the stage of data exploration is data loss due to individual reasons such as not using the wristbands during sleep at night or running out of battery or synchronization problems (Purta et al., 2016). For this reason, when users without sleep data were filtered, the data set decreased to 454 entities. To ensure consistency in the data, those who wear Fitbit watches during sleep for at least 182 days of the year, that is, half of the year were filtered out. The minimum compliance rate for the number of steps for the

sample set corresponding to the filtering in the sleep data was 54%. The total data decreased to 273 after this filtering.

Communication data is included in the data after the FitBit part. When null values are deducted from the communication data for the same period, 504 participants remain. Here, the communication data is divided into two main headings as mentioned earlier:

- Average length of incoming and outgoing messages per day
- Average daily incoming and outgoing call duration

When the egoids here are matched with the incoming data by the sensor, the width of the data set decreases to 191. The filtering steps of the data are also shown in Figure 3.3 step by step. By the help of the *egoid*, physical activity, survey and communication results matched.

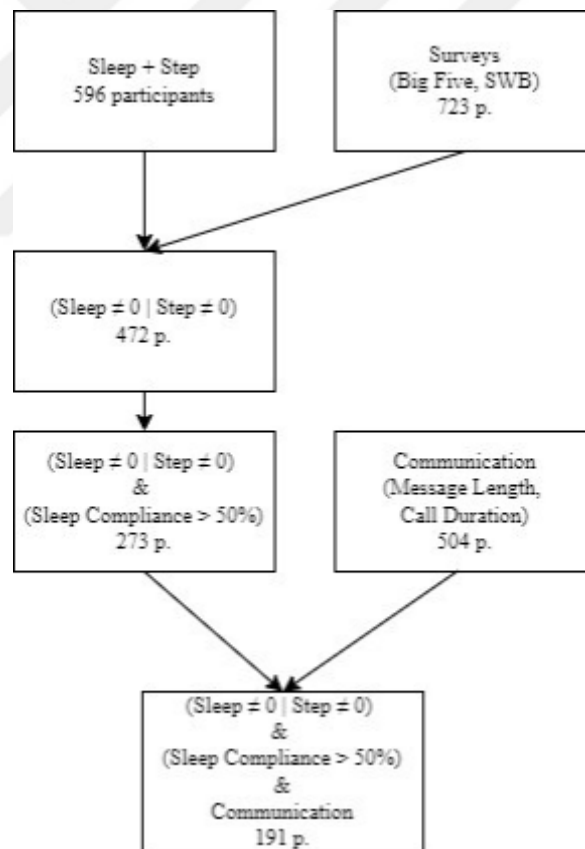


Figure 3.3: Data filtration results.

The distribution of the sample set of the data set by gender is given in Table 3.1. Low SWB and high SWB were almost equally distributed among the gender, while female participants in the population had lower SWBs.

Table 3.1: Examination of the data set by genders.

	n=101	n=98
SWB	M	F
Low SWB	39 (%39)	57 (%58)
High SWB	62 (%61)	41 (%42)

Normalization has been applied to the attributes. In the model, the standardized Health, Happiness, and Health Satisfaction values were collected as the target. Each self-assessment test result was summed up respectively and then results were normalized. After normalization, all of them were summed up again and obtained as SWB index. Maximum value became three and minimum value became zero. The average value within the data set specified as threshold and if a person's SWB value is greater than average it was accepted as high SWB, otherwise specified as low SWB. Distribution is given in Table 3.1. Formulation is given below. (He: Health, Hp: Happiness, HSI: Health Satisfaction Index)

$$SWB = \frac{He - \min(He)}{\max(He) - \min(He)} + \frac{Hp - \min(Hp)}{\max(Hp) - \min(Hp)} + \frac{HSI - \min(HSI)}{\max(HSI) - \min(HSI)} \quad (1)$$

$$Target = \begin{cases} 1, & SWB \geq \mu_{SWB} \\ 0, & SWB < \mu_{SWB} \end{cases} \quad (2)$$

3.3 Classifiers

There are nine attributes in total in the applied model. Six different classifiers were trained using nine attributes, and with these classifiers, the SWBs of the participants in the dataset were predicted to be high or low. Here, the threshold value is used as the median for low/high labelling since we used a dataset previously used by another study group to create a balanced (homogeneously distributed) dataset. Thus, the dataset was divided into 96 low SWBs and 103 high SWBs in total. Compared with other studies in the literature, the model has achieved high performance with the data of low-cost and easily available devices such as smartwatches and mobile phones (Gedam & Paul, 2021).

In the classification of the data Decision Tree, Logistic Regression, Naive Bayes, SVM, KNN, and Ensemble classifiers were used both in Python programming language by using "SciKit-Learn" and under the "Classification Learner" plugin of MATLAB. These six classifiers are also widely used in the literature and perform well in classification-based problems (Shoaib et al., 2015). Stratified 10-fold cross-validation was used to solve the validation problem. As can be seen in Figure 3.4, the data set is divided into parts consisting of equal data and the data other than the part used for testing the model are used for training purposes; the other set is then used for testing. Thus, all created parts are used in the training of the model.

