SILESIAN UNIVERSITY OF TECHNOLOGY
FACULTY OF BIOMEDICAL ENGINEERING

Methods of Computer-Aided Diagnosis of People with Eating Disorders Using Elements of Natural Language Processing

— DOCTORAL DISSERTATION—

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List of Abbreviations

APA	American Psychological Association
AN	Anorexia Nervosa
AI	Artificial Intelligence
ANN	Artificial Neural Network
BID	Body Image Disturbance
BMI	Body Mass Index
BN	Bulimia Nervosa
BPTT	Backpropagation Through Time
CBOW	Continuous Bag of Words
DSM-5	Diagnostic and Statistical Manual of Mental Disorders
DCTSA	Diagnostic Computer Tool for Sentiment Analysis
GRU	Gated Recurrent Unit
HNC	Head and Neck Cancer
ICD	International Classification of Diseases
LIWC	Linguistic Inquiry and Word Count
LSTM	Long Short-Term Memory
NLP	Natural Language Processing
NAWL	Nencki Affective Word List

POS Part of Speech

PEG Percutaneous Endoscopic Gastrostomy

Pro-ana Pro-anorexia

RNN Recurrent Neural Network

SVM Support Vector Machines

WHO World Health Organization

Streszczenie

Rozprawa dotyczy nowatorskiego podejścia zastosowania elementów przetwarzania języka naturalnego do komputerowego wspomagania diagnostyki osób z zaburzeniami odżywiania, w szczególności anoreksji. Rozprawa obejmuje wprowadzenie do zagadnień zaburzeń odżywiania oraz komputerowego wspomagania diagnostyki tych zaburzeń oraz przegląd literatury w zakresie tematu pracy. W dalszej części zawarto opis zaproponowanych metod przetwarzania języka naturalnego w zastosowaniach do wspomagania personelu opiekującego się osobami cierpiącymi na zaburzenia odżywiania.

Wśród najistotniejszych osiągnięć badawczych można wymienić opracowanie metody projekcyjnej, która pozwala na swobodną wypowiedź osoby na temat swojego ciała. Zebrany w ten sposób zbiór notatek, zarówno wśród osób zdrowych, jak i chorych, stanowi materiał badawczy. Poznawczym celem badań jest odkrycie tych cech języka naturalnego, które różnicują język osób chorujących na zaburzenia odżywiania od osób zdrowych. Osiągnięcie tego celu było możliwe poprzez zaproponowanie metod badawczych, wśród których na początku należy wymienić automatyczną metodę klasyfikacji notatek na temat obrazu własnego ciała w czterech zdefiniowanych kategoriach. W zaproponowanej architekturze klasyfikatorów użyto elementów sztucznej inteligencji w postaci modeli głębokich sieci rekurencyjnych. W jednej z badanych kategorii, tzn. kategorii sentymentu, zastosowano także autorską metodę słownikową, która osiągnęła lepsze rezultaty od modeli głębokich sieci rekurencyjnych.

Drugą część badań stanowiła analiza gramatyczno-leksykalna, uwzględniająca m.in. statystyki częstości występowania w notatkach poszczególnych części mowy, czasowników kognitywnych, częstość występowania zaimka "*ja*". Celem tej analizy było opracowanie profilu lingwistycznego osoby chorującej na zaburzenia odżywiania. Trzecią część badań stanowiły zaproponowane metody ewaluacji w postaci opracowanych ankiet umożliwiających ocenę możliwości zastosowania opracowanych metod badawczych w praktyce. W tej części, nacisk został położony na odbiór opracowanych metod w środowisku zarówno personelu pierwszego kontaktu, jak i specjalistów psychologów klinicznych zajmujących się diagnostyką i leczeniem zaburzeń odżywiania.

Uzyskane rezultaty poprzez zastosowanie zaproponowanych metod badawczych pozwoliły na potwierdzenie tezy pracy: *Wykorzystanie elementów przetwarzania języka naturalnego w swobodnych wypowiedziach pisemnych badanych na temat obrazu swojego ciała umożliwia komputerowe wspomaganie diagnostyki psychologicznej zaburzeń odżywiania.*

Abstract

The dissertation presents an innovative approach to applying elements of natural language processing to computer-aided diagnosis of individuals with eating disorders, in particular anorexia nervosa. The dissertation comprises an introduction to the issues of eating disorders and computer-aided diagnosis of these conditions. It includes a review of relevant literature. Subsequent sections provide a detailed description of the proposed natural language processing methods designed to support professionals treating individuals with eating disorders.

One of the most significant research achievements includes the development of the projective method to obtain a collection of open-ended written statements about body image perception among research participants. The notes collected in this way, among healthy and sick people, constitute research database for the research. The cognitive goal of the research is to discover specific features of natural language that differentiate the language of people suffering from eating disorders from healthy people. This goal was achieved by proposing research methods, including an automatic method for classifying notes about body image into four categories. The proposed classifier architecture uses elements of artificial intelligence, including deep recurrent network models. An original dictionary-based method was also proposed in one of the tested categories, i.e., the sentiment category, which achieved better results than deep recurrent network models.

The second part of the research regarded grammatical and lexical analysis, which comprised the statistics of the frequency of occurrence of individual parts of speech in the notes, verbs relating to cognitive category, and frequency of the pronoun "I". This analysis aimed to develop a linguistic profile of a person suffering from an eating disorder. The third part of the research consisted of proposed evaluation methods in the form of surveys enabling the assessment of the possibility of practical application of the developed methods by emphasising their practical aspect, incorporating feedback from first-contact staff as well as clinical psychologists specialising in diagnosing and treating eating disorders.

The results obtained through the use of the proposed research methods allowed to confirm the thesis of the work: *The use of elements of natural language processing in participants' written statements about their body image enables computer-aided psychological diagnosis of eating disorders.*

1. Introduction

Over the last decades, the topic of eating disorders has become very popular in various environments due to the growing number of people affected by these disorders, the constant cult of thinness and beauty, the popularization of various diets and eating styles, and the simultaneous pressure of achievement and self-control. According to specialists, adolescents are considered to be the group of the highest risks, as their biopsychosocial changes related to puberty promote greater sensitivity in the area of body and self-esteem [180]. The social pressure we have encountered in recent years, mainly in social media, establishes unrealistic demands on the appearance of the female part of society, persuading that only physical appearance is the most important and emphasising that only a slim body guarantees happiness and recognition. Such inappropriate comparisons can diminish self-esteem and ultimately lead to eating disorders. Most young girls and women are unaware that what is shown on the Internet results from photo manipulation, digital processing and the use of special filters [79].

Lack of education and workshops on this topic and socio-family problems are additional risk factors. Unfortunately, sociocultural pressures are not the only source contributing to eating disorders. Scientists classify eating disorders as biopsychosocial diseases of heterogenous, often unknown etiologies, where the dominant element is gender [13].

These disorders are referred to as complex diseases typically arising from the interaction of various biological, psychological and social factors. The main etiological factors of eating disorders include:

1. Biological factors:

    (a) Genetics: the recent studies have proved that some genes can influence the vulnerability to eating disorders. The risk of inheriting anorexia and bulimia in people who have relatives with a history of eating disorders is likely and can be up to 60 %. Scientists associate the risk of eating disorders with chromosome mutations (in chromosome 1 for anorexia nervosa (AN) and in 10 for bulimia nervosa (BN)) responsible for the activity of the serotonergic system [124, 161].

   (b) Neurobiology: eating disorders often involve impairment in the nervous system, including appetite regulation, hunger and satiety signals, and the functioning of brain areas associated with controlling eating behaviour [85].

2. Psychological factors:

   (a) Individual traits such as low self-esteem, perfectionism, high ambition [7], susceptibility to external criticism, depression, anxiety, or high stress level may contribute to onset of anorexia. Predisposed people may try to control their lives by controlling their weight and eating [159].

   (b) Unhealthy beliefs and social opinions that create beauty standards and promote the idealised image of a thin or even skinny body, especially those promoted by the media, may contribute to the development of eating disorders. Especially young people who lack a strong personality, as they have not developed the proper pattern yet, are particularly prone to such influences [63].

   (c) Trauma and experiences in youth: traumatic experiences, such as physical, sexual or emotional abuse, may increase the risk of eating disorders [1].

3. Social factors:

   (a) Social pressure: both among peers and within the family can impact the increase of eating disorders. Engaging in peer groups is an inseparable element of puberty and a period of seeking a social identity. Moreover, unreachable, unrealistic expectations the modern society imposes on women, such as being perfect in every sphere, are another risk factors. In addition, certain professional groups, such as ballerinas, athletes and models, are at high risk of anorexia due to their regimented diet and the need to maintain low body weight [161].

(b) Culture and media, as mentioned above, promote unhealthy beauty standards that may drive individuals to try to conform to these ideal body images. In addition, there are groups associated with the pro-ana (pro-anorexia) movement on social media, whose followers are trying to persuade teenagers that anorexia is not a disease but only a way to maintain a slim figure [75].

(c) Food Availability: easy access to high-calorie, low-nutritional foods may promote excess caloric intake and lead to obesity, which may in turn be a risk factor for eating disorders [147].

4. Family-related factors:

   (a) Unhealthy family eating patterns: eating behaviours in a family influence children's future eating habits [20].

   (b) Family conflicts: tensions and conflicts in the family may also be the factor triggering eating disorders [147].

It is worth mentioning that eating disorders are often the consequence of a complex interaction of multiple of these factors. Understanding these etiological aspects is crucial for the effective prevention, diagnosis and treatment of people experiencing eating disorders. Those who suffer from eating disorders often need the aid of specialists such as psychologists, psychiatrists, dietitians and nutritional therapists to achieve a healthy physical and mental state [74].

Although the history of medical literature mentions some records related to eating disorders already from the Middle Ages, the systematization and development of specialized diagnostics should be dated back to the second half of the 20th century [67]. Historical data largely deals with the lives of saints, i.e. fasting as part of a religious cult, but scientists do not have clear evidence whether those disorders were of a purely medical nature or originated from, social, class or cultural backgrounds [77].

Technological progress in various fields, particularly in medical sciences, has categorized eating disorders as a group of mental and behavioural conditions with unsystematized etiology originating from biological, psychological, social, and familial factors. The nature of these disorders is the exposure and escalation of destructive eating habits, including food restriction and behaviour related to obsessive maintenance of low body weight, which ultimately leads to somatic and mental disturbances and, in numerous cases, to cachexia (wasting syndrome) and death [8].

Among all classified eating disorders, anorexia nervosa and bulimia nervosa have the highest prevalence rates, but anorexia is reported to have the highest mortality rate of all [87].

1.1 Anorexia and bulimia as the examples of eating disorders

Anorexia nervosa is a syndrome in which the patient deliberately limits the food intake to lose weight and then tries to keep this weight as low as possible. Most patients suffering from anorexia are at the age of puberty, i.e. 14–18 years old, although specialists warn that the age of eating disorders continues to decrease [152]. The most characteristic diagnostic criteria for anorexia nervosa include underweight equal to or below 15% of the expected body weight or, according to Quetelet's Body Mass Index (BMI), lower than 18.5 kg/m^2. Psychological criteria include constant fear of weight gain and disturbed body image, which will promote limiting the consumption of meals, eliminating specific food groups from the diet, especially those containing fats, carbohydrates and sweets, using intense physical exercises, inducing vomiting, using laxatives and diuretics in order to lose weight. The medical consequences of these behaviours are hormonal, cardiac and gastrointestinal disorders and metabolic abnormalities, which induce or enhance mental disorders, such as mood disorders. Patients with anorexia nervosa often demonstrate no or limited criticism towards their emaciation and health condition. At the same time, they try to hide the symptoms of their illness by dressing in loose clothes, hiding food or vomiting, exercising at night or in the absence of family members [89].

In patients suffering from anorexia, apart from physiological ailments, the perception of one's own body plays a very important role. These people perceive themselves as obese and fat, of abnormal size, even though, in reality, they are emaciated. The patient falls into a rigid thought framework, denies his or her reality and low weight, and lives in constant tension and fear of gaining weight. The patient's entire life becomes dominated by an unrealistic vision and the reflection in the mirror. This obsessive behaviour leads to depression and psychosomatic exhaustion [156]. The characteristics of somatic, physiological and mental disorders accompanying anorexia and resulting from starvation are presented in the Figure 1.1.

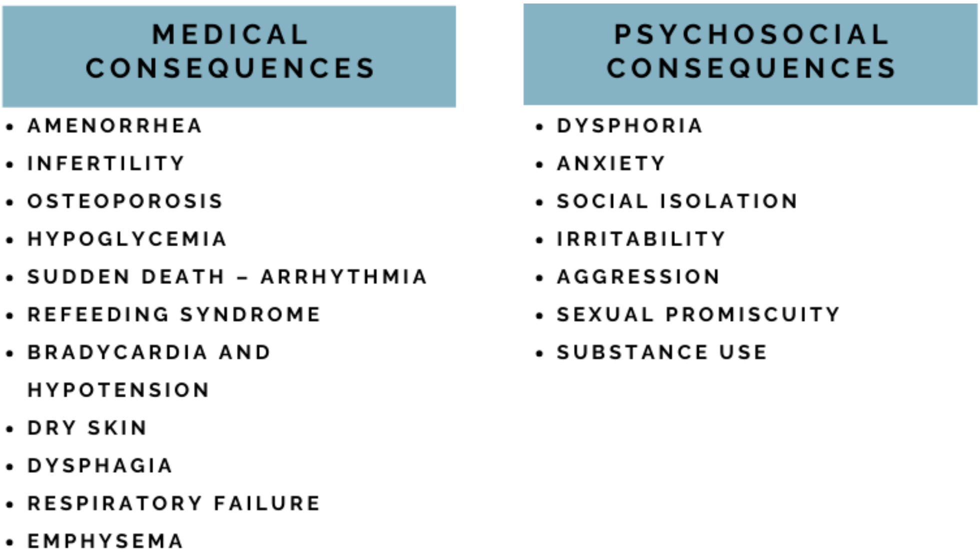

Fig. 1.1: Medical and psychological consequences of AN (based on [169, 178]).

The diagnostic characteristic of bulimia (or ravenous hunger) includes episodes of unrestrained overeating interspersed with compensatory behaviours in order to avoid the effects of gluttony, including vomiting, purging or starvation. The frequency of overeating episodes and attempts to control body weight are important in the diagnosis. It is assumed that such episodes occurring at least once a week for three months indicate bulimia [55]. Vomiting in bulimia is not a permanent part of the disease, which is why specialists distinguish between purgative and non-purgative types. However, it is often comorbid, and therefore, people with bulimia are often diagnosed with pathological changes caused by constant vomiting. The most common changes include enlargement of salivary glands, damage to the back of the hand (inducing vomiting), and damage to teeth [112]. Similarly to anorexia, there are many somatic, physiological and mental disorders that result from the destructive behaviours. The most characteristic disorders resulting from bulimia are presented in the Figure 1.2.

MEDICAL CONSEQUENCES

- DEHYDRATION AND ELECTROLYTE IMBALANCE
- EROSION OF THE TOOTH ENAMEL
- GINGIVITIS (GUM DISEASE)
- OESOPHAGUS DAMAGE
- CARDIAC ARREST
- PEPTIC ULCERS (SORES IN THE LINING OF THE STOMACH)
- STOMACH RUPTURE
- PANCREATITIS
- INFERTILITY
- LOSS OF MENSTRUATION FOR FEMALES

PSYCHOSOCIAL CONSEQUENCES

- DEPRESSION
- ANXIETY
- SUBSTANCE ABUSE
- LOW SELF-ESTEEM
- SELF-HARM BEHAVIOURS
- SUICIDE
- SELF-HATRED

Fig. 1.2: Characteristics of somatic-physiological and mental disorders accompanying BN (based on [169, 178]).