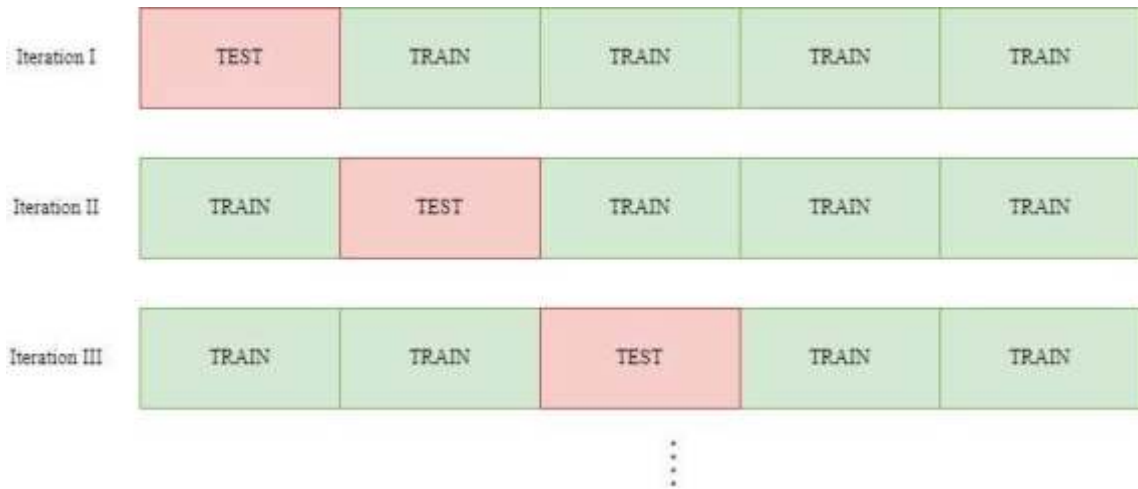


Figure 3.4: Cross validation.

3.4 Performance Measures

First performance measure used was accuracy which is a metric to evaluate classification models. It is the fraction of predictions that model made right. As second metric, precision was used gives the proportion of positive labels identified correctly.

Table 3.2: Formulation for each performance metric.

Accuracy	Precision	Recall	F1 Score
$\frac{TN + TP}{TN + FP + TP + FN}$	$\frac{TP}{TP + FP}$	$\frac{TP}{TP + FN}$	$2 * \frac{Precision * Recall}{Precision + Recall}$

Third metric used was recall and it gives the proportion of actual positives identified correctly. As fourth metric, F1 score used which had been developed rely on both precision and recall scores and calculated by weighted average of these two metrics (Dimitrios, 2022). Table 3.2 shows the formulation for each metric.

Other metrics are ROC curve and AUC (Area Under Curve). ROC is a graph showing the performance at all classification thresholds and has two parameters as True Positive Rate (recall) and False Positive Rate. TPR vs. FPR is plotted on a ROC curve at various categorization levels. Lowering the classification threshold causes more items to be classified as positive, which increases both False Positives and True Positives (Dimitrios, 2022), and AUC provides an aggregate measure of performance across all possible classification thresholds by summing up the area under ROC curve both are shown within the Figure 3.5.

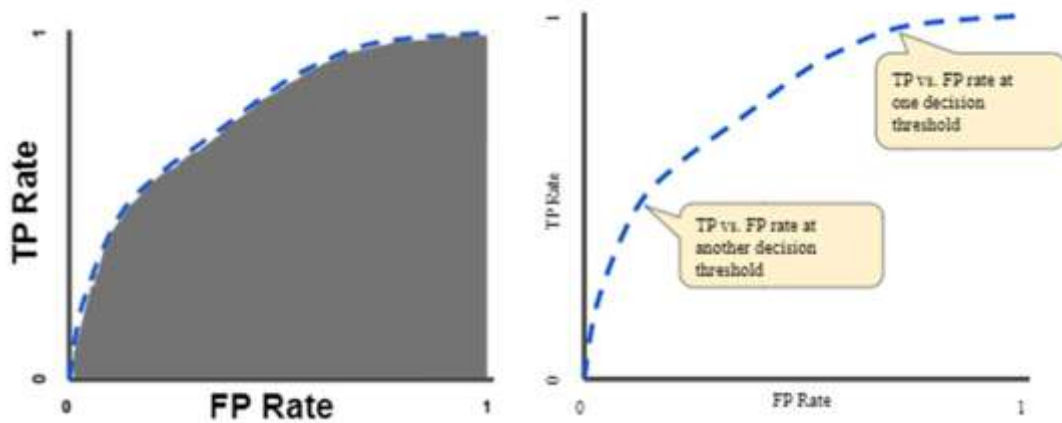


Figure 3.5: ROC curve on left and AUC specified as grey on right.