Both eating disorders have many common features. Their main analogy is the patient's belief of being too overweight and making the effort to diminish the fear of weight gain. Both types have a common goal, but the ways of achieving this goal are different. In the case of AN, the patient avoids eating, constantly monitors his or her body weight and obsessively focuses on the appearance. The body's weight decreases, leading to emaciation or even death [98]. Currently, there are no pharmacological solutions for anorexia, only psychological therapy. Regarding BN, drug therapy is limited only to adults and involves the use of fluoxetine [32]. However, in bulimia, frequent episodes of overeating occur, and the size of the meal usually exceeds the caloric and quantitative portion appropriate to the person's age and abilities. Binge eating is followed by a compensation phase to avoid weight gain. However, in the case of bulimia, the patient often has an average weight, which, unfortunately, is misleading medical symptoms [35].

According to the International Classification of Diseases and Related Health Problems (ICD) developed by the World Health Organization (WHO), eating disorders belong to the group of behavioural syndromes associated with physiological disorders and physical factors (F50-F59) (ICD-10) [70]. Diagnosis of eating disorders in Poland uses mainly the ICD-10 classification, which lists eating disorders in the group of mental illnesses under the range of Behavioral syndromes associated with physiological disorders and physical factors (ICD codes: F50–F59) [84]. Table 1.1 illustrates the classification of eating disorders according to ICD-10. However, on January 1, 2022, the WHO released an updated version of the classification of diseases and health problems (ICD-11) [71]. However, the ICD-10 version is still in force in Poland due to the 5-year implementation and transition period required for the updated ICD-11 version. Figure 1.3 shows the updated classification requirements according to ICD-11. The new version applies different diagnostic thresholds, including the minimum duration of anorexia stands for 4 weeks, elimination of amenorrhea as a diagnostic element, and change in BMI from 17.5 kg/m^2 to 18.5 kg/m^2 [30].

Tab. 1.1: Classification of eating disorders according to ICD-10 [70, 129].

F	Mental and Behavioural Disorders
F50-F59	Behavioral syndromes associated with physiological disturbances and physical factors
F50	Eating disorders
F50.0	Anorexia nervosa
F50.1	Atypical anorexia nervosa
F50.2	Bulimia nervosa
F50.3	Atypical bulimia nervosa
F50.4	Overeating associated with other psychological disturbances
F50.5	Vomiting associated with other psychological disturbances
F50.8	Other eating disorders
F50.9	Eating disorder, unspecified

For research purposes, therapists prefer to use the Diagnostic and Statistical Manual of Mental Disorders, DSM-5, developed by the American Psychiatric Association (APA). DSM-5 includes updated diagnostic criteria to define more specifically and determine detailed symptoms patients face in their lives which do not fit into any other disorder categories [13, 165]. In consequence, researchers developed a new classification of eating disorders, presented in the Table 1.2.

- ▽ Feeding or eating disorders
  - ▽ **6B80** Anorexia Nervosa
    - ▽ **6B80.0** Anorexia Nervosa with significantly low body weight
      - **6B80.00** Anorexia Nervosa with significantly low body weight, restricting pattern
      - **6B80.01** Anorexia Nervosa with significantly low body weight, binge-purge pattern
      - **6B80.0Z** Anorexia Nervosa with significantly low body weight, unspecified
    - ▽ **6B80.1** Anorexia Nervosa with dangerously low body weight
      - **6B80.10** Anorexia Nervosa with dangerously low body weight, restricting pattern
      - **6B80.11** Anorexia Nervosa with dangerously low body weight, binge-purge pattern
      - **6B80.1Z** Anorexia Nervosa with dangerously low body weight, unspecified
    - **6B80.2** Anorexia Nervosa in recovery with normal body weight
    - **6B80.Y** Other specified anorexia Nervosa
    - **6B80.Z** Anorexia Nervosa, unspecified
  - **6B81** Bulimia Nervosa
  - **6B82** Binge eating disorder
  - **6B83** Avoidant-restrictive food intake disorder
  - **6B84** Pica
  - **6B85** Rumination-regurgitation disorder
  - **6B8Y** Other specified feeding or eating disorders
  - **6B8Z** Feeding or eating disorders, unspecified

Fig. 1.3: Classification of eating disorders according to ICD-11 [71].

According to statistical data and epidemiological studies conducted in Western countries and the United States, eating disorders affect people to an increasing extent, not only in adolescence and adulthood but also in younger people. It should also be marked that eating disorders are no longer the domain of the female gender because, as statistics show, an increasing number of boys and young men have also become affected.

Tab. 1.2: Classification of eating disorders according to DSM-5 [60, 106].

	Feeding and eating disorders
1	Anorexia Nervosa (AN)
2	Bulimia Nervosa (BN)
3	Binge eating disorder (BED)
4	Pica syndrome
5	Rumination disorder
6	Avoidant/restrictive food intake disorder (ARFID)
7	Other specified feeding or eating disorder (OSFED)
8	Unspecified feeding or eating disorder (UFED)

The latest global research shows that within the years 2000–2018, the prevalence of eating disorders increased from 3.5% to 7.8% [50]. According to Józefik [77], it affects 0.5–1% of the adolescent population. In Western countries, the prevalence of anorexia among females is <1–4%, and <1–2% of girls struggle with bulimia. In turn, among the male part of the population, eating disorders are recorded in 0.3–0.7% [80]. According to Kozik [161], the number of diagnosed cases of anorexia among boys is 10%. Studies using the criteria included in the DSM-5 indicate that bulimia affects university student (8% girls and 0,7% boys) [101]. Among adults, the prevalence of anorexia is between 0.2–0.8%, and bulimia nervosa is 0.7–1.3% [77].

According to the authors of the work [145], the global Covid-19 pandemic of 2019–2024 had a significant impact on people struggling with a particularly restrictive form of eating disorders, which can be a consequence of lockdown, limited access to specialists, or minimized social contacts.

As the world data show, the prevalence of anorexia nervosa among women ranges from 0.3% to 1.5%, while in men, it ranges from 0.1% to 0.5% [81]. The mortality rate is approximately 12 times higher compared to all other causes combined [4]. The estimations show it oscillates between 15–25% of patients, while the highest prevalence is especially among young girls (up to 40% of new cases) [161]. AN disproportionately affects females compared to males [81]. Approximately 25% of people recovering may experience a relapse or develop bulimia [45]. However, the leading cause of death (60%) related to anorexia is sudden cardiac arrest, organ failure or suicide caused by depression [4]. According to the latest research, 46% of patients manage to fully recover, and 20% constantly struggle with chronically recurring somatic diseases as a consequence of anorexia [168]. As mentioned, the typical age of onset is 16–17 years, but recently, the disease has also affected an increasing number of younger children under the age of 12 [81, 161]. Over recent decades, the prevalence of anorexia has increased in many countries, mainly Western countries and the United States [105]. There is also an increase in Arab countries mainly due to globalization, urbanization and industrialization [66] and the general trend of thinness [117]. Women aged 15–24 stand at the highest risk, but scientists have noticed an increase in the number of cases among men [155].

Statistical data on bulimia indicate that this disease occurs in 1–3% of adolescents [161] and approximately 2% of adult women and 0.5–0.7% of men. The average age for bulimia nervosa onset is 18, although recent research suggests that the age for bulimia nervosa is getting lower [81]. According to the authors of the work [26] in 8% of people who have bulimia, the disease may turn into anorexia, and 9% may be diagnosed with binge eating disorder. According to statistics, approximately 35% of patients will probably achieve full recovery thanks to psychotherapy [95]. However, of those who recovered after bulimia treatment, 17% may experience a relapse [26, 81]. In some instances, 50% achieved full recovery without any treatment [44]. Self-harming behaviour is often observed in bulimia (35% of people) [45], and over 95% of people who have bulimia also suffer from another mental disorder and an anxiety disorder. Almost 40% of people with bulimia report substance abuse [21].

Statistical data indicate bulimia to be a more widespread disorder than anorexia. However, AN is characterized by specific risk factors that account for the complexity and difficulty of diagnostic assessment and treatment. The following aspect comprises the highest mortality rate among all mental diseases, body wasting, a constant increase in the number of cases also affecting the male sex, the age decline, difficulties in medical assessment, and a long-term treatment process, sometimes involving entire families.

Diagnostic difficulties and treating anorexia in a psychological context often result from the patient's physiological condition when admitted to the hospital. Therefore, it is necessary to exclude any other diseases or disorders that may cause symptoms of anorexia but are not anorexia [74]. As the criteria of the American Psychiatric Association suggest [158] the treatment of anorexia includes three stages:

1. Medical stabilization – aims to improve and normalize the patient in terms of life processes. It includes actions that stabilize the circulatory, electrolyte, metabolism, and digestive systems.

2. Nutritional rehabilitation – involves selecting the appropriate diet so the patient could gradually gain weight. At this stage, the patient should undergo psychotherapy as the primary form of treatment.

3. Weight maintenance stage – emphasizes maintaining a healthy lifestyle, coping with challenges related to eating and stress, and preventing relapses. Further psychological and medical support is important to prevent recurrence of anorexia episodes.

Psychological diagnosis of eating disorders includes several steps where the psychologist, in addition to diagnostic methods including tests and expert knowledge along with experience, can be supported by modern tools in the field of Natural Language Processing (NLP). When diagnosing, the psychologist uses clinical methods, such as interviewing the patient or observations; sometimes, the opinion is based on a medical experiment, or the expert applies projective methods. This approach requires extensive experience and professional insight. In the next step, the expert formulates diagnostic hypotheses that can be verified through psychological tests. However, at this point, the psychologist can be aided by a new tool that provides additional support in a minimally invasive manner and often shortens the diagnostic process's time. The diagram of the diagnostic process of a person with anorexia illustrates the Figure 1.4.

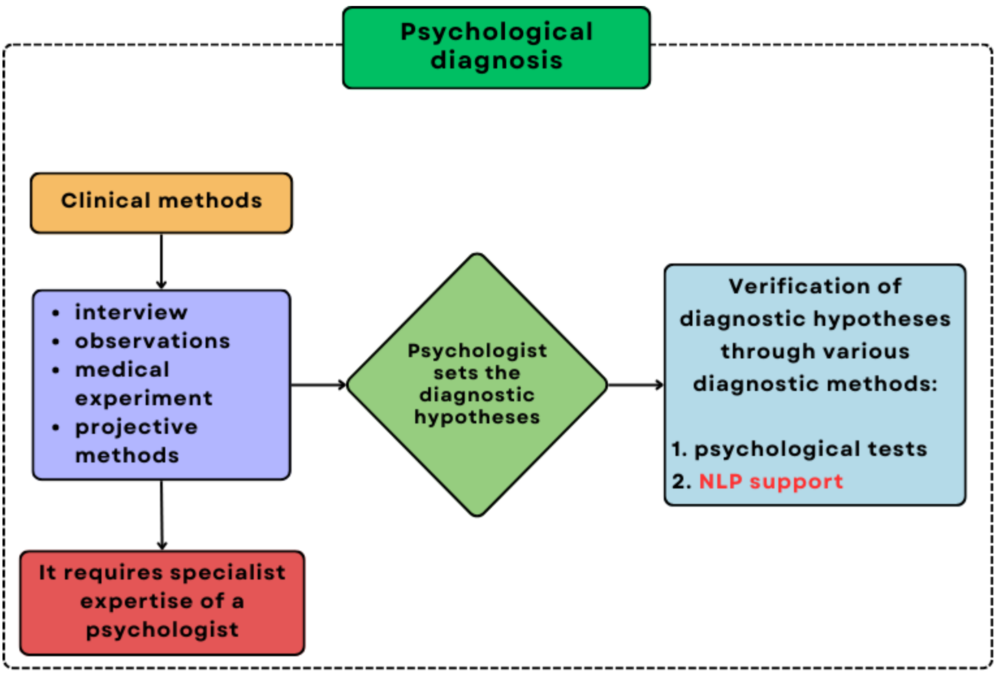

Fig. 1.4: Diagram of the psychological diagnosis process in anorexia [169, 178].

In the light of the APA guidelines, it is worth noting that psychological diagnosis takes place already in the first phase of treatment, and the frequent resistance of a patient who refuses treatment is an additional challenge for the therapist. Moreover, the psychologist can encounter some limitations in using more advanced tools due to the patient's condition requiring acute hospitalisation. The use of minimally invasive projection tools may be helpful in the diagnosis of patients with resistance. Some studies [6, 160] suggest that difficulties in the diagnosis and therapy of patients are referred to as patient resistance. During therapy, patients often try to avoid contact with the therapist or confront their internal conflicts, are often late for meetings, change the topic of the conversation, or show a lack of honesty towards the therapist. Ultimately, for these reasons, building good relations with the therapist and the success of the therapy fail. The above points motivated the author to conduct research in order to verify the possibility of using NLP methods that can support the diagnosis of eating disorders. A further justification was the possibility of conducting research and collecting research material in the form of written notes among patients who have anorexia.

1.2 Eating disorders due to comorbidities on the example of patients with head and neck cancer

Psychiatric-based eating disorders associated with anorexia are characterised by a wide range of symptoms, influences of external factors, individual traits of the patient and unknown etiology. Diagnostics is complex, and selecting the appropriate therapy is sometimes a great challenge due to difficult contact with the patient and limited access to specialists. However, there are many other diseases in medicine where patients struggle with eating disorders due to previous surgeries and invasive therapies. The leading group of patients experiencing the above-mentioned nutritional difficulties are people suffering from head and neck cancer. The WHO estimates that cancer is one of the leading causes of death in the world [23]. According to world cancer statistics, approximately 18.1 million new cases of cancer occurred worldwide in 2020. Of these cases, 9.3 million affected men and 8.8 million women [173]. The data from the National Cancer Registry show that in Poland, the percentage of people suffering from Head and Neck Cancers (HNC) is 5.5–6.2% of all cancers, i.e. 5500 to 6000 cases per year [122]. Similar incidence statistics are available in other European countries and the USA.

Head and neck cancers cover multiple prevalence of cancers that can occur in areas such as the mouth, throat, tongue, nose, sinuses, salivary glands, and skin of the face and neck. These cancers have different cellular origins and different risk factors [157]. The most common types of head and neck cancer are [157, 170]:

1. Oral cancer: affects areas such as the lips, tongue, gums, palate and floor of the mouth.

2. Throat cancer: this affects areas such as the epiglottis, larynx, and the back of the mouth and throat.

3. Nose and sinus cancer: can develop in the nose, sinuses and surrounding areas.

4. Salivary gland cancer: can occur in the parotid, submandibular, or sublingual glands.

5. Skin melanoma: it develops on the skin of the face and neck.

Smoking and excessive alcohol consumption are general risk factors for many head and neck cancers. HPV (human papillomavirus) infections increase the risk of developing certain cancers, such as throat cancer. Exposure to UV (ultraviolet) radiation may, in turn, increase the risk of skin melanoma in the face and neck area. Certain genetic factors may also predispose a person to the disease [56].

Treatment includes surgery, radiation therapy, chemotherapy or molecularly targeted therapies, depending on the cancer type, its stage and other factors. Surgical methods may be combined with radiotherapy to complement the treatment. In more advanced stages, radiotherapy may be aided with chemotherapy [111]. Cancer treatments cause a variety of side effects, depending on the therapy type and the location of the tumour. For example, surgery to remove a large tumour may affect the patient's appearance. Patients undergoing therapy for head and neck cancer may experience difficulty breathing, eating, swallowing or speaking after treatment [29].

HNC treatment is extraordinarily demanding and invasive. Changes in the patient's appearance and functioning induce discomfort and difficulties while doing basic activities. The consequences of the disease and the therapy are difficulties swallowing and taking food, failure to maintain an appropriate diet and, consequently, malnutrition. HNC patients find problems in swallowing, pain when eating, or significant weight loss, so an alternative source of nutrition is necessary. One of the procedures is to install a percutaneous endoscopic gastrostomy (PEG) in the patient. Since its introduction in the 1980s, PEG has become the preferred method of providing long-term enteral nutrition in people with inadequate oral nutritional intake. Additionally, using PEG has a lower risk of medical complications and provides better comfort to the patient [57]. However, none of the alternative methods of nutritional support can provide the patient with the appropriate level of nutrients. One important reason for the increased burden of HNC patients is malnutrition and nutrient deficiencies, which significantly impacts health outcomes and overall quality of life [2]. Malnutrition can be defined using various criteria, such as weight loss exceeding 5% in three months or 10% in six months or a BMI below 20 kg/m^2. Additionally, albumin levels below 35 g/L may suggest the presence of malnutrition [16, 65, 126]. The primary function of food is to provide the body with the necessary nutrients to maintain homeostasis. The proper functioning of the body as a whole results from supplying each of its cells with vitamins, minerals, proteins, sugars, fats, and other substances from which the body draws. However, nowadays, food has influenced many other areas of human life. First, it is a fundamental existential need that builds social and cultural bonds. Each country can be defined in the context of its national cuisine, which determines its identity and wealth. Therefore, depriving a person of this pleasure affects his mental state.

Patients suffering from challenging food intake experience the inability to maintain a properly balanced diet, i.e., ensuring the desired amount of nutrients and caloric value of the meal, and are forced to change their lifestyle due to enteral nutrition. Moreover, a patient who does not feel pleasure from eating, for whom every bite is torture, or is ashamed to show himself with a PEG attached limits contacts with loved ones and friends, as a result of which social relationships may collapse [19]. Furthermore, it influences patient's mood and causes depression.

Invasive medical treatments that HNC patients undergo, including surgery, chemotherapy and radiotherapy, have many negative side effects for the patient. Many of them mainly affect the appearance of patients, who may suffer from skin burns, hair loss, deterioration of the skin condition, or deformations in the face and neck due to surgical procedures [135].

It has been revealed that these treatments may reduce the feeling of attractiveness, self-confidence or increase shame, which leads to body image disorders [59]. It is especially visible in women who are exceptionally aware of their bodies and convinced of their attractiveness. Their level of body dissatisfaction is higher during treatment, which may correlate with the severity of depression [46]. Physical changes associated with cancer affect patients of all ages and genders. Despite the availability of appearance restoration services, the percentage of cancer patients suffering from body image disturbances remains high, ranging from 25% to 77% [49, 107, 135].

Considering the high prevalence of HNC, extremely long and demanding treatment, which constitutes a psycho-somatic challenge for the patient, it arises a justified need to create a tool to support psycho-oncological therapy for the patient. Such a tool uses parameters similar to those used in the case of anorexia. Due to certain analogies in the written notes of AN and cancer patients, tools that use elements of natural language to process patients' open-ended statements were proposed. Such an analysis aims to draw attention to the factors responsible for negative body image and attitude towards the patient's body. Moreover, the analysis results can serve as a reliable source for the therapist to create appropriate therapy to rebuild the proper body image.

1.3 Objectives and thesis of the dissertation

The process of diagnosing and treating anorexia is fraught with many challenges. The barrier between patient-therapist, patient's resistance, and lack of willingness to cooperate with the therapist is an essential negative element in accurate diagnosis and appropriate therapy selection. For this reason, there was a need to create a tool using elements of artificial intelligence to support the psychologist's work in the diagnostic process to verify and validate the hypotheses.

Scientific objective

The scientific objective is to find the features of natural language in written form used by people suffering from eating disorders that differentiate sick people from healthy ones. When analyzing the characteristics of the language used, the following factors were considered: automatic note classification, vocabulary statistics, and both grammatical and lexical analysis.

Utilitarian objective

The utilitarian objective is to develop tools integrating elements of natural language processing to computer-aided assessment of the patient's condition during psychological diagnosis of eating disorders. Achieving this goal will contribute to shortening the diagnosis time and to the appropriate selection of therapy and its further evaluation. Additionally, the research will facilitate a better understanding of the linguistic mechanisms in a person who has anorexia.

Didactic objective

The didactic objective of the paper is to share and spread the knowledge about the discovered features of natural language in written form used by patients suffering from eating disorders.

The detailed analysis of the current state of knowledge and the result of conducted research contributed to formulating the thesis of the dissertation, which is presented below.

Thesis of the dissertation

The use of elements of natural language processing in participants' written statements about their body image enables computer-aided psychological diagnosis of eating disorders.

Proving the validity of the thesis required defining the scope of work presented in the list below.

1. A review of current scientific literature related to the topic of the work, which includes:
   (a) computer-aided assessment of the patient's condition during diagnosis, therapy and evaluation of the therapy process;
   (b) computer-aided methods to psychological diagnostic;
   (c) the use of NLP methods in computer-aided diagnosis of eating disorders.
2. Elaborating a plan for collecting research material in research and control groups after receiving consent from the Bioethics Committee. The procedures for collecting research material in the form of written statements about one's body image.
3. Elaborating a methodology for applying NLP methods in the analysis of written statements about body image:
   (a) automatic classification of notes in the four proposed categories: healthy/sick, sentiment, irony, and past tense using machine learning and dictionary methods;
   (b) statistics of vocabulary used in notes regarding parts of speech (POS) tagging, detection of characteristic words and verb tense form;
   (c) grammatical and lexical analysis in order to determine characteristic expressions and grammatical patterns concerning participant's body image.
4. Evaluation of the developed methods concerning the results of quantitative analysis and assessment of the tools developed on the proposed methods by the first-contact staff and clinical specialists involved in diagnosing and treating eating disorders.

1.4 The structure of the dissertation

This dissertation consists of five chapters. The first chapter contains an introduction to the subject of eating disorders and describes in detail the symptoms, diagnosis and treatment process of anorexia and bulimia. The following section presents eating disorders resulting from head and neck cancer. Furthermore, this chapter presents the main goals and thesis of the work.

The second chapter includes an overview of the current state of knowledge in computer-aided diagnosis and assessment of the patient's condition in psychology.

The third chapter describes the developed rules for computer support of the patient's condition, presents the process of collecting research material, the research group and the control group, and the inclusion criteria for the study. The next part discusses the methodology for automatic text analysis and dictionary methods used for grammatical-lexical and sentiment analysis. The further section of the work presents the proposed method for assessing the usefulness of the presented solution by psychologists specializing in the treatment of eating disorders and first-contact staff.

Chapter four discusses the results of the text data analysis based on the proposed methods. The first part presents the results of the automatic classification of notes, followed by the sentiment assessment based on the dictionary method. The rest of the chapter discusses the results obtained for vocabulary statistics and the grammatical-lexical analysis in the research and control groups, and separately in the group of cancer patients. The last part of the chapter presents the results verifying the method's usefulness among medical and school personnel.

The last chapter of the dissertation, contains a summary of the conclusions drawn, proposals for the practical application of the system, and plans for further research arising from this work.

2. The state of the art in the field of computer-aided assessment of the patient's condition during therapy in psychology and psychiatry

This chapter outlines an overview of currently used technologies and methods for assessing the patient's condition in psychology. The chapter considers various aspects of engaging the current solutions for various purposes. First, it concerns using NLP to support clinical diagnostics, monitoring therapy, and personalizing treatment methods to the individual needs and conditions of the patient. Artificial intelligence (AI) algorithms have recently been successfully applied in medicine and offer dedicated technological solutions such as chatbots or applications for quick emotional support, advice, or assistance. With the awareness of the increasing burden and complexity of mental health globally, there is a justified need to search for and integrate systems using advanced technologies in AI, Machine Learning or NLP. Besides, the chapter explains the challenges and limitations of using these technologies for therapeutic purposes.

2.1 Computer-aided in psychology

Assessment of a person's mental state and functioning is one of the leading trends in psychology. Nowadays, to improve the phases of processing collected information about the patient's psychological condition and to better analyze the information received, scientists apply tools known in computer sciences and distinguish similar stages: acquisition, organization and synthesis [11, 104, 113, 175]. The research conducted by Wilm et al. [11] showed the advantages of this approach in studying children on the autism spectrum. In [93], the authors demonstrated the possibility of improving the interpretation of test results through computer analysis of the diagnostic decision-making process.

The review of the Elsevier Scopus database and exploration of the database for the topic 'Computer-aided diagnosis of anorexia', revealed significant research interest in this field.

The present challenges in computer-aided diagnosis of anorexia nervosa impose the necessity for early and precise diagnosis, mainly in primary care, where non-specialist clinicians may be unfamiliar with eating disorders. Ethical considerations in applying computer-aided diagnosis for anorexia rely upon the need for expert interventions early in the disorder, the potential for automated diagnosis to provide expertise, and the valuable expert opinion in interpreting algorithmic results. The computer-aided diagnosis of anorexia embraces the key technologies and tools that include natural language processing, machine learning, and web-based systems for accurate diagnosis and automated algorithms for estimating the probability of an eating disorder. Figure 2.1 illustrates the concept map of computer-aided diagnostic of anorexia. The concept map was generated by the Scopus AI tool, and it covers the review of scientific research papers indexed in the Scopus database since 2013. The database indicates the major fields of interest among researchers, which include:

1. **Computer-Aided Diagnosis and Therapy**: Using achievements within natural language processing and machine learning methods have been evaluated for diagnosing anorexia nervosa. These methods have shown efficacy in analyzing emotions, body perception, and areas of difficulty for computer support of psychological diagnosis.

2. **Therapeutic Diagnosis**: Computer-aided tools have been proposed for testing and confirming assumptions made by psychologists, aiming to establish a quick diagnosis and start immediate therapy.

3. **Early Diagnosis**: Computer-assisted diagnostic procedures offer a possible solution for early and accurate diagnosis, particularly in primary care, by providing expertise via an algorithm developed from multiple diagnosed cases.

4. **Neuroimaging Data**: Analysis of brain imaging in patients with anorexia nervosa has revealed significant differences in brain structure, including changes in the volumes of grey matter and white matter.

5. **Diagnostic Criteria Evolution**: The diagnostic criteria for anorexia nervosa have evolved over time, with changes related to the need for amenorrhea, minimum body mass index, severity levels, and remission of the disorder.

The use of computer-aided tools, including natural language processing and machine learning, seems promising in supporting the diagnosis and therapy of anorexia nervosa. Additionally, the advancements in neuroimaging and evolving diagnostic measures contribute to the enduring improvement of diagnostic and therapeutic approaches for anorexia nervosa.

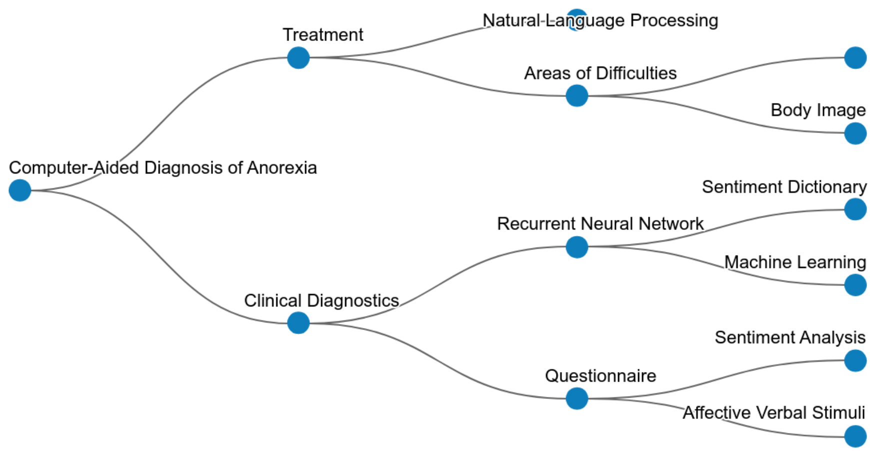

Fig. 2.1: Concept map of computer aided diagnostic of anorexia (based on Scopuc AI generator).

In the expert literature, some studies indicate the relationship between the patient's psychiatric condition, such as anxiety, depression or neurosis, and his thoughts and expressions [22, 72, 134]. Frequently, neuro-linguistic programming tools are used to diagnose potential areas of mental disorders.

More recent research on automatically identifying people with eating disorders focused on clinical diagnosis. For example, one study [12], used NLP methods to diagnose binge eating disorder based on medical notes taken by a doctor during therapy sessions with a patient. In this case, the conversation with the patient was supervised by a doctor, which facilitated the identification of the disorder. Nevertheless, very little is known about applying natural language processing methods for automatic language analysis, supporting the work of psychologists.

The application of NLP methods occurs mainly in the field of linguistics, which is called clinical linguistics, and their objective is to support the therapy of patients with speech pathologies and neurological defects, such as dementia. Nevertheless, little research has focused on linguistic characteristics among patients with AN. Spoken language contains a significant amount of information about the cognitive state of speakers because it can be analyzed by observing speech disfluencies such as spontaneous errors, fillers, pauses, and false starts. Therefore, spoken language poses challenges for automatic parsing [37].

In the paper [37], the researchers report that certain features of anorexia, such as negative body image, obsessive thoughts, or anxious or depressive traits, may influence the language used by patients and can be detected using NLP tools. Patients with anorexia often encounter emotional and cognitive disorders, leading to atypical forms of oral and written speech. Hence, the authors highlight that such disruptions can be identified at the syntactic, lexical and semantic levels, enabling the creation of ”digital linguistic biomarkers”.

Regarding anorexia, entries on internet forums were the subject of analysis by Spanish researchers to detect the disease [96]. By combining various characteristics of a person, these studies make it possible to create a linguistic profile of a healthy and a sick person [10, 179]. Zeng et al. [179] focused on analyzing the structured and unstructured clinical records of cancer patients to identify the treatment methods arranged for the patient and to manage the patient’s medical documentation to tailor the process of further therapy.

Eating disorders are also associated with cancer diseases, which have a long-term impact on the patient’s lifestyle [33]. Additionally, the patients experience discomfort from a constant effort to overcome the disease, which is also related to nutrition aspects. In addition, the patient is under social pressure, especially during the recovery phase. Patients face severe dysfunction that affects crucial aspects of life, including a decline in cognitive abilities, poorer work ability, and personal life.

Oncological treatment, especially for HNC patients, results in significant deterioration of body image. Consequences of invasive treatment include hair loss, swelling, fatigue, deterioration of skin condition, and direct loss of body parts due to surgical intervention [64]. It is also pointed out by other authors [136]. Additionally, there are communication blocks, identity disorders, and a lack of motivation to achieve treatment success.

The relationship between a quantitative decline in body image and cancer was reported by [48, 110]. The researchers used The University of Washington Quality of Life Scale (UWQOL) in the experiment. The research proposed by authors of the paper [12] focuses on a dictionary approach to detect the correlation between a patient's vocabulary and his condition.

2.2 Computer vision in psychology

Computer vision is an approach which, as some researchers claim, can give promising results in the context of anorexia nervosa and related eating disorders. Its algorithms can serve to analyze and quantify body image distortion in people with anorexia. It may include assessing how individuals perceive their bodies compared to objective measures, enabling a more quantitative assessment of body image disturbances. Another important finding indicates the application of computer vision to assess experienced emotions [78]. The authors claim that this solution provides better objectivity of psychological test results. Another work indicates a new type of consultation: remote consultations (structured letter therapy) due to difficult access to a specialist, especially during the COVID-19 pandemic [174]. This approach uses patients' forms, intervention forms, and continuation. Each form includes questions on personal data, well-being and the reason for consultation. According to the authors, this new approach may provide significant assistance at consultation, diagnosis, and treatment stages.

"Somatomap" is a multi-platform digital tool for assessing body image disorders. It uses a visual representation of specific body areas in two-dimensional (2D) and three-dimensional (3D) avatars. The purpose of this tool is to facilitate the assessment of body image disturbances (BID) related to specific areas throughout the body [133]. Figure 2.2 shows body maps displaying the most disturbing areas for anorexia and healthy groups. The authors of the work [133] claimed that people with anorexia showed more significant regional abnormalities in the perception of their body, greater discrepancies between the current and ideal body, and a higher level of body dissatisfaction. Sick people were more likely to focus on the abdomen and thighs.