4. IMPLEMENTATION AND RESULTS

In this section, the results of our application will be mentioned. As stated before, in this study, there are a total of 9 feature sets listed under 3 main headings, 1 target consisting of 3 components, and 6 classifiers. The test results using these components were analyzed. While making these analyzes, a laptop computer with an i7-9750H CPU, 2.6 GHz processor, 16 GB RAM, and 64-bit operating system was used. All features are normalized using min-max normalization. Accuracy, Precision, and Recall scores are used to see the general consistency of the model. Figure 8 shows the Pearson's correlation heatmap for all attributes and the SWB target. As seen in the figure, the highest correlation values were observed in Big Five Personality Traits and daily sleep duration. P-values of personality traits other than openness were also less than 0.05 and significant.

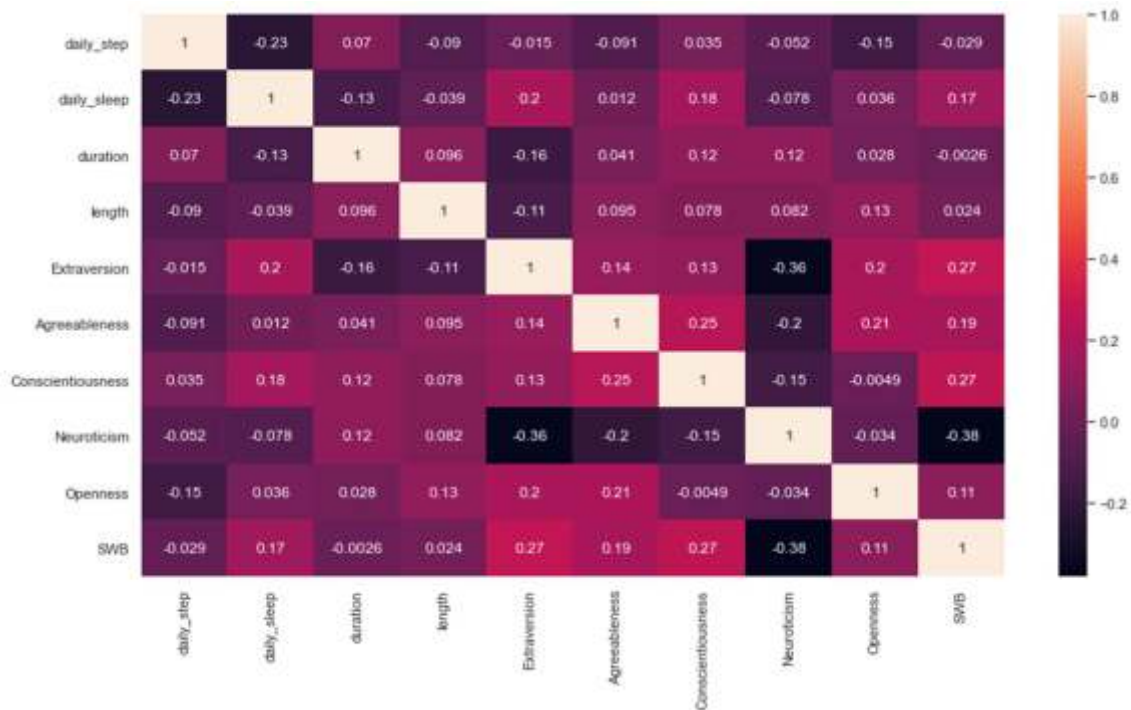


Figure 4.1: Correlation heatmap.

According to the relationship established over the previous theoretical analysis, the SWB index was created and the problem was approached as binary classification. The results for the applied models are given in Table 4.1. While KNN gave the highest score with 72.25% in Accuracy, Ensemble gave the highest score with 70.41% in Precision, and KNN gave the highest score with 80.41% in Recall, followed by Decision Tree with %76.29 which is still a high percentage compared to other classifiers. Based on these scores, the following inferences can be made:

- If the aim is to properly identify all persons with low and high well-being, KNN has the highest Accuracy.
- If the aim is to accurately identify those with high well-being while keeping the false positive (FP) ratio low, Ensemble has the highest Precision.
- If the goal is to correctly identify those with high well-being while keeping the false negative (FN) ratio low, KNN has the highest Recall rate.
- Since this sort of model may be utilized in processes such as recommendation and intervention, assistance to an individual with low SWB should also be prioritized. As a result, it is critical for the model to maintain a low FP ratio and to avoid inaccurate prediction of persons with low SWB. As a result, Precision rate prioritized as performance metric.

Table 4.1: Classifiers, parameters and performance metrics.