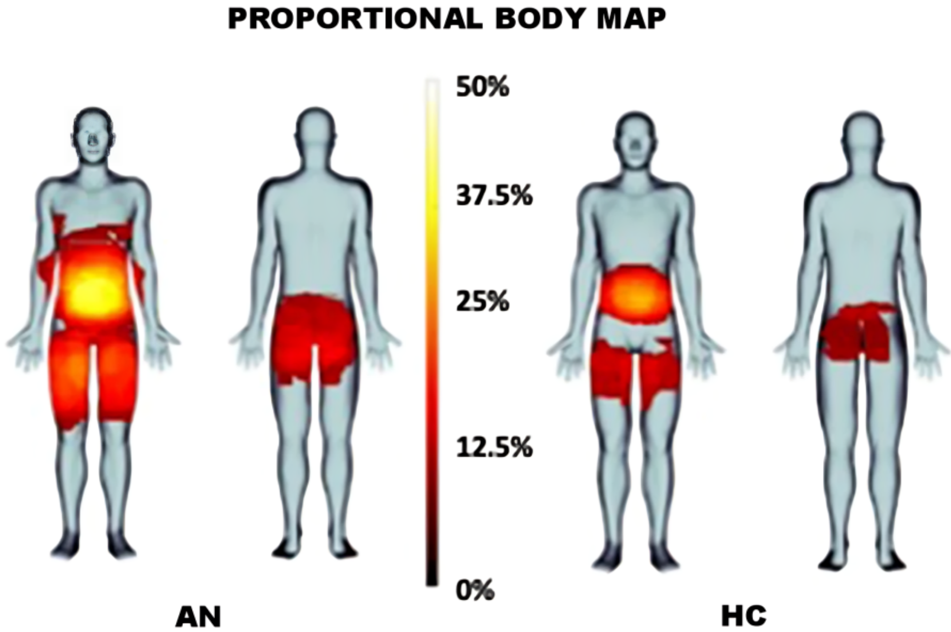

Fig. 2.2: Proportional body maps displaying the majority of body concern areas for anorexia AN (left) and healthy HC (right) group [133].

Another tool uses a three-dimensional (3D) scanner to create an avatar imitating the patient's body. The authors used a stereoscopic, virtual, real, life-size 3D display body scanner and a statistical body model that allows for realistic manipulation of the weight of photo-realistic virtual avatars and a naturalistic presentation of these avatars in a scenario using a mirror [153].

Computer vision analysis methods serve as a tool to analyze emotions in the targeted research group. Many of these methods use facial analysis in terms of expressed emotions. The human face is the source of multiple emotions developed from an early age, and recognizing them is a fundamental skill acquired by a human being throughout life [144].

Because emotions can be expressed through various facial manifestations, depending on the many cultural circles, the researchers needed many years of study to systematize and classify basic emotions. In 1987, Ekman proposed the separation of universal emotions, which include anger, disgust, fear, joy, sadness and surprise [42].

For many years, it was believed that people suffering from anorexia had difficulties expressing or perceiving certain emotions. Further studies linked those impairments to alexithymia, a term defined as difficulty recognizing, describing and experiencing one's emotions. Affected people are not able to express their feelings verbally and understand exactly what they are feeling [17].

Many studies on eating disorders have revealed the occurrence of alexithymia more frequent in patients with eating disorders compared to healthy people [31, 121]. Besides difficulties defining and expressing emotions, many studies indicate a reduced ability of AN patients to identify emotions in human faces. One study claims that people with anorexia cannot recognize the emotions of surprise [82, 123]. According to others, it concerns sadness, fear [88], and disgust [128]. Previous works focused on determining the problem of emotion recognition; however, the practical solution proposed by the authors in [91]. They based the analysis of emotional expressions on the faces of people with eating disorders, using a computer image analysis method and Noldus FaceReader software [176]. This approach made it possible to identify six primary emotions: happiness, sadness, anger, fear, surprise, disgust and neutral states. However, the authors' primary goal was to identify emotions such as happiness and sadness expressed by anorexia patients while watching short video clips. Scientists assessed that healthy participants in the control group showed more positive emotions when playing positive video content compared to the group of people with anorexia. However, there is a similarity between the groups in expressing sad and negative emotions when watching sad fragments of films. On the other hand, other authors, [176], excelled at identifying emotional changes induced by experimental stimulation. Using the FaceReader program, they analyzed the expression of primary emotions (joy, sadness, anger, fear, disgust, surprise and contempt) evoked by International Affective Picture System (IAPS) emotional stimuli with various affective dimensions (positive/negative value and high/low level of arousal).

Another study [125] on the perception of emotions in AN conducted by Australian researchers focused on analyzing the expression of emotions on the participants' faces and other people. In the first part of the experiment (implicit emotion processing), participants performed an unconscious emotion processing task that involved identifying the gender of stimuli, i.e. the process of recognizing or assigning gender to presented stimuli, such as human faces, during fMRI (Functional Magnetic Resonance Imaging) scanning. This part was accompanied by eye tracking (using the EyeLink1000 remote tracker - monocular with a frequency of 500 Hz). The second phase of the experiment involved a conscious emotion recognition task using an eye-tracking technique. Studies have revealed that in anorexic women, emotion identification of affective facial stimuli and distinct hyperscanning behaviour when viewing faces are intact.

Additionally, researchers have drawn interesting conclusions that when processing one's own face in AN, there is greater visual attention to irrelevant features and increased activity in the lower and middle temporal and lingual parts of the brain compared to healthy people. These findings suggest a correlation with anxiety disorders, as evidenced by hyperscanning display behaviours and increased anxiety, particularly for images of one's own face through avoidance of salient features. Together with the fMRI findings, the study suggests that the processing of self-facial images is different in AN and may contribute to the distorted self-perception experienced by individuals [125].

2.3 Application of voice analysis methods

The expeditious growth of machine learning and Artificial Intelligence algorithms opened new application opportunities in healthcare. The latest tools use the human voice to detect, analyse or predict some health disorders. This area is highly interesting since the human voice carries a lot of information. The studies focus on searching for markers corresponding to individual features, such as the way of uttering the words, coughing, sneezing, or even breathing.

Voice analysis solutions (Voice Analysis for Medical Professionals, VAMP) is a method developed to detect neurological disorders. It analyzes the pitch, timbre, loudness and pace of oral utterance, then creates the so-called vocal biomarkers based on the data obtained. They help detect neurodegenerative and lifestyle diseases [139, 164]. The market offers commercial products like the one developed by BeyondVerbal, Healthymize and NeuoLex for analyzing English [51]. They aim to determine the patient's health, mood and emotions by analyzing various acoustic features from the speaker's voice. Nevertheless, the main pitfall of this method is the inability to apply it to other languages. Every spoken language abounds in paralinguistic elements, such as intonation, accent, voice timbre and pauses. In addition, the parameters related to breathing while speaking also vary.

Stress and emotions are correlated with voice expression. Multiple studies investigate voice features to detect depression. An example of a favourable tool evaluated by [115] is an automated telephone system to assess biological indicators of voice acoustics concerning the severity of depression and treatment effectiveness. The authors collected voice samples from 105 participants with depression in a four-week, randomised, double-blind, placebo-controlled study. The data were analysed by clinicians to serve as biomarkers of depression.

Voice analysis can also help recognise neurological disturbances like Alzheimer's or Parkinson's diseases. Some methods serve as digital voice biomarkers for Alzheimer's disease. They extract lexical-semantic and acoustic measures [61]. In the case of Parkinson's disease, developing tools for voice pattern recognition is crucial, as it ranks the world's second most prevalent neurological disorder, characterised by neuron degeneration, which outcomes in general motor function impairment [137]. Advanced deep-learning-based speech processing proved its reliability in detecting distinctive elements of patients with Parkinson's disease before and after dopaminergic treatment. The method proposed by [73] used personalised Convolutional Recurrent Neural Networks (p-CRNN) and Phone Attribute Codebooks (PAC). Its promising results constitute a valuable source in the clinical assessment of Parkinson's disease by detecting dopaminergic effects on an individual's speech.

2.4 Conclusion

To sum up, the literature review regarding the scope of the doctoral dissertation indicates the existence of many different methods of computer-aided assessment of a person's condition, including NLP, voice analysis and computer vision. As the above discussion showed, NLP has found application in various fields of medicine and psychology, not to mention eating disorders. However, despite a growing number of literature concerning eating disorders, little is known of detailed dedicated methods for specific eating disorders, including anorexia an bulimia. Due to the ambiguity of the vocabulary used and the tremendous psychological diversity of people suffering from the disease, computer-aided diagnosis of eating disorders is a current research problem. An additional factor motivating to undertake research is the high mortality rate among patients, especially those who have anorexia, and difficult access to specialists.

The conclusions from the literature review prompted the author to establish cooperation with the Medical University of Silesia in Zabrze, Poland. Together with the assigned auxiliary supervisor, a projective method was created, which involves collecting written notes from healthy people and people who have anorexia about their body image. After presenting the developed method and procedures, the Bioethics Committee of the Medical University of Silesia declared a positive opinion and acceptance for collecting the research material.

3. Developed rules for computer-aided assessment of the patient's condition

This chapter presents the developed methods and language rules based on dictionary methods and recurrent network architectures. In the beginning, section 3.1 presents the collected research material and characterises the research, control and HNC groups. The following subsections present the developed methods of processing the collected research material. Section 3.2 discusses the automatic classification of body image and explains the classifier architecture (deep recurrent networks) in detail. The most important parameters of the selected architecture and the method of training this class of machine learning models are also presented here. The following section 3.3, introduces the method of grammatical and lexical analysis using dictionary methods. This part of the analysis includes extracting the desired parts of speech with particular emphasis on adjectives and verbs, searching for the verb "*to be*" in the present and past form, the pronoun "*I*" and the possessive pronoun "*My*". The last part of the subchapter describes the method for detecting characteristic words referring to individual parts of the body. Section 3.4 proposes an alternative approach to assessing notes in terms of sentiment using the developed dictionary method. In turn, section 3.5 presents a method for assessing the proposed approach in the context of its usefulness among eating disorder specialists and first-contact staff.

3.1 Collected research data

The research used written notes prepared by participants in the research and control groups. The research group comprised patients with restrictive form anorexia who were during the therapy. The cooperation with the medical experts from Clinical Hospital No.1 in Zabrze, Poland, named after Professor S. Szyszko of the Medical University of Silesia, was established for the research. It enabled the author to collect the research material from sick participants. The control group comprised female adolescents and young adults attending primary and secondary schools in Gliwice and Zabrze, Poland. The participants in both groups were asked to write a short note (the length of the note was not suggested) on their attitude to their bodies. The final research database consisted of 115 notes from anorexia patients and 86 from healthy schoolgirls.

The research procedure employed specific criteria for including participants into determined groups. The criteria and data tagging were developed in close collaboration with experts in anorexia nervosa. The inclusion criteria for the research group included adolescent individuals (aged 12–19) diagnosed with anorexia made by a psychiatrist, lack of coexisting psychological disorders and a duration of anorexia up to 3 years. The control group, conversely, included the same age group of participants (12–19) without any diagnosed psychological illnesses.

The detailed inclusive criteria for 115 females in the research group with the restrictive form of anorexia are given below. As mentioned, the participants covered the age group 12–19, with an average age of 15.7 ± 2. The diagnostic procedure used the ICD-10 and DSM-5 criteria. The girls' average weight was 35.1 ± 4.7 kg, and BMI oscillated from 11.3 to 20.2 kg/m^2, with an average of 15.1 ± 2.8 kg/m^2 ($p < 0.001$ vs. control group). The BMI SDS (BMI Standard Deviation Sccore) ranged from –4.2 to 0.9 kg/m^2, with an average of -2.72 ± 1.49 kg/m^2 ($p < 0.001$ vs. control group).

In the control group, there were 85 healthy girls aged 12–20, an average age was 15.1 ± 1.9. The average weight was 57.1 ± 10.1 kg, and BMIs ranged from 16.5 to 25.8 kg/m^2, with an average of 21.5 ± 3.4 kg/m^2. The range of BMI SDS was from –2.7 to 3.6, with a mean value of 0.19 ± 1.44 kg/m^2.

For better validation of the method, the research also involved HNC patients group [53, 143]. This group comprised 50 participants (26 women and 24 men). The mean age was 57 ($25–75 \pm 11.2$). Participants were oncological patients with upper gastrointestinal tract or head and neck area cancer and required enteral nutrition. The diagnosis used the ICD-10 classification. The patients were designated to three treatment stages: I - during the diagnosis, II -

during the advanced treatment, and III - palliative stage. Malignant neoplasms involved other and unspecified parts of the oropharynx (n = 9), the tonsils (n = 7), the larynx (n = 7), the oesophagus (n = 5), the accessory sinuses (n = 5), palate (n = 4), the parotid gland (n = 4), the cerebrum, except lobes and ventricles (n = 4), the thyroid gland (n = 2), tongue (n = 1), other and unspecified major salivary glands (n = 1), bone and articular cartilage of other and unspecified sites (n = 1). The inclusive criterion required good verbal and logical communication. The research assessed the body image, and patients were asked to write notes on the following topic: "Describe in your own words how you perceive your body or what your body looks like".

3.2 Automatic classification of notes on body image

The major challenge in analyzing text notes is the ambiguity of the information contained. In the considered case, the collected notes on body image underwent an expert analysis by a group of psychologists dealing with diagnosing and treating eating disorders and specialists dealing with natural language processing. As part of this analysis, several important categories were established concerning recommendations for classifying notes. The developed categories and the justification of their inclusion in the research discuss the following part:

1. **Healthy/sick** (medical category),
2. **Sentiment** (psychological category – the patient's attitude towards his or her body image),
3. **Past tense** (NLP category related to the ambiguity of natural language - the past tense in the context of eating disorders may indicate the desire of the sick person to return to well-being before the period of illness),
4. **Irony** (NLP category related to the ambiguity of natural language - irony can distort the semantic interpretation of a statement).

3.2.1 Selection of the architecture of the classifier used

NLP applies model architectures for classification. The choice of architectures used in NLP is vast and varies depending on their specificity. They find different possibilities of application. This section presents a synthetic review of the classifier architectures. Particular attention, discussed in detail, was drawn to the selected deep recurrent network architectures used in the research. The chapter contains diagrams of the cell types used and a quantitative description of their basic parameters.

Classical architectures based on machine learning

Classical machine learning architectures refer to traditional models and algorithms widely used before the widespread implementation of deep learning. These architectures have proven their effectiveness in various applications through their simplicity and shallower structure compared to modern learning models. In other words, classical approaches stand as the solid basis of machine learning and still seem relevant today, especially in the case of scarce data or interpretability requirements. Their straightforward properties and application serve multiple purposes, especially in text analysis [38].

Naive Bayes classifier is defined as a probabilistic model based on Bayes' theorem, characterised by simple structure and vast computational efficiency [28]. It assumes autonomy among attributes, which successfully engages it in text classification concerning spam filtering and sentiment analysis. Moreover, it serves various other domains, including medical diagnosis, document categorisation, and recommendation systems. Its advantage, which stands for its popularity, is the ability to operate on a small number of training data [28]. Naive Bayes classifiers can determine the sentiment expressed in textual data (positive, negative, or neutral). The algorithm considers the occurrence of words and their association with sentiments.

Support Vector Machines (SVM) is a supervised machine learning algorithm applied for classification and regression tasks to find a hyperplane that effectively separates data points belonging to different classes. SVMs are effective in high-dimensional spaces and copying with complex decision boundaries. The key concepts in SVMs are support vectors, also called the data points, crucial in defining the optimal hyperplane, and the margin used for determining the algorithm's generalization to new, unseen data [43]. SVMs are helpful in various domains, such as text classification, bioinformatics, speech recognition, image clustering for image compression, image classification, or hand-written digit recognition problems [27, 167].