Classifier	Tested Parameters	Optimum Parameters	Accuracy	Precision	Recall
<i>Decision Tree</i>	-Maximum number of splits: 1-190 -Split criterion: Gini's diversity index, Maximum deviance reduction	-2 Splits -Criteria: Max. Deviance Reduction	70.16%	68.52%	76.29%
<i>Logistic Regression</i>	-	-	64.40%	64.95%	64.95%

Naive Bayes	-Distribution names: Gaussian, Kernel -Kernel type: Gaussian, Box, Epanechnikov, Triangle	-Gaussian Distribution. -Kernel: Box	65.97%	67.78%	62.89%
SVM	-Multiclass method: One- vs-All, One-vs-One -Box constraint level: 0.001-1000 -Kernel scale: 0.001-1000 -Kernel function: Gaussian, Linear, Quadratic, Cubic	-Kernel: Quadratic -Box constr. level: 0.17127 -Multiclass method: One-vs-All	67.02%	67.35%	68.04%
KNN	-Number of neighbors: 1-96 -Distance metric: City block, Chebyshev, Correlation, Cosine, Euclidean, Hamming, Jaccard, Mahalanobis, Minkowski (cubic), Spearman -Distance weight: Equal, Inverse, Squared inverse	-# of neighbors: 7 -Distance metric: Chebyshev -Distance weight: Squared inverse	72.25%	69.64%	80.41%
Ensemble	-Ensemble method: Bag, GentleBoost, LogitBoost, AdaBoost, RUSBoost -Number of learners: 10- 500 -Learning rate: 0.001-1 -Maximum number of splits: 1-190 -Number of predictors to sample: 1-12	-Method: AdaBoost -Max. Split: 1 -# of learner: 17 -Learning rate: 0.0012265	70.16%	70.41%	71.13%

Lastly, the computation time for each model is given below in Table 4.2. From the table, it can be seen that Ensemble has the highest and Logistic Regression has the lowest computation time among models. It also is easy to see that KNN is advantageous to use as it has the second-lowest computation time but best result for Accuracy, Recall, and the second-best for the Precision score. Additionally, the rate that gives us the prediction of the happy people (high SWB) is highest for Ensemble with a 70.41%, but

if aim is revised as predicting the unhappy people (low SWB), the best predicting ratio for true negatives is Naive Bayes and Ensemble with a 69.15%. The confusion matrix for each model is given in the Table 4.3. Also, the performance is approximately at the same level compared to literature given in the Table 2.1.

Table 4.2: Computation time of classifiers.

Classifier	Compute Time
<i>Decision Tree</i>	29.816 sec
<i>Logistic Regression</i>	1.3097 sec
<i>Naive Bayes</i>	34.597 sec
<i>SVM</i>	31.56 sec
<i>KNN</i>	24.138 sec
<i>Ensemble</i>	111.02 sec

Table 4.3: Confusion matrix for each model.

			Predicted	
			N	P
Actual	Decision Tree	N	60	34
		P	23	74
	Logistic Regression	N	60	34
		P	34	63
	Naive Bayes	N	65	29
		P	36	61
	SVM	N	62	32
		P	31	66
	KNN	N	60	34
		P	19	78
	Ensemble	N	65	29
		P	28	69

5. CONCLUSION

In this thesis, usage of machine learning algorithms to determining is taken into consideration as a new approach in SWB. From the questionnaires conducted, the personality trait levels were extracted within the previous studies. In some studies, these traits also have been estimated accurately from the sensors and social media usage of a person. So, this study shows us with this type of technology, this opportunity could be used to identify the well-being level of a person without any interaction.

This type of multivariate data is very difficult to collect and process in terms of time and money. Hence, in the study, Net Health dataset used which is an open source multi longitudinal study of social networks and health provided by University of Notre Dame. The dataset includes step number, heart rate, sleep duration, and psychological questionnaires such as depression, health, happiness surveys. The necessary features selected according to previous studies and used Python and MATLAB to create prediction model.

Six algorithms; Decision Tree, Logistic Regression, Naive Bayes, SVM, KNN, Ensemble are chosen according to literature review and by considering their suitability to a dataset given in this structure. We compared the results for each model and found that the accuracy for each model is higher than 60%, and performance metrics spread between 60-80% and shows that the SWB is predictable by using sensor and personality traits. Best accuracy is provided by KNN and it also is the second-best alternative by computing times.

Currently, social media platforms collect an enormous amount of data from users, and it is easy to read that these applications use people's mental situations to generate more profit. In contrast, the main goal of this paper is to estimate the SWB score of a person

from a small size dataset for a scientific purpose. The main purpose is assessing mental health for humanitarian purposes and as future work, target could be making this analysis with less interaction with a human, like without surveys, questionnaires, etc. Also, technological improvements like 5G will provide the big data transfers within a short time period, and it will make possible more complex models to make more accurate predictions about human behavior.



REFERENCES

- Allport, G. W. (1937). *Personality: a psychological interpretation*. Holt.
- Allport, G. W., & Odbert, H. S. (1936). Trait-names: A psycho-lexical study., *Psychological monographs* 47(1) : i.
- Appau, S., Churchill, S. A., & Farrell, L. (2019). Social integration and subjective wellbeing., *Applied Economics* 51(16) : 1748-1761.
- Bartolini, S., & Bilancini, E. Pugno M. (2011). Did the Decline in Social Connections Depress Americans' Happiness?., *Social Indicators Research* DOI : 10.
- Becker, C. B., Verzijl, C. L., Kilpela, L. S., Wilfred, S. A., & Stewart, T. (2019). Body image in adult women: Associations with health behaviors, quality of life, and functional impairment., *Journal of health psychology* 24(11) : 1536-1547.
- Benyamini, Y., & Idler, E. L. (1999). Community studies reporting association between self-rated health and mortality: additional studies, 1995 to 1998., *Research on aging* 21(3) : 392-401.
- Benyamini, Y., Leventhal, E. A., & Leventhal, H. (1999). Self-assessments of health: What do people know that predicts their mortality?, *Research on aging* 21(3) : 477-500.
- Birchler-Pedross, A., Schröder, C. M., Münch, M., Knoblauch, V., Blatter, K., Schnitzler-Sack, C., ... & Cajochen, C. (2009). Subjective well-being is modulated by circadian phase, sleep pressure, age, and gender., *Journal of biological rhythms* 24(3) : 232-242.
- Boser, B. E., Guyon, I. M., & Vapnik, V. N. (1992). A training algorithm for optimal margin classifiers., *Proceedings of the fifth annual workshop on Computational learning theory* : 144-152.
- Bucchianeri, M. M., Arikian, A. J., Hannan, P. J., Eisenberg, M. E., & Neumark-Sztainer, D. (2013). Body dissatisfaction from adolescence to young adulthood: Findings from a 10-year longitudinal study., *Body image* 10(1) : 1-7.

- Bucchianeri, M. M. and Neumark-Sztainer, D. (2014), Body dissatisfaction: an overlooked public health concern., *Journal of Public Mental Health* 13(2) : 64-69.
- Can, Y. S., Arnrich, B., & Ersoy, C. (2019). Stress detection in daily life scenarios using smart phones and wearable sensors: A survey., *Journal of biomedical informatics* 92 : 103139.
- Carneiro, D., Castillo, J. C., Novais, P., Fernández-Caballero, A., & Neves, J. (2012). Multimodal behavioral analysis for non-invasive stress detection., *Expert Systems with Applications* 39(18): 13376-13389.
- Cash, T. F., & Pruzinsky, T. E. (1990). Body images: Development, deviance, and change, Guilford press.
- Caspersen, C. J., Powell, K. E., & Christenson, G. M. (1985). Physical activity, exercise, and physical fitness: definitions and distinctions for health-related research., *Public health reports* 100(2) : 126.
- Cerulo, K. A., & Ruane, J. M. (1998). Coming together: New taxonomies for the analysis of social relations., *Sociological Inquiry* 68(3) : 398-425.
- Csikszentmihalyi, M., & Hunter, J. (2014). Happiness in everyday life: The uses of experience sampling., *Flow and the foundations of positive psychology* : 89-101
- Dauvilliers, Y., Maret, S., & Tafti, M. (2005). Genetics of normal and pathological sleep in humans., *Sleep medicine reviews* 9(2) : 91-100.
- Deaton, A., & Stone, A. A. (2016). Understanding context effects for a measure of life evaluation: How responses matter., *Oxford Economic Papers* 68(4) : 861-870.
- Derryberry, D., & Reed, M. A. (1994). Temperament and attention: orienting toward and away from positive and negative signals., *Journal of personality and social psychology* 66(6) : 1128.
- Diener, E. (1984). Subjective well-being. *Psychological Bulletin* 95(3) : 542-575.
- Diener, E., Sapyta, J. J., & Suh, E. (1998). Subjective well-being is essential to well-being., *Psychological inquiry* 9(1) : 33-37.
- Diener, E., Suh, E. M., Lucas, R. E., & Smith, H. L. (1999). Subjective well-being: Three decades of progress., *Psychological bulletin* 125(2) : 276.
- Diener, E., Oishi, S., & Lucas, R. E. (2003). Personality, culture, and subjective well-being: Emotional and cognitive evaluations of life., *Annual review of psychology* 54(1) : 403-425.