Decision Tree is a model structured in a hierarchical way as a tree consisting of nodes (root, internal, and leaf nodes) and branches. Each node has a determined role. A root node is a root without any incoming nodes. It represents a decision or a test condition. Internal has at least one outgoing edge, and the leaf node is terminal, as it provides the final decision or prediction [142]. It serves for classification and regression tasks. Branches coming out from each node lead to subsequent nodes based on the outcomes of those decisions. The learning process involves recursively splitting the data based on the most informative features at each node. Decision Trees use various splitting criteria for classification tasks or mean squared error for regression tasks to determine the optimal feature and threshold for splitting the data [148]. Decision Trees often find applications in various fields due to their ability to handle numerical and categorical data with minimal preprocessing. Similarly, in medicine and health care, where a decision must be accurate and rapid [127].

Neural Networks, also called Artificial Neural Networks (ANNs), are machine learning models that reflect the structure and functioning of humans' biological nervous systems. They consist of interconnected nodes and neurons organized into layers. A typical neural network comprises three main layers: the input layer, one or more hidden layers, and the output layer [86, 162]. The neural network's architecture is characterised by the connections between neurons, each associated with a weight that adjusts during training. The learning process involves adjusting these weights to enable the network to map input data to the desired output accurately [9]. The weight influences the signal intensity at a connection [97]. The output is generated utilising the signal from this activation value, which is the weighted sum of the summing unit [9].

Recurrent neural networks

Recurrent neural networks (RNN) are designed to process sequential data, such as time sequences or text. Their main feature is an internal state that allows them to store information about earlier elements of a sequence, which allows for modelling temporal or spatial relationships between data. The key idea of RNNs is to use the same set of weights in the learning process for each time step or element of the sequence [15]. At each time step, the RNN processes input and updates its internal state based on that input and the state from the previous time step. This allows RNNs to detect and exploit dependencies between sequence elements.

The simplest form of RNN consists of one hidden layer in the form of a recurrent layer. The more complex architectures include multilayer recurrent networks (MRNN) or recurrent networks with memory cells such as Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU).

RNNs are widely used in various fields, including NLP, such as machine translation, text generation, and sentiment analysis. Another application encompasses speech processing (speech recognition, speech synthesis), temporal data analysis (forecasting, time steps classification), and other fields a sequential structure data.

Structure of reccurent neural networks (RNN)

Recurrent neural networks consist of repeating units that form layers. Each unit in the RNN takes input from the previous time step and the current internal state and generates the output and new internal state for the next time step [15]. The structure of the RNN network shows Figure 3.1.

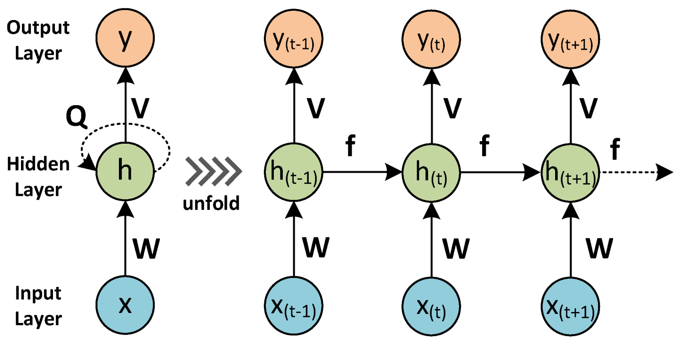

Fig. 3.1: A schematic of a recurrent neutral network and its unfolded structure.

Basic Structure of an RNN contains:

1. **Input Layer**
   The input to an RNN is a sequence of vectors $(x_1, x_2, ..., x_T)$ where $x_{(t)}$ represents the input at time step t. Each $x_{(t)}$ can be a word, a feature vector, or any other form of data point in the sequence.

2. **Hidden Layer (Recurrent Layer)**
   The hidden layer in an RNN has a crucial role in maintaining the state of

the network over time. At each time step t, hidden state $h_{(t)}$ is updated based on the current input $x_{(t)}$ and the preceding hidden state $h_{(t-1)}$. The update rule for the hidden state is typically defined as:

$$h_{(t)} = f_a \left(W_{hx} \cdot x_{(t)} + W_{hh} \cdot h_{(t-1)} + b_h \right) \tag{3.1}$$

where:
t — time step,
f_a — is a non-linear activation function,
$x_{(t)}$ — is the input at the ongoing time step,
$h_{(t-1)}$ — is the hidden state from the preceding time step,
W_{hx} — is the weight matrix for the input $x_{(t)}$,
W_{hh} — is the weight matrix for the previous hidden state $h_{(t-1)}$,
b_h — is the bias vector for the hidden state.

3. **Output Layer**
The output $y_{(t)}$ at each time step is computed utilising the ongoing hidden state $h_{(t)}$:

$$y_{(t)} = g_a \left(W_{hy} \cdot h_{(t)} + b_y \right) \tag{3.2}$$

where:
g_a — is an activation function appropriate for the task,
$h_{(t)}$ — is the hidden state at the current time step,
W_{hy} — is the weight matrix for the hidden state $h_{(t)}$,
b_y — is the bias vector for the output.

RNN Training Process – Backpropagation Through Time (BPTT) algorithm

In the RNN training process, the ongoing updating of network weights occurs to minimize the error occurring between the ground truth and the predicted output. It uses the current values of the model parameters and the training history. Assuming that the input sequences have a constant length, the network can be transformed into a unidirectional network developed over time (Fig. 3.1). The BPTT algorithm is an extension of the Back Propagation idea but more computationally complex [40, 103]. The weights updating in the backpropagation process involves estimating the gradient of the cost function relative to the network weights and adjusting the weights to minimize the prediction error. Gradient updates for the weights W_{hx}, W_{hh} and W_{hy}, include summing the gradients from each time step:

$$\frac{\partial L}{\partial W_{hx}} = \sum_{t=1}^{T} \frac{\partial L_{(t)}}{\partial W_{hx}} \tag{3.3}$$

$$\frac{\partial L}{\partial W_{hh}} = \sum_{t=1}^{T} \frac{\partial L_{(t)}}{\partial W_{hh}} \tag{3.4}$$

$$\frac{\partial L}{\partial W_{hy}} = \sum_{t=1}^{T} \frac{\partial L_{(t)}}{\partial W_{hy}} \tag{3.5}$$

where:
L — total loss function,
$L_{(t)}$ — loss at time step t,
$\frac{\partial L_{(t)}}{\partial W}$ — gradient of the loss $L_{(t)}$ at time step t with respect to W.

The next step employs the optimizer to update the weights based on the calculated gradients:

$$W_{hx} \leftarrow W_{hx} - \eta \frac{\partial L}{\partial W_{hx}} \tag{3.6}$$

$$W_{hh} \leftarrow W_{hh} - \eta \frac{\partial L}{\partial W_{hh}} \tag{3.7}$$

$$W_{hy} \leftarrow W_{hy} - \eta \frac{\partial L}{\partial W_{hy}} \tag{3.8}$$

where:
η — the learning rate.

One of the main challenges of RNNs is the vanishing or exploding gradient problem [118]. The gradients that propagate backwards over long sequences can vanish or explode, leading to difficulties in learning long-term dependencies. Dealing with this problem requires more advanced RNN architectures, such as LSTM and GRU, which use specific gating mechanisms to control the flow of information through the network. Recurrent deep neural networks, utilising memory cells such as Long Short-Term Memory and Gated Recurrent Unit, are key tools in natural language processing.

Long Short-Term Memory cell (LSTM)

LSTM is a recurrent neural network type capable of retaining and updating information for an extended period. The idea of this model was to create a more advanced neuron, possibly using it in a computational graph with a complex structure, eliminating the risk of loss of the gradient or its explosion [163]. It prevents the vanishing gradient problem by using special internal structures such as an input gate, a forgetting gate and an output gate. This results in the possibility of modelling long-term dependencies in sequential data. The general operating diagram of LSTM is presented in Figure 3.2.

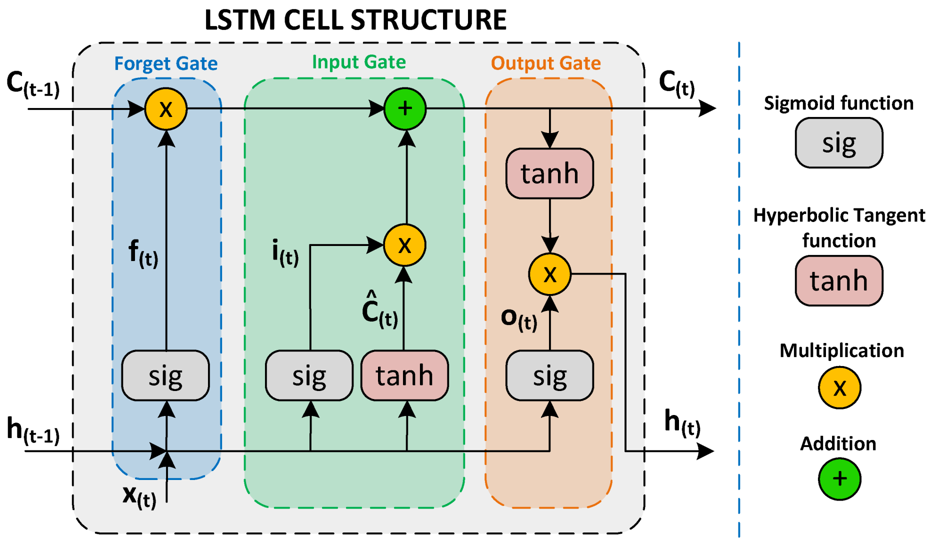

Fig. 3.2: Schematic of the LSTM recurrent neural network cell.

The cell equation of state is as follows:

$$C_{(t)} = \left(\overline{f}_{(t)} \circ C_{(t-1)}\right) + \left(\overline{i}_{(t)} \circ \hat{C}_{(t)}\right) \tag{3.9}$$

where:

t — time step,

$C_{(t)}$ — cell state information,

$f_{(t)}$ — forget gate at t,
$i_{(t)}$ — input gate at t,
$C_{(t-1)}$ — cell state information at previous timestemp,
$\hat{C}_{(t)}$ — value generated by tanh function.

The main components of LSTM include:

- **Forget Gate**: It gives the network the opportunity to decide which information should be forgotten from the memory location. The information from the ongoing input $x_{(t)}$ and hidden state $h_{(t-1)}$ are passed through the sigmoid function.

$$\overline{f}_{(t)} = \sigma \left(W_f * \begin{pmatrix} \overline{h}_{(t-1)} \\ \overline{x}_{(t)} \end{pmatrix} + \overline{b}_f \right) \tag{3.10}$$

  where:
  $f_{(t)}$ — forget gate at t,
  σ — sigmoid activation function,
  $h_{(t-1)}$ — previous hiden state,
  $x_{(t)}$ — input at t,
  W_f — weight matrix between forget gate and input gate,
  b_f — connection bias at t.

- **Input Gate**: It regulates updating a memory cell by deciding what new information should be added. First, the ongoing state $x_{(t)}$ and previously hidden state $h_{(t-1)}$ are sent to the second sigmoid function. Next, the same hidden and current state information will be passed through the tanh function.

$$\overline{i}_{(t)} = \sigma \left(W_i * \begin{pmatrix} \overline{h}_{(t-1)} \\ \overline{x}_{(t)} \end{pmatrix} + \overline{b}_i \right) \tag{3.11}$$

  where:
  $i_{(t)}$ — input gate at t,
  W_i — weight matrix of sigmoid operator between input gate and output gate,
  b_i — bias vector with regard to W_i.

- **Output Gate**: It controls what information goes to the output from the memory location. First, the values of the ongoing state and preceding hidden state are passed into the third sigmoid function. The new cell state, generated from the current cell state, passes through the tanh function. The outputs of both operations are then multiplied element-wise. Based on the resulting values, the network determines which information the hidden state should retain.

$$\overline{o}_{(t)} = \sigma\left(W_o * \begin{pmatrix} \overline{h}_{(t-1)} \\ \overline{x}_{(t)} \end{pmatrix} + \overline{b}_o\right) \tag{3.12}$$

$$\overline{h}_{(t)} = \overline{o}_{(t)} \circ \tanh\left(C_{(t)}\right) \tag{3.13}$$

where:
$o_{(t)}$ — output gate at t,
W_o — weight matrix of output gate,
b_o — bias vector with regard to W_o,
$C_{(t)}$ — cell state information,
$h_{(t)}$ — LSTM output.

The internal state of the LSTM cell depends on the dynamic balance between the previous experience and its re-evaluation in relation to the new experience (regulated by a forgetting gate) and the so-called semantic effect from the current input signal (regulated by the input gate) and the potentially additive result of the activation function. These mechanisms enable LSTM to efficiently store and update information in its memory longer, which is crucial in complex natural language processing tasks.

Gated Recurrent Unit cell (GRU)

GRU is another form of recurrent neural network similar to LSTM. Unlike LSTM, GRU has fewer parameters and a less complex structure, which can boost the learning process and reduce the need for computational resources [5]. Similarly to LSTM, GRU deals with the vanishing gradient problem using update and reset gates. The diagram of a GRU cell presents Figure 3.3. The main elements of GRU include:

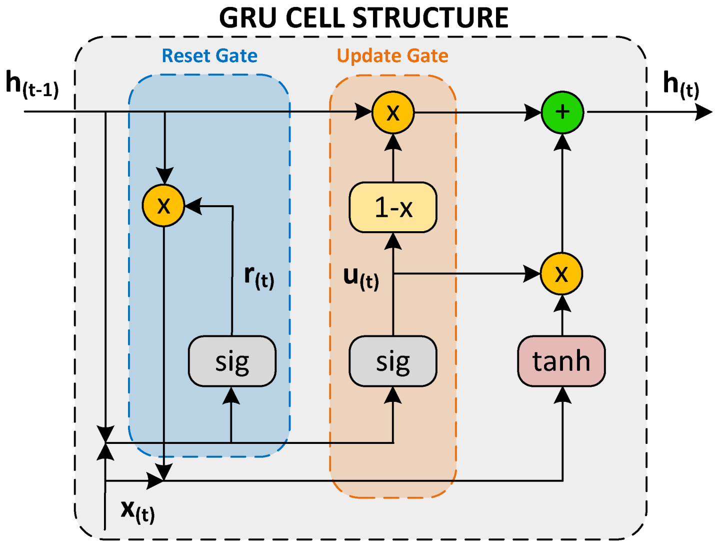

Fig. 3.3: Schematic of the GRU recurrent neural network cell.

- **Reset Gate**: Controls how much information from previous time step should be forgotten in the current time step. Its function is analogous to that of a forgetting gate:

$$\overline{r}_{(t)} = \sigma\left(W_r * \begin{pmatrix} \overline{h}_{(t-1)} \\ \overline{x}_{(t)} \end{pmatrix} + \overline{b}_r\right) \tag{3.14}$$

where:
$r_{(t)}$ — reset gate at t,
W_r — weight matrix of reset gate,
b_r — bias vector for the reset gate.

The argument of the tanh function is the sum of the linear function of the new input signal and the weighted term constituting the function of the previous state. In summary, this gate regulates the amount of history (accumulated in the value of the previous output) to be retained - the contribution to the new output $\hat{h}_{(t)}$. However, more than a zero gate alone is required to determine the correct result with sufficient accuracy, considering short and long-term dependencies. To increase the expressiveness of the unit, an update gate is introduced, which has a function similar to the input gate in the LSTM unit. The candidate activation $\hat{h}_{(t)}$ is calculated:

$$\hat{h}_{(t)} = \tanh\left(W_h * \begin{pmatrix} \overline{r}_{(t)} \circ \overline{h}_{(t-1)} \\ \overline{x}_{(t)} \end{pmatrix} + \overline{b}_h\right) \tag{3.15}$$

where:
W_h — the weight matrix for the candidate activation,
b_h — bias vector for the candidate activation.

- **Update Gate**: Decides on how much information from the previous time step should be transferred to the current time step. Its value is limited between 0 and 1, so GRUs learn to combine the old result with the new additive input:

$$\overline{u}_{(t)} = \sigma\left(W_u * \begin{pmatrix} \overline{h}_{(t-1)} \\ \overline{x}_{(t)} \end{pmatrix} + \overline{b}_u\right) \tag{3.16}$$

where:
W_u — weight matrix for the update gate,
b_u — bias vector for the update gate.

The new hidden state $h_{(t)}$ combines the previous hidden state $h_{(t-1)}$ and the candidate new state $\hat{h}_{(t)}$ weighted by the update gate $u_{(t)}$. The final hidden state $h_{(t)}$ combines the old state (modified by the update gateway) and the new candidate state (also modified by the update gateway):

$$\overline{h}_{(t)} = (1 - \overline{u}_{(t)}) \circ \overline{h}_{(t-1)} + \overline{u}_{(t)} \circ \hat{h}_{(t)} \tag{3.17}$$

These gates enable GRU to effectively deal with long-time dependencies in sequential data, making it a popular choice in NLP [15]. Both these architectures are applicable in NLP as they can effectively model complex relationships in text data over short and long time intervals. The decision on choosing LSTM or GRU may depend on the task specifications, available computational resources, and user preferences - usually, when selecting the RNN network architecture, both cells are used, experimentally verifying the suitability of each of them in solving the given task.

Transformers

Transformer is an innovative neural network architecture proposed by Vaswani et al. [94] that has demonstrated revolutionary achievements in NLP. It abandons traditional recursive mechanisms in favour of an attention mechanism that enables parallel processing of sequences and effective modelling of complex relationships between them.

As mentioned above, the Transformer uses an attention mechanism which allows the model to selectively focus on relevant parts of the data sequence. This mechanism consists of three main elements: Query, Key and Value, which calculate attention weights for each element in the sequence. Then, weighted sums of values are calculated, allowing the model to efficiently process information, including its context.

The overall architecture of the Transformer consists of a set of layers divided into larger encoder and decoder blocks. Each of these layers contains sublayers, such as attention layers and feedforward layers, which are applied sequentially. The encoder layers process the input data sequence, while the decoder layers are responsible for generating the output sequence so that this model can work in many-to-many modes. All layers are connected using residual connections and layer normalization, which helps in faster learning and model stability.

Transformer has been widely used in various tasks of NLP, such as machine translation, sentiment analysis, text generation, question and answer processing, language modelling, etc. Transformer-based models, e.g., BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre -trained Transformer), achieve excellent results on many NLP benchmarks [130].

The transformer architecture represents a breakthrough in NLP, eliminating vanishing gradient problems and enabling efficient modelling of long dependencies in text data. However, the main burden of these models is their internal complexity, which requires greater computing power and the preparation of broad datasets compared to simpler models.

3.2.2 Choice of encoding method

Tokenization

Tokenization is a process of dividing a monolithic text into given components - tokens. Usually, a single token is a word, a letter, a sentence, a paragraph, or even an entire document. The purpose of this process is to facilitate further analysis or processing of the text. There are several different tokenization techniques, depending on the context and application requirements

The basic form of tokenization occurs at word level (word) tokenization, which involves dividing text into individual words. Another technique regards sentence tokenization, separating the text into individual sentences. The third type, character tokenization, involves splitting the text into individual characters.

More advanced tokenization techniques, like regular expression tokenization, operate on tokens to be identified and classified based on specific patterns. Alphabetic expression tokenization, on the other hand, ignores non-alphabetic characters. Tokenization is crucial in text processing because it prepares text to be represented in a way that is more suitable for further analysis [132].

Stop words filtering and standardization

Some groups of tokens in the analysed text are valueless for further analysis and removed from the data. The exclusion process uses a generally available list of stop words for a desired language. If a token is in the stop list, it is removed from the text and not considered in further analysis.

Word normalization

The next step is to normalise the words. For this purpose, one of two operations is used:

- stemming – extracting stem from the word – a root that is not subject to variations;
- lemmatization – reducing a word to its basic form – lexeme.

The above operations significantly reduce the number of words in the dictionary for their better representativeness in the corpus.

Word embidings

Word embedding is a technique for encoding words in text as vectors. This technique appeared in the early 2000s thanks to a series of works by Yoshua Bengio, but its real flowering occurred in 2013 thanks to the research papers of the Google team led by Tomas Mikolov [109]. The most important feature of semantics is that words with a similar semantic meaning have a similar vector representation (the distances between them are near) than words without such a relationship. Practically speaking, various patterns of creating word embeddings occur [92]:

1. **Frequency-based Approaches**:
   (a) Count Vector: represents text as a vector, where each item corresponds to the number of occurrences of a given term (word) in the corpus.
   (b) Term Frequency-Inverse Document Frequency (TF-IDF Vectorization): weights the term frequency in a single document relative to its frequency in the entire corpus, thereby reducing the impact of common words.
   (c) Co-Occurrence Matrix with a Fixed Context Window: forms a matrix where each cell contains the number of co-occurrences of two words in a specific context window.
2. **Prediction-based Approaches**
   (a) Continuous Bag of Words (CBOW): predicts a word based on its context (surrounding words). The model learns word representations by minimizing a loss function which is charged for measuring the difference between the predicted and actual words.
   (b) Continuous Skip-gram: predicts surrounding words based on the given word. The model learns word representations that predict context well.

Prediction-based word embeddings such as CBOW and skip-gram are particularly favoured as they are able to seize the semantic and syntactic relationships between words. These models, e.g. Word2Vec and GloVe, generate vectors in a continuous space where words with similar meanings have similar vectors. This approach is more computationally and memory efficient and better reflects relationships between words compared to traditional frequency-based methods [116].

3.2.3 The choice of an optimization algorithm – Adam algorithm

Adam (ADAptive Moment estimation) is an adaptive optimization algorithm used to update weights in the machine learning process. It was proposed by Kingma and Ba in 2014 [83] as an improvement to the classic stochastic gradient descent (SGD) algorithm [177]. The Adam algorithm combines the advantages of momentum and RMSProp (Root Mean Square Propagation) algorithms, making it a popular choice for many machine learning tasks [177]. It maintains a moving average first-order gradient moment that is updated during each iteration. This moment is used to estimate the direction of gradient descent. Additionally, Adam maintains a second-order moving average moment of the gradient, updated during each iteration. This moment estimates the gradient variance. In the initial iterations, when the moments are initialized close to zero, Adam may be biased towards zero first-order moment and low second-order moment. To prevent this, Adam performs bias correction, which corrects these biases in the first iterations. Based on the calculated first- and second-order moments, the Adam algorithm updates the weights according to specific learning rules, such as the learning rate. Adam is often more effective than classic SGD in training, especially for large datasets or complex models. By adaptively adjusting the learning rate for each parameter, Adam can get closer to the optimal weight configuration faster.

3.2.4 Initialization of model weights – Xavier algorithm

The Xavier algorithm, also known as Xavier Initialization, is a technique for initializing weights in neural networks to ensure stable and efficient model learning. The authors of this model are Xavier Glorot and Yoshua Bengio [54]. The authors draw attention to the fact that the key issue is the proper initialization of weights to ensure the stability of the model during learning. It allows for better transfer of gradients in the error backpropagation process.

The Xavier algorithm involves random initialization of weights from a Gaussian distribution with mean zero and variance, which depends on the number of input neurons to a given neuron. The next step is to scale the variance by the square root of the number of input neurons, which helps maintain a stable flow of information through the network and effectively transfer gradients during the learning process. Thanks to this, the Xavier algorithm contributes to faster and more stable model learning. Xavier is widely used in deep machine learning practice due to its effectiveness and simplicity of implementation. It is often used when training deep feed-forward neural networks, especially for large architectures.

3.2.5 Selected aspects of learning the created classifier

A pivotal step in building and optimizing the model is tuning hyperparameters. Model tuning in machine learning refers to optimizing a model's hyperparameters to improve its performance and effectiveness. It is a principal stage (the experimental process in creating a model), allowing for finding parameter settings selected for a given research problem and a specific set of data. The first step in model tuning is to tune various elements to obtain optimal data. Such parameters may include the learning coefficient, layers and neurons numbers in the neural network, kernel parameters in SVM methods or the depth of trees in tree algorithms.

Defining the hyper-parameter space is the next step, including the different values the selected parameters can take. It can encompass a range of numerical values, discrete values or probability distribution functions. In order to find the best settings for the model, methods such as grid search, Bayesian optimization, random search or gradient optimization are used. Moreover, cross-validation is used to evaluate the effectiveness of different hyper-parameter settings. This technique divides the dataset into a training and validation set and evaluates the model based on its performance on the validation dataset. After optimization, the model with the best performance on the validation set is selected. This approach often tests the final model on an independent test set to assess its overall performance. Model tuning is often an iterative process that requires a lot of trial and error. A minor inconvenience of this process is that it can be time-consuming due to repeating the tests multiple times. It is necessary to ensure the optimal hyper-parameter settings.

Selection of meta-parameter values for RNN-based note classification models

After considering various values of the model's meta-parameters and conducting many tests, the following set of parameters was chosen:

1. **Weight initialization method.** Seven different weight initialization methods were selected: CAUCHY, MSRA, MSRA1, MSRA2, NORMAL, XAVIER and two variants XAVIER1 and XAVIER2.

2. **Cell type in hidden layers.** Two cell types were selected: LSTM and GRU.

3. **Number of neurons in hidden layers.** Five different values for the number of neurons in hidden layers were tested: 5, 10, 15, 20, 25.

4. **Optimization algorithm parameter values for minibatchSize.** Seven different values for the minibatchSize parameter were tested: 2, 4, 5, 8, 16, 32.

5. **Maximum number of epochs (maxEpochs).** Five different values for the maximum number of epochs were tested: 2, 4, 7, 16, 32.

6. **Optimization method.** When choosing the optimization method, several optimizers were taken into account, such as ADAM, LBFGS, MOMENTUM or VANILLA, but ultimately ADAM was chosen.

Dataset splitting

The research adopted the dataset splitting in the following proportions: 70% as training set, 15% for validation set, and another 15% for the test set. This approach was chosen to assess and optimize the model's performance properly. Moreover, such division ensures a balance between data availability for training, verification and final evaluation of the model.

After compiling the datasets, multiple experiments were performed to find the optimal model settings. First, the model was trained on the training set with various hyperparameter configurations. During this process, the validation set evaluated the model after each training epoch, allowing hype parameters to be adjusted to avoid overfitting (overfitting) and improve the overall model performance. The satisfactory results on the validation set allowed the final evaluation of the model to be conducted. This phase used the test set to help estimate the the model's generalization ability.

Through an iterative experimental process that involved analyzing results on the validation set and conducting a final evaluation on the test set, optimal model settings were identified. These settings ensure high performance with respect to both predictive accuracy and generalization capability to new data.

Transfer learning

Training deep models requires a large, proportional number of training samples due to the model's multitude number of internal parameters, whose values change during learning [97]. This is usually the reason why the use of models in various fields of detail is limited. A solution that partially circumvents this problem is transfer learning, which takes advantage of the fact that deep network models are hierarchical models that learn in a structured way.

The current research also applied transfer learning. The methodological approach included training the model from scratch (initializing the values of the model parameters using the weight initialization algorithm). Next, the values obtained in the first stage of learning were the initial values in the next stage of learning. The effectiveness of this approach has yet to be proven but established on good empirical results. Therefore, the author decided to include this approach in the research.

In the conducted research, the initial training of the model used notes prepared by people suffering from eating disorders due to various types of head and neck cancer. The model was fine-tuned using a dataset containing notes from people who have anorexia.

Proposed method of learning the model

The research employed a deep recurrent neural network (RNN) model for the learning phase. The study model was evaluated across three experimental scenarios. **Experiment 1** involved training the model exclusively on notes from anorexic patients. **Experiment 2** expanded the training set to include the entire dataset, combining notes from anorexic patients and those with HNC participants. The approach taken in **Experiment 3** utilized transfer learning. Due to the limited size of the anorexia text corpus, the author decided to such solution. Initially, the model training used notes from HNC patients. These notes covered a range of patient demographics and treatment stages but focused on body image perceptions. In the subsequent phase, the model was further trained using the anorexia notes to enhance its learning process

A method for validating a classifier model during training

The model was trained using an optimization algorithm (e.g. Adam) based on a cost function that measured the difference between the model's predictions and the actual values. The validation set evaluated the model after each training epoch to monitor its performance and possible regularization. After training, the model testing occurred on an independent test set, different from training or validation sets. This technique helped evaluate the overall performance of the model on new, unknown data. The choice of validation measures depended on the type of problem and expectations for model performance.

3.2.6 Evaluation metrics for classification models

Several fundamental metrics are applied to evaluate the performance of classification models. These metrics provide insights into the classifier's performance, such as accuracy, precision, recall, and overall effectiveness. A confusion matrix will be used to illustrate the results and describe the performance of a classification model. It consists of four components:

- **True Positives (TP)**: It refers to the count of predictions where the classifier correctly predicts the positive class as positive.
- **True Negatives (TN)**: It refers to the count of predictions where the classifier correctly predicts the negative class as negative.
- **False Positives (FP)**: It refers to the count of predictions where the classifier incorrectly predicts the negative class as positive.
- **False Negatives (FN)**: It refers to the count of predictions where the classifier incorrectly predicts the positive class as negative.

Below are detailed descriptions and formulas for calculating these metrics:

- **Precision**
  Also known as positive predictive value, it quantifies the accuracy of positive predictions made by the classifier. It is the ratio of true positive predictions to the total count of positive predictions, including both true positives and false positives.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{3.18}$$

- **Recall**
  Recall, also known as sensitivity or true positive rate. It measures the model ability to identify all relevant instances within a dataset correctly. Recall, on the other hand, measures how often a machine learning model correctly identifies positive instances (true positives) from all the actual positive samples in the dataset.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3.19}$$

- **F1-score**
  F1-score is a metric that evaluates the execution of a classification model, mainly when dealing with imbalanced classes. It is the harmonic mean of precision and recall, which balances these two metrics.

$$\text{F1-score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3.20}$$

- **Accuracy**
  It measures the ratio of correctly predicted instances (both positive and negative) out of the total number of instances. While accuracy is a useful and easy-to-understand metric, it should be used alongside other metrics like precision, recall, and the F1-score, especially in cases of class imbalance, to get a more comprehensive understanding of the model's performance.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{3.21}$$

- **Misclassification Error**
  It measures the proportion of incorrect predictions out of the total number of predictions made by the model. Misclassification Error is a useful metric for understanding the rate of incorrect predictions made by a model. However, it should be used alongside other metrics, especially in the case of imbalanced datasets, to gain a more comprehensive view of a model's performance.

$$\text{Misclassification Error} = \frac{\text{FP} + \text{FN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} = 1 - \text{Accuracy} \quad (3.22)$$

- **Weighted F1-score**
  The Weighted F1-score is an evaluation metric that accounts for class imbalance by calculating the F1-score for each class and then taking a weighted average based on the number of true instances for each class. This ensures that the contribution of each class to the final score is proportional to its frequency in the dataset.

  For an "N"-class dataset, the sample-weighted F1-score is:

$$\text{Weighted F1-score} = \sum_{i=1}^{N} w_i \times (\text{F1-score})_i \quad (3.23)$$

  where:

$$w_i = \frac{\text{No. of samples in class } i}{\text{Total number of samples}}$$

3.3 Grammatical and lexical analysis

General language rules, according to Crystal [36] are common relationships between language elements that perform given functions and language structure and structures. Elements of language, also known as linguistic units, include nominative units, such as words or phrases; communicative units, i.e. sentences; and structural units, which include morphemes and phonemes [47].