- Diener, E., & Chan, M. Y. (2011). Happy people live longer: Subjective well-being contributes to health and longevity., *Applied Psychology: Health and Well-Being* 3(1) : 1-43.
- Diener, E., Inglehart, R., & Tay, L. (2013). Theory and validity of life satisfaction scales., *Social indicators research* 112(3) : 497-527.
- Diener, E., & Seligman, M. E. (2018). Beyond money: Progress on an economy of well-being., *Perspectives on Psychological Science* 13(2) : 171-175.
- Dumitrescu, E., Hue, S., Hurlin, C., & Tokpavi, S. (2022). Machine learning for credit scoring: Improving logistic regression with non-linear decision-tree effects., *European Journal of Operational Research* 297(3) : 1178-1192.
- Faraut, B., Boudjeltia, K. Z., Vanhamme, L., & Kerkhofs, M. (2012). Immune, inflammatory and cardiovascular consequences of sleep restriction and recovery., *Sleep medicine reviews* 16(2) : 137-149.
- Ferraro, K. F., & Farmer, M. M. (1999). Utility of Health Data from Social Surveys: Is There a Gold Standard for Measuring Morbidity?, *American Sociological Review* 64(2) : 303–315.
- Freund, Y., & Schapire, R. E. (1996). Experiments with a new boosting algorithm., *International Conference on Machine Learning* 96 : 148-156.
- Garcia-Ceja, E., Osmani, V., & Mayora, O. (2015). Automatic stress detection in working environments from smartphones' accelerometer data: a first step. *IEEE journal of biomedical and health informatics* 20(4) : 1053-1060.
- Grünerbl, A., Muaremi, A., Osmani, V., Bahle, G., Oehler, S., Tröster, G., Mayora, O., Haring, C., & Lukowicz, P. (2014). Smartphone-based recognition of states and state changes in bipolar disorder patients. *IEEE journal of biomedical and health informatics*, 19(1), 140-148.
- Gedam, S., & Paul, S. (2021). A review on mental stress detection using wearable sensors and machine learning techniques., *IEEE Access* 9 : 84045-84066.
- Gençalp, E. (2020). *Atm Demand Prediction With Machine Learning Methods*, Master's thesis, University of Galatasaray.
- Goldberg, L. R. (1990). An alternative" description of personality": the big-five factor structure., *Journal of personality and social psychology* 59(6) : 1216.

- Grabe, S., Ward, L. M., & Hyde, J. S. (2008). The role of the media in body image concerns among women: a meta-analysis of experimental and correlational studies., *Psychological bulletin* 134(3) : 460.
- Greene, D. S., Mullins, M., Cherry, D., & Baggett, P. (2019). Teaching Note—BSW Students' Experiences With an MBSR Assignment and the Five Facets of Mindfulness., *Journal of Social Work Education* 55(2) : 409-416.
- Halliwell, E. (2015). Future directions for positive body image research. *Body image* 14 : 177-189.
- Hayes, N., & Joseph, S. (2003). Big 5 correlates of three measures of subjective well-being., *Personality and Individual differences* 34(4) : 723-727.
- Hoffner, C. A., & Lee, S. (2015). Mobile phone use, emotion regulation, and well-being., *Cyberpsychology, Behavior, and Social Networking* 18(7) : 411-416.
- Hosmer Jr, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). Applied logistic regression, Vol. 398, John Wiley & Sons.
- Jin, B., & Park, N. (2010). In-person contact begets calling and texting: Interpersonal motives for cell phone use, face-to-face interaction, and loneliness., *Cyberpsychology, Behavior, and Social Networking* 13(6) : 611-618.
- Kahneman, D., Krueger, A. B., Schkade, D. A., Schwarz, N., & Stone, A. A. (2004). A survey method for characterizing daily life experience: The day reconstruction method., *Science* 306(5702) : 1776-1780.
- Knutson, K. L. (2010). Sleep duration and cardiometabolic risk: a review of the epidemiologic evidence., *Best practice & research Clinical endocrinology & metabolism* 24(5) : 731-743.
- Krause, N. M., & Jay, G. M. (1994). What do global self-rated health items measure?, *Medical care* 32(9) : 930-942.
- Kryger, M. H., Roth, T., & Dement, W. C. (2010). Principles and Practice of Sleep Medicine-E-Book, Elsevier Health Sciences.
- Lau, E. Y. Y., Hui, C. H., Cheung, S. F., & Lam, J. (2015). Bidirectional relationship between sleep and optimism with depressive mood as a mediator: a longitudinal study of Chinese working adults., *Journal of Psychosomatic Research* 79(5) : 428-434.
- Leung, K. M. (2007). Naive bayesian classifier., *Polytechnic University Department of Computer Science/Finance and Risk Engineering* 2007 : 123-156.