In any national language, one can trace the number of occurrences of particular parts of speech, which, for cultural or historical reasons, are not universal and are characterized by some subtle differences [52]. The literature indicates that the speaker's characteristics significantly influence these statistics. Personal characteristics may be reflected in speaking, in creating sentences, and in using particular linguistic patterns and vocabulary. The manner of expression may also reveal the speaker's origins in a given geographical area or social group [24, 102]. State-of-the-art research also attempts to use these measures to differentiate people's disorders based on their vocabulary. It motivated the author to examine the statistics of the frequency of occurrence of individual parts of speech among the research and control groups, divided into healthy people and those with a clinically diagnosed eating disorder. Anorexia is considered an egosyntonic disease [58]. Patients often identify with the disease, adapt to it, and do not treat it as a factor requiring treatment. Thus, they have great difficulty finding the motivation to start treatment because they feel that they may lose something by starting treatment [166]. Hence, they may "juggle" emotions or hide symptoms. Therefore, vocabulary analysis may be an additional source of knowledge about the patient and help recognise the emotional charge. Taking into account the multifactorial nature of anorexia, its complex etiology and diagnostic challenges, the research focused on developing rules for extracting the characteristic linguistic features of a given patient from the text material and isolating the frequency of use of the following parts of speech. The choice of the presented lexical and grammatical rules was dictated by a previous analysis of the literature, taking into account typical features of AN and practical knowledge obtained from specialists in the field of eating disorders during consultations.

A separate research group included patients suffering from HNC at various stages of the disease and therapy. As mentioned in Chapter 1, cancer therapy is very invasive and affects the patients' appearance, often deforming their appearance. Additionally, prior surgeries can result in food intake, which, in consequence, may develop eating disorders. However, they may have different backgrounds than anorexia. The oncological treatment causes significant changes in appearance, sometimes temporary, such as hair loss, weight loss, and skin changes [41]. To sum up, it seems evident that the above factors have an enormous impact on the functioning and the process of acceptance of the new reality, which can often lead to depression and disturbed body image.

3.3.1 Parts of speech tagging

In this part of the analysis, the SAS Viya analytical environment was used to generate the desired rules and detect specific features in notes [99]. The available dictionary models offered by the platform were used to mark parts of speech (POS). Part of speech tagging involves the following steps:

1. Tokenization: this step encompasses splitting text into separate words or tokens, removing punctuation and converting the text to a suitable format for further analysis.

2. Lowercase conversion in which the text is converted into lowercase and handles special characters or numbers.

3. Stemming and lemmatization: Stemming is the process of removing the inflected words to their base form; however, stemming removes any affixes in words, whereas lemmatization guarantees that the resulting word is a recognized, normalized form of the original word (like ”lemma”), which is present in a dictionary.

4. POS tagging: Dictionary-based models help identifying the parts of speech in the text. Each word in the text is assigned a part-of-speech tag. Common tags include nouns (N), verbs (V), adjectives (A), adverbs (Adv), pronouns (PRP), conjunctions (Conj), prepositions (Prep.), and more.

5. Removing stop words: Eliminate frequently occurring but low-impact words such as ”*i*”, ”*w*”, ”*na*”.

6. Removing or appropriately handling punctuation.

7. Spelling correction.

8. Correcting spelling errors in the text.

Figure 3.4 presents the example of developed concept rules written using Language Interpretation for Textual Information (LITI) syntax in SAS Viya. The following subsections discuss the validity of selected POS in open-ended statements of research participants.

```
CONCEPT:mój@
CONCEPT::V
CONCEPT: być@
CONCEPT::A
CONCEPT::N
CONCEPT::nlpNounGroup
CONCEPT_RULE:(ORDDIST_3, „mój„ , "_c{ciało}")
```

Fig. 3.4: The example of developed concept rules in LITI syntax used during the research.

The results in Chapter 4 present the mean and median occurrences of POS in patients' notes, with a percentage indicating the number of notes in which these POS appeared.

Developed rules for adjectives

According to Merriam-Webster Dictionary of English Usage [108], adjectives constitute a group of words used to describe something or someone. They usually accompany nouns or pronouns and provide additional information about size, age, material, colour, or origin. They also stand to modify an object in terms of degree (comparative and superlative form) or enhance some qualities. Not to mention that they carry emotional intensity, feelings or attitudes towards describing objects [68]. Normally, adjectives come before nouns and modify them, but some come after sense verbs, like feel, be, seem,look, and appear. In that case, they influence the subject of a sentence [131]. The mentioned features of adjectives were used for text analysis to determine the general number of these words in textual data and to check what nouns they modify in each group of participants. In addition to the typical frequency of adjectives, the analysis included labelling them into adjectives with positive and negative connotations in the context of body image. The division used Nencki's affective words list (NAWL), a database of almost 3000 Polish words divided into speech parts with an emotional value assessment [138, 171]. The presented analysis approach and clinical psychologists from the Medical University of

Silesia enabled the development of an original list of adjectives divided into positive and negative.

Developed rules for verbs

Verbs are another part of speech with a specific role in a sentence. They indicate psychical or mental actions, state of being, feelings or occurrences. They denote what the subject of a sentence does or what happens to him [68]. Verbs are one of the most important structures of the language, and they have numerous functions, categories, and forms. As the most important features, we may denote sentence building and subject depiction. Verbs have various forms (past, present, future) and voices (active or passive) [68]. Moreover, verbs constitute various categories, such as transitive, intransitive, and ditransitive, which refer to indirect and direct objects of a sentence. Due to their diverse functionality, the proposed method examined the frequency of the total number of verbs in notes in individual groups [131]. Further research focused on determining the verb forms, which seemed crucial regarding the patient's body image. The objective of this analysis was to compare the number of past form verbs to present ones because, as the specialist claims, anorexia patients declare complex relations with the past. Especially those undergoing the treatment become, at some point, aware of the damages and the consequences of the illness (cost of the illness), and they search for some nice past memories that can bring them some relief.

Verb "to be"

The verb "*to be*" is one of the most fundamental and versatile verbs that every single language contains. It holds a variety of vital functions in expressing different aspects of reality and relations between subjects and their attributes. In the context of the Polish language, the verb "*to be*" is represented by the verb "*być*." It is an irregular verb whose conjugation varies depending on tenses and persons. The Polish language distinguishes 3 verb tense forms: past, present, and future, which were considered in the research. Another important aspect of consideration is the role of the verb "*to be*". It can denote identity and equivalence, the existence of something or someone, and indicate a person's condition or state. Finally, it defines relationships between subjects and their descriptors or complements. The primary objective of examining the various verb forms, particularly dynamic verbs and the verb "*to be*", was to ascertain whether individuals with anorexia nervosa predominantly orient their focus toward past experiences or present circumstances.

Cognition verbs

Since the literature indicates [34, 39] anorexic patients may have impaired cognitive processing and focus chiefly on dynamic rather than cognitive verbs, the proposed method reviews text data in terms of searching for cognitive verbs relating mainly to thought processes perception or consciousness. Such words include *think, want, feel, believe, know, realize,* etc. For the measure of cognition verbs, the analysis used the Linguistic Inquiry and Word Count (LIWC) text analytic software developed by Dr. James W. Pennebaker [18]. This tool enables automated categorization of words into various psychological and linguistic dimensions and aims to analyze emotional, cognitive, and structural components of textual data. It is widely applied in psychology, health research, social sciences, and other fields to understand psychological or emotional conditions and social dynamics through textual data [18, 76]. The tool provides a quantitative output of word categories, facilitating the interpretation of psychological and emotional content in text. Originally, the tool LIWC serves multiple languages except Polish. Therefore, there was a need to adapt this part of the analysis to the Polish language. Based on the collection of cognitive terms in LIWC description, a Polish translation was developed for research purposes. The LIWC dictionary served as a source of cognition words; next, the chosen words were translated into Polish, and, in the final step, the analysis was conducted for the research database to detect the matched cognition terms through these texts.

3.3.2 Pronoun "*I*" and the possessive adjective "*My*"

The literature analysis on anorexia indicated that people diagnosed with anorexia tend to focus on their appearance or their body in their statements. The efforts that a person with anorexia makes to maintain low body weight constitute their only goal, and all their thoughts and actions are focused on themselves and their body. Moreover, it has been proven [140] that people with other mental disorders, such as depression or social phobia, also tend to use these forms of language frequently. These people focus strongly on themselves. For this reason, one of the assumptions of the analysis was to examine whether people with anorexia use personal pronouns in the first person singular "*I*" more often compared to the control group. Consequently, a rule to count the occurrences of the pronoun "*I*" was developed. Another developed rule referred to counting the occurrences of the possessive pronoun "*My*", along with its inflectional forms, in relation to the body.

3.3.3 Key terms associated to body image

The main feature of anorexia is an altered perception of the patient's own body. Cash et al. [25] defines the body image as consisting of the cognitive aspect, including the body schema, and the emotional aspect, regarding the emotional attitude towards the body. Therefore, the research targeted the search for characteristics and terms in the context of the body. Such terms can constitute valuable markers for creating a linguistic profile of a person with anorexia, and other language attributes can contribute to the holistic complement of a method. The assumption of the analysis was to determine the total number of nouns in the dataset and identify the primary term "*body*" as a whole and its various parts. The next step included examining all word compounds, noun phrases, and adjectives that describe these core terms.

The proposed analysis was conducted in all 3 groups of participants to outline the discrepancies and characteristic features that could help better understand the emotional state of anorexia patients indicate the problematic spheres and distinguish the altered language.

3.4 Sentiment analysis based on dictionary method

Dictionary sentiment scoring, also known as dictionary-based sentiment analysis, is one of the popular techniques used in NLP to evaluate the emotional content of text. It is widely used in scientific research and practical applications, such as opinion analysis, market sentiment analysis, or social media monitoring. Dictionary sentiment assessment involves assigning sentiment values to individual words in the text based on a predefined dictionary. Each word in the dictionary is associated with one or more sentiment values, which can include categories such as positive, negative, and neutral, as well as more specific emotions (e.g. happy, sad, angry). The process of assessing sentiment using a dictionary includes several steps:

1. **Tokenization**: Splitting text into smaller units, usually words.
2. **Normalization**: Reducing words into their basic form (lemmatization) and removing punctuation marks and other irrelevant elements.
3. **Mapping to dictionary**: Assigning a sentiment value to each word based on the dictionary.
4. **Sentiment Value Aggregation**: Computing the overall sentiment of the text by aggregating the sentiment values of individual words. Aggregation methods may include simple summation, arithmetic mean, or more advanced weighted methods.

Although conceptually simple, the described method requires feeding the positive, neutral, and negative sentiment carriers with dictionaries. As part of the research, the sentiment dictionary developed by Wilson, Wiebe and Hoffman [172] was used to develop the dictionary for the Polish language. This dictionary, known as the MPQA Subjectivity Lexicon, is part of the larger MPQA (Multi-Perspective Question Answering) project and contains annotations on the subjectivity and polarity of words and phrases [154]. It is widely used in research on sentiment analysis and text subjectivity analysis. The dictionary contains information about:

1. **Polarization**: indicates whether the word is positive, negative or neutral.
2. **Subjectivity**: indicates whether the word is subjective (expresses an opinion) or objective (neutral).
3. **Polarization intensiveness**: determines the intensity of the sentiment.

For research and analysis purposes, the Wilson, Wiebe and Hoffman dictionary was translated into Polish while maintaining information about polarization, subjectivity and the strength of polarization. Besides, the division into sentiment categories was verified by specialists in eating disorders to include specific features of the language used by sick people.

The research used the equation 3.24 to quantitatively represent sentiment values. Expressing sentiment in a numerical form allows for quantifying emotions contained in texts, which is necessary for statistical and comparative analysis.

$$\text{Sentiment}_{score} = \frac{n_{positive} - n_{negative}}{n_{positive} + n_{negative} + n_{neutral}} \tag{3.24}$$

where:
$n_{positive}$ — number of positive words in text,
$n_{negative}$ — number of negative words in text,
$n_{neutral}$ — number of neutral words in text.

The ranges for classifying sentiment as positive, negative, or neutral can vary depending on the specific application and the sentiment analysis model used. The following sentiment division ranges were used in the presented research:

- **Positive**: for $\text{Sentiment}_{score} > 0.1$
- **Neutral**: for $-0.1 \leqslant \text{Sentiment}_{score} \leqslant 0.1$
- **Negative**: for $\text{Sentiment}_{score} < -0.1$

3.5 A method for assessing the usefulness of developed methods of computer-aided psychological diagnostics

The author, being aware of the limited availability of similar tools that support the diagnosis of eating disorders using NLP elements, proposed, in the research plan, a method to evaluate the effectiveness of the developed approaches. The proposed evaluation methods were divided according to the specialization of people supporting people suffering from eating disorders. Under this criterion, the following were distinguished: clinical psychologists specializing in diagnosing and treating eating disorders. Another group of participants who assessed the developed tools was the first-contact staff, comprising nurses and school psychologists.

3.5.1 Evaluation among eating disorder specialists

The research proposed three categories of topics, developed after an in-depth literature review and interviews with specialists [141]. Within the research, a broad set of samples was elaborated and later assessed by competence arbiters. The final version of the assessment form presents the below sections. For each question, the participant could answer: Yes, No, Not sure. Survey for evaluating the impact of a developed NLP method on psychologists' professional practice presents the below list:

1. **RELATION WITH A PATIENT**
   - Can the use of developed diagnostic computer tool for sentiment analysis (DCTSA) reduce the patient's resistance to psychological examination?
   - Can examination with DCTSA be conducive to a greater sense of security and intimacy in the initial phase of psychological diagnosis?
   - Does the examination with DCTSA allow the patient to influence answering difficult questions without verbal contact with the researcher?
2. **SUBSTANTIVE ASPECTS OF A DIAGNOSIS**
   - Can the situation of a test with DCTSA through a series of free associations of a patient support his self-reflection and self-diagnosis?
   - Is the situation of test with DCTSA conducive to an in-depth exploration of the patient's problem areas?
   - Do you think that the use of DCTSA based on a series of free patient associations on any subject related to his psychopathology can support the assessment of the patient's dominant affect related to the applied topic?
   - Can the situation of testing using DCTSA help the psychologist to make diagnostic hypotheses?
   - Can the situation of the DCTSA test influence the accuracy of the psychological diagnosis?

- Can DCTSA be used in the evaluation process of therapeutic interactions for a given patient?

3. **DIAGNOSTIC PROCEDURES**

- Can the situation of the DCTSA test significantly support the psychological diagnosis process?
- Do you think that the process of psychological diagnosis using DCTSA is significantly different from that without using the mentioned tool?
- In your opinion, can testing using DCTSA increase the comfort of a psychologist during the diagnostic process?

3.5.2 Evaluation among first-contact staff

This group of participants included school psychologists and nurses. The developed questionnaire [100] included questions detailing the tools for classifying notes in 4 categories: healthy/sick, sentiment, irony, and past tense. Each question was rated on a Likert scale ranging from 1-5, where 1 means ”Not usefull at all” and 5 means ”Very usefull”. The questions in the questionnaire are presented below:

1. Is the form of the tool helpful as a screening tool?
2. Is the sentiment towards the body a useful information?
3. Is irony a useful information?
4. Is past tense a useful information?
5. Is Healthy/sick tag a useful information?
6. Combined with a vocabulary assessment, does the tool help assess a person’s condition?

A further motivation for including the mentioned subgroups in the research is that they are the first-contact staff in school institutions, where part of the population in a given region is most likely to have eating disorders.