- Lucas, R. E., & Lawless, N. M. (2013). Does life seem better on a sunny day? Examining the association between daily weather conditions and life satisfaction judgments., *Journal of personality and social psychology* 104(5) : 872.
- Manderbacka, K. (1998). Examining what self-rated health question is understood to mean by respondents., *Scandinavian journal of social medicine* 26(2) : 145-153.
- Matthews, G., Deary, I. J., & Whiteman, M. C. (2003). Personality traits, Cambridge University Press.
- Mavaddat, N., Kinmonth, A. L., Sanderson, S., Surtees, P., Bingham, S., & Khaw, K. T. (2011). What determines Self-Rated Health (SRH)? A cross-sectional study of SF-36 health domains in the EPIC-Norfolk cohort., *Journal of Epidemiology & Community Health* 65(9) : 800-806.
- Maxhuni, A., Muñoz-Meléndez, A., Osmani, V., Perez, H., Mayora, O., & Morales, E. F. (2016). Classification of bipolar disorder episodes based on analysis of voice and motor activity of patients. *Pervasive and Mobile Computing* 31 : 50-66.
- McAuley, E., & Rudolph, D. (1995). Physical activity, aging, and psychological well-being., *Journal of aging and physical activity* 3(1) : 67-96.
- McCrae, R. R., & Costa Jr, P. T. (1986). Personality, coping, and coping effectiveness in an adult sample., *Journal of personality* 54(2) : 385-404.
- McCrae, R. R., & Costa, P. T. (1987). Validation of the five-factor model of personality across instruments and observers., *Journal of personality and social psychology* 52(1) : 81.
- McCrae, R. R., & Costa Jr, P. T. (1991). Adding Liebe und Arbeit: The full five-factor model and well-being., *Personality and social psychology bulletin* 17(2) : 227-232.
- McCrae, R. R., & John, O. P. (1992). An introduction to the five-factor model and its applications., *Journal of personality* 60(2) : 175-215.
- McHorney, C.A. (1999). Concepts and measurement of health status and health-related quality of life, *The Handbook of Social Studies in Health & Medicine*, London: Sage Publications, pp. 339-358.
- Michalski, R. S., Carbonell, J. G., & Mitchell, T. M. (2013). Machine learning: An artificial intelligence approach, Springer Science & Business Media.
- Mitchell, T. M. (1997). Machine Learning, McGraw-Hill, pp. 154-200.

- Mokhtarian, P. L., Salomon, I., & Redmond, L. S. (2001). Understanding the demand for travel: It's not purely derived', *Innovation: The European Journal of Social Science Research* 14(4) : 355-380.
- Muaremi, A., Arnrich, B., & Tröster, G. (2013). Towards measuring stress with smartphones and wearable devices during workday and sleep., *BioNanoScience* 3(2) : 172-183.
- Ngamaba, K. H., Panagioti, M., & Armitage, C. J. (2017). How strongly related are health status and subjective well-being? Systematic review and meta-analysis., *The European Journal of Public Health* 27(5) : 879-885.
- North, T. C., McCullagh, P., Tran, Z. V., & Lavalley, D., Williams, J. M., Jones, M. V. (Eds.), & Papathomas, A. (Collaborator). (2008). Effect of exercise on depression., *Key studies in sport and exercise psychology* : 258-284.
- Okun, M. A., Stock, W. A., Haring, M. J., & Witter, R. A. (1984). Health and subjective well-being: A meta-analysis., *The International journal of aging and human development* 19(2) : 111-132.
- Ong, A. D., Kim, S., Young, S., & Steptoe, A. (2017). Positive affect and sleep: A systematic review., *Sleep medicine reviews* 35 : 21-32.
- Paluszek, M., & Thomas, S. (2017). An Overview of Machine Learning., *MATLAB Machine Learning* : 3-15.
- Petruzzello, S. J., Landers, D. M., Hatfield, B. D., Kubitz, K. A., & Salazar, W. (1991). A meta-analysis on the anxiety-reducing effects of acute and chronic exercise., *Sports medicine* 11(3) : 143-182.
- Piegl, L. A., & Tiller, W. (2002). Algorithm for finding all k nearest neighbors., *Computer-Aided Design* 34(2) : 167-172.
- Pilcher, J. J., & Huffcutt, A. I. (1996). Effects of sleep deprivation on performance: a meta-analysis., *Sleep* 19(4) : 318-326.
- Pitts, W., & McCulloch, W. S. (1947). How we know universals the perception of auditory and visual forms., *The Bulletin of mathematical biophysics* 9(3) : 127-147.
- Purta, R., Mattingly, S., Song, L., Lizardo, O., Hachen, D., Poellabauer, C., & Striegel, A. (2016). Experiences measuring sleep and physical activity patterns across a large college cohort with fitbits., *Proceedings of the 2016 ACM international symposium on wearable computers* : 28-35.

- Reece, A. G., & Danforth, C. M. (2017). Instagram photos reveal predictive markers of depression., *EPJ Data Science* 6(1) : 15.
- Rish, I. (2001). An empirical study of the naive Bayes classifier., *IJCAI 2001 workshop on empirical methods in artificial intelligence* 3(22) : 41-46.
- Rubin, R. B., Perse, E. M., & Barbato, C. A. (1988). Conceptualization and measurement of interpersonal communication motives., *Human Communication Research* 14(4) : 602-628.
- Rusting, C. L., & Larsen, R. J. (1997). Extraversion, neuroticism, and susceptibility to positive and negative affect: A test of two theoretical models., *Personality and individual differences* 22(5) : 607-612.
- Ryan, R. M., & Deci, E. L. (2001). On happiness and human potentials: A review of research on hedonic and eudaimonic well-being., *Annual review of psychology* 52(1) : 141-166.
- Sano, A., & Picard, R. W. (2013). Stress recognition using wearable sensors and mobile phones. *Humaine association conference on affective computing and intelligent interaction* 2013 : 671-676.
- Safavian, S. R., & Landgrebe, D. (1991). A survey of decision tree classifier methodology., *IEEE transactions on systems, man, and cybernetics* 21(3) : 660-674.
- Schapire, R. E. (1999). A brief introduction to boosting., *Ijcai* 99 : 1401-1406.
- Schapire, R. E., & Singer, Y. (1999). Improved boosting algorithms using confidence-rated predictions., *Machine learning* 37(3) : 297-336.
- Shaw, L. H., & Gant, L. M. (2002). Users divided? Exploring the gender gap in Internet use., *CyberPsychology & Behavior* 5(6) : 517-527.
- Shoaib, M., Bosch, S., Incel, O., Scholten, H., & Havinga, P. (2015). A Survey of Online Activity Recognition Using Mobile Phones., *Sensors* 15(1) : 2059–2085.
- Silverman, B. W., & Jones, M. C. (1989). E. Fix and J.L. Hodges (1951): An Important Contribution to Nonparametric Discriminant Analysis and Density Estimation: Commentary on Fix and Hodges (1951). *International Statistical Review / Revue Internationale de Statistique* 57(3) : 233–238.
- Spirduso, W. W., Francis, K. L., & MacRae, P. G. (1995). Physical dimensions of aging, Vol. 798 of Human kinetics, Champaign.
- Srivastava, L. (2005). Mobile phones and the evolution of social behaviour., *Behaviour & information technology* 24(2) : 111-129.

- Steptoe, A., O'Donnell, K., Marmot, M., & Wardle, J. (2008). Positive affect, psychological well-being, and good sleep., *Journal of psychosomatic research* 64(4) : 409-415.
- Stice, E., & Shaw, H. E. (2002). Role of body dissatisfaction in the onset and maintenance of eating pathology: A synthesis of research findings., *Journal of psychosomatic research* 53(5) : 985-993.
- Swain, P. H., & Hauska, H. (1977). The decision tree classifier: Design and potential., *IEEE Transactions on Geoscience Electronics* 15(3) : 142-147.
- Swami, V., Weis, L., Barron, D., & Furnham, A. (2018). Positive body image is positively associated with hedonic (emotional) and eudaimonic (psychological and social) well-being in British adults., *The Journal of social psychology* 158(5) : 541-552.
- Tay, L., Chan, D., & Diener, E. (2014). The metrics of societal happiness., *Social Indicators Research* 117(2) : 577-600.
- Thompson, J. K., & Stice, E. (2001). Thin-ideal internalization: Mounting evidence for a new risk factor for body-image disturbance and eating pathology., *Current directions in psychological science* 10(5) : 181-183.
- Turing, A. M. (1950). Computing Machinery and Intelligence., *Mind* 59(236) : 433-460.
- Uziel, L. (2006). The extraverted and the neurotic glasses are of different colors., *Personality and Individual Differences* 41(4) : 745-754.
- Van Dongen, H., Maislin, G., Mullington, J. M., & Dinges, D. F. (2003). The cumulative cost of additional wakefulness: dose-response effects on neurobehavioral functions and sleep physiology from chronic sleep restriction and total sleep deprivation., *Sleep* 26(2) : 117-126.
- Veenhoven, R. (2012). World Database of Happiness-Rotterdam: Erasmus University.
URL : http://worlddatabaseofhappiness.eur.nl/hap_cor/cor_fp.htm
- Voukelatou, V., Gabrielli, L., Miliou, I., Cresci, S., Sharma, R., Tesconi, M., & Pappalardo, L. (2021). Measuring objective and subjective well-being: dimensions and data sources., *International Journal of Data Science and Analytics* 11(4) : 279-309.
- Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: the PANAS scales., *Journal of personality and social psychology* 54(6) : 1063.

- Watson, D., & Clark, L. A. (1994). *The PANAS-X: Manual for the positive and negative affect schedule-expanded form*, University of Iowa.
- Wellman, B., Carrington, P., & Hall, A. (1988). Networks as personal communities., *Social structures: A network approach* 2 : 130-84.
- Wilson, R. E., Latner, J. D., & Hayashi, K. (2013). More than just body weight: The role of body image in psychological and physical functioning., *Body image* 10(4) : 644-647.
- Yap, S. C., Wortman, J., Anusic, I., Baker, S. G., Scherer, L. D., Donnellan, M. B., & Lucas, R. E. (2017). The effect of mood on judgments of subjective well-being: Nine tests of the judgment model., *Journal of Personality and Social Psychology* 113(6) : 939.

BIOGRAPHICAL SKETCH

Akif Can Kılıç was born. He studied at Bağcılar Akşemsettin Anadolu High School where he was graduated in 2011. He attended the undergraduate program of Industrial Engineering in İstanbul Kültür University with full scholarship. After graduation, he worked in the aviation sector. Now, he is research and teaching assistant in İstanbul Kültür University. Also, he is working towards Master of Science degree in Logistics and Financial Management under the supervision of Assoc. Prof. Dr. S. Emre Alptekin from the Institute of Science and Engineering, Galatasaray University.

PUBLICATIONS

- No publication.