3.6 Conclusion

The above chapter discussed the developed methods for analyzing open-ended written notes about body image within the planned scope of research. The decision to use machine learning methods based on the deep recurrent network model was driven by the goal of prototyping and initially automating the classification process within the developed categories, thereby supporting the next stage of diagnosing a person's condition. In turn, the purpose of using dictionary methods was to elicit and designate individual tokens (words) to the desired parts of speech category. The next step was to detect characteristic terms, which could outline certain subtle linguistic features of the patient in an even more precise way and be helpful in further diagnostics. The final section of the chapter presented the evaluation method for assessing the proposed solution by psychologists and first-contact staff.

4. Results

This chapter presents the results obtained using the developed methods following the order of procedures presented in Chapter 3. The first section presents the results of the automatic classification of notes within 4 designated flags (categories). In the next step, the results of vocabulary statistics, separating individual POS, and grammatical and lexical analysis were discussed, including the presentation of keywords and entries referring to the body. The final section focused on presenting and discussing the results for the characteristic vocabulary describing the body in the psychological context, towards which the study participants demonstrate their feelings and the relationship between the mind and the body. The results were presented for three groups of collected notes: notes of people who have anorexia (research group), healthy people (control group), and people suffering from eating disorders as a result of head-neck cancer (HNC patients group). These are patients at risk of problems resulting from changes in appearance due to progressive disease and invasive treatment.

4.1 Results of automatic classification of notes in the proposed categories

Table 4.1 presents the results of the automatic classification of notes in the proposed 4 categories: healthy/sick, sentiment, past tense and irony [100]. The proposed categories were established with experts specializing in diagnosing and treating eating disorders. They also resulted from the ambiguity of words used by the participants within the diagnosis of eating disorders.

Tab. 4.1: The results of misclassification error in machine learning method [100].

Flag Parameter	Healthy / Sick	Sentiment	Past Tense	Irony
	Misclassification Error (%)			
Experiment 1	26.9	63.2	**10.0**	**3.5**
Experiment 2	**18.3**	52.6	21.1	10.8
Experiment 3	30.9	**38.3**	30.9	15.4

Different accuracy and misclassification error was obtained for different categories tested. It implies the validity of using different data schemes when training classification models. The poorer results were revealed to be in the sentiment category. This finding implies that automatic sentiment analysis is insufficient for computer-aided diagnosis of eating disorders. The remaining categories have a validity of potential use.

In the proposed research scheme, a separate classifier instance trained each designed category. As the results indicate, various values of misclassification error were observed - Table 4.1. At the same time, the lowest error values for different categories occurred for different patterns of data use (healthy/sick - Experiment 2, sentiment - Experiment 3, past tense - Experiment 1, irony - Experiment 1). More detailed results, divided into subgroups according to expert flag values, are presented in the Figures 4.1-4.4 and Tables 4.2-4.5. Analyzing the obtained results in more detail, as previously mentioned, different levels of misclassification error but balanced across subgroups within a given category.

a) Experiment 1

Target / Output	Healthy	Sick	SUM
Healthy	27.86%	11.94%	70.00% 30.00%
Sick	14.93%	45.27%	75.21% 24.79%
SUM	65.12% 34.88%	79.13% 20.87%	73.13% 26.87%

b) Experiment 2

Target / Output	Healthy	Sick	SUM
Healthy	25.50%	9.56%	72.73% 27.27%
Sick	8.76%	56.18%	86.50% 13.50%
SUM	74.42% 25.58%	85.45% 14.55%	81.67% 18.33%

c) Experiment 3

Target / Output	Healthy	Sick	SUM
Healthy	25.87%	13.93%	65.00% 35.00%
Sick	16.92%	43.28%	71.90% 28.10%
SUM	60.47% 39.53%	75.65% 24.35%	69.15% 30.85%

Fig. 4.1: Confusion Matrix for flag "Healthy/Sick" in experiments 1-3.

Tab. 4.2: Statistical measures for flag "Healthy/Sick" in experiments 1-3.

Class Name	Experiment 1			Experiment 2			Experiment 3		
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
Healthy	0.700	0.651	0.675	0.727	0.744	0.736	0.650	0.605	0.627
Sick	0.752	0.791	0.771	0.865	0.865	0.860	0.719	0.281	0.737
Accuracy	0.731			0.817			0.692		
Misclassification Error	0.269			0.183			0.308		
Weighted F1-score	0.730			0.817			0.690		

a) Experiment 1

Target / Output	Sent. POS	Sent. NEG	SUM
Sent. POS	15.92%	36.32%	30.48% 69.52%
Sent. NEG	26.87%	20.90%	43.75% 56.25%
SUM	37.21% 62.79%	36.52% 63.48%	36.82% 63.18%

b) Experiment 2

Target / Output	Sent. POS	Sent. NEG	SUM
Sent. POS	8.76%	27.09%	24.44% 75.56%
Sent. NEG	25.50%	38.65%	60.25% 39.75%
SUM	25.58% 74.42%	58.79% 41.21%	47.41% 52.59%

c) Experiment 3

Target / Output	Sent. POS	Sent. NEG	SUM
Sent. POS	23.38%	18.91%	55.29% 44.71%
Sent. NEG	19.40%	38.31%	66.38% 33.62%
SUM	54.65% 45.35%	66.96% 33.04%	61.69% 38.31%

Fig. 4.2: Confusion Matrix for flag "Sentiment Pos/Neg" in experiments 1-3.

Tab. 4.3: Statistical measures for flag "Sentiment Pos/Neg" in experiments 1-3.

Class Name	Experiment 1			Experiment 2			Experiment 3		
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
Sentiment Positive	0.305	0.372	0.335	0.244	0.256	0.250	0.553	0.547	0.550
Sentiment Negative	0.438	0.365	0.398	0.602	0.588	0.595	0.664	0.670	0.667
Accuracy	0.368			0.474			0.617		
Misclassification Error	0.632			0.526			0.383		
Weighted F1-score	0.371			0.477			0.617		

a) Experiment 1

Target / Output	Past Tense	No Past Tense	SUM
Past Tense	38.31%	5.47%	87.50% 12.50%
No Past Tense	4.48%	51.74%	92.04% 7.96%
SUM	89.53% 10.47%	90.43% 9.57%	90.05% 9.95%

b) Experiment 2

Target / Output	Past Tense	No Past Tense	SUM
Past Tense	25.10%	11.95%	67.74% 32.26%
Sick	9.16%	53.78%	85.44% 14.56%
SUM	73.26% 26.74%	81.82% 18.18%	78.88% 21.12%

c) Experiment 3

Target / Output	Past Tense	No Past Tense	SUM
Past Tense	23.38%	11.44%	67.14% 32.86%
Sick	19.40%	45.77%	70.23% 29.77%
SUM	54.65% 45.35%	80.00% 20.00%	69.15% 30.85%

Fig. 4.3: Confusion Matrix for flag ”Past Tense” in experiments 1-3.

Tab. 4.4: Statistical measures for flag ”Past Tense” in experiments 1-3.

Class Name	Experiment 1			Experiment 2			Experiment 3		
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
Past Tense	0.875	0.895	0.885	0.677	0.733	0.704	0.671	0.547	0.603
No Past Tense	0.920	0.904	0.912	0.854	0.818	0.836	0.702	0.800	0.748
Accuracy	0.900			0.789			0.692		
Misclassification Error	0.100			0.211			0.308		
Weighted F1-score	0.901			0.791			0.686		

a) Experiment 1

Target / Output	Irony	No Irony	SUM
Irony	40.30%	1.00%	97.59% 2.41%
No Irony	2.49%	56.22%	95.76% 4.24%
SUM	94.19% 5.81%	98.26% 1.74%	96.52% 3.48%

b) Experiment 2

Target / Output	Irony	No Irony	SUM
Irony	29.08%	5.58%	83.91% 16.09%
No Irony	5.18%	60.16%	92.07% 7.93%
SUM	84.88% 15.12%	91.52% 8.48%	89.24% 10.76%

c) Experiment 3

Target / Output	Irony	No Irony	SUM
Irony	35.82%	8.46%	80.90% 19.10%
No Irony	6.97%	48.76%	87.50% 12.50%
SUM	83.72% 16.28%	85.22% 14.78%	84.58% 15.42%

Fig. 4.4: Confusion Matrix for flag ”Irony” in experiments 1-3.

Tab. 4.5: Statistical measures for flag "Irony" in experiments 1-3.

Class Name	Experiment 1			Experiment 2			Experiment 3		
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
Irony	0.976	0.942	0.959	0.839	0.849	0.844	0.809	0.837	0.823
No Irony	0.958	0.983	0.970	0.921	0.915	0.918	0.875	0.852	0.863
Accuracy	0.965			0.892			0.846		
Misclassification Error	0.035			0.108			0.154		
Weighted F1-score	0.965			0.893			0.846		

The highest error values were for the "sentiment" category. Therefore, the results of the other proposed methodology based on the dictionary method of sentiment assessment are presented in the further section of the chapter.

4.2 Results of sentiment assessment using the dictionary method

Due to the unsatisfactory results obtained in the automatic classification method in the sentiment category, the results of sentiment analysis obtained using the dictionary method are shown in Figure 4.5 and Table 4.6. The obtained classification error values from the dictionary method are within 13%. A balanced error rate is also observed within the sentiment category subgroups.

Output \ Target	Sent. POS	Sent. NEG	SUM
Sent. POS	38.80%	6.50%	85.70% 14.30%
Sent. NEG	6.00%	48.80%	89.10% 10.90%
SUM	86.70% 13.30%	88.3% 11.70%	87.60% 12.40%

Fig. 4.5: Confusion Matrix for flag "Sentiment" in dictionary method experiment.

Tab. 4.6: Statistical measures for flag "Sentiment" in dictionary method experiment.

Class Name	Experiment – Dictionary Method		
	Precision	Recall	F1-score
Healthy	0.857	0.867	0.862
Sick	0.891	0.883	0.887
Accuracy	0.876		
Misclassification Error	0.124		
Weighted F1-score	0.876		

4.3 Results of vocabulary statistics and grammatical-lexical analysis

The study used a dataset of 115 notes from people diagnosed with anorexia and 85 from healthy people. The first part of the analysis focused on determining the part of speech in each note. The study considered verbs, adjectives, and nouns, the personal pronoun "*I*" and the adjective pronoun "*My*". Moreover, in the case of adjectives, they were divided into those with positive and negative connotations. In turn, in the study of verbs, in addition to the general frequency of occurrences in the note, its form (past and present) was also determined. In the analysis, special attention was put to distinguishing the forms of the verb "*to be*" in the past, present and future tense.

4.3.1 Vocabulary statistics analysis results for a set of notes related to anorexia

The results of the analysis of vocabulary statistics for the set of notes related to anorexia presented in the box plot in Figure 4.6 showed that in the case of verbs among the sick participants (research group), the average number of overall uses of this part of speech per note is 5.98, while in the control group is 4.18 (Table 4.7).

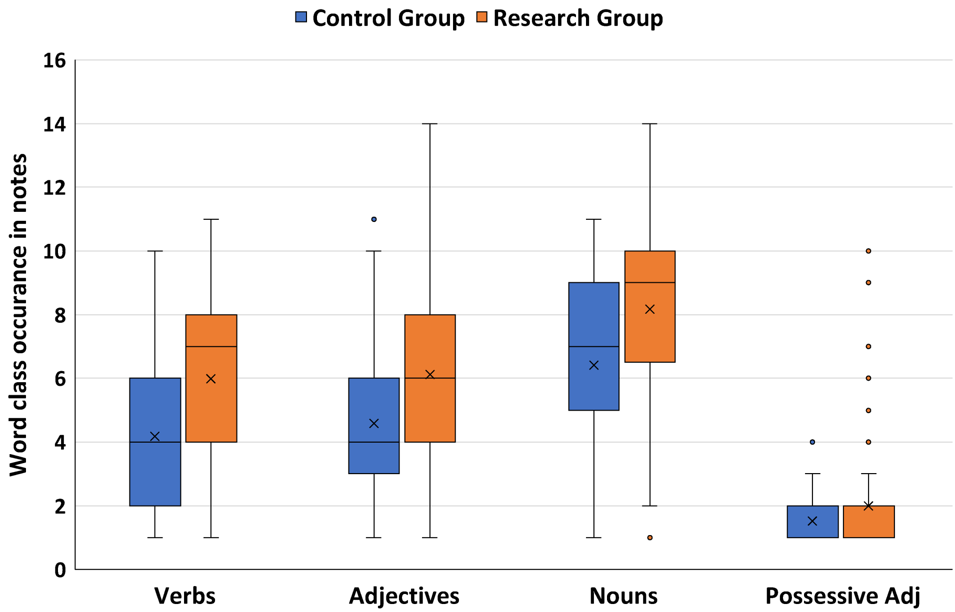

Fig. 4.6: Occurrence of word class categories in control and research group notes.

Tab. 4.7: Word classes analysis for research and control group.

Word Class	**Research Group** Number of notes with the word class occurrence [%] / (average number/median of word class occurrences per note)	**Control Group** Number of notes with the word class occurrence [%] / (average number/median of word class occurrences per note)
Verbs	94.78% (5.98 / 7.00)	70.93% (4.18 / 4.00)
Adjectives	98.26% (6.12 / 6.00)	89.53% (4.60 / 4.00)
Nouns	100.00% (8.18 / 9.00)	98.84% (6.42 / 7.00)
Possessive Adjectives	64.35% (1.99 / 1.00)	54.65% (1.51 / 1.00)

The results of the verb form analysis for individual groups are presented in the Figure 4.7 and in the Table 4.8. Present tense verb matching in the research group was found in almost 93% of the notes, with an average of 4.8. The patients also used references to the past in their statements, as shown by the analysis of the past tense of the verb - the average was 2.76 (43.5% of notes). In the control group, the average occurrence of the present tense per note was 4.07 (almost 71% of notes), and the average of the past tense was 1.17 (around 7% of notes).

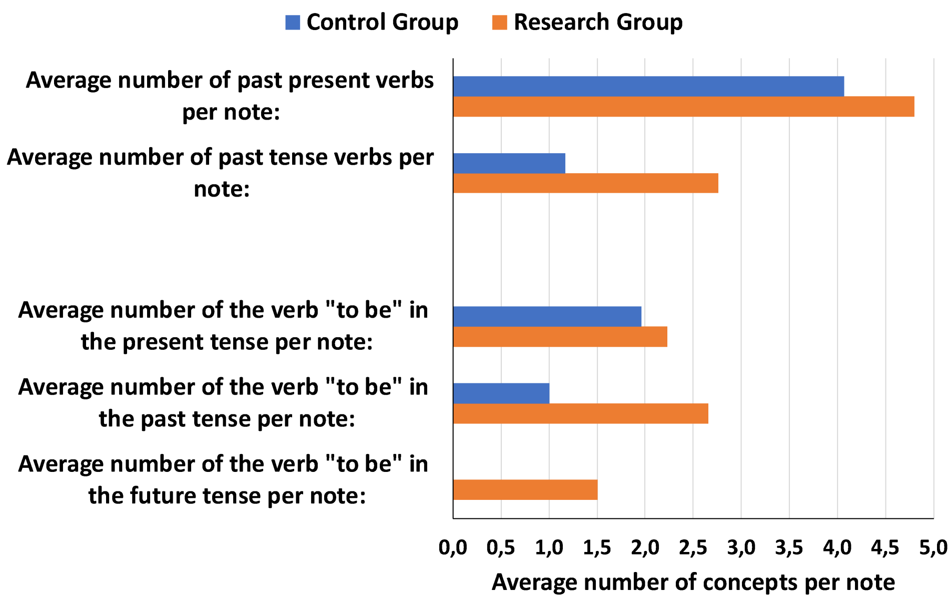

Fig. 4.7: Average number of concepts per note in control and research group notes.

The results of the analysis regarding adjectives show that there was a lot more of this part of speech in the notes of sick people compared to healthy people. The average occurrence of adjectives for the research group was 6.12, which appeared in over 98% of all notes (Table 4.7) and for the control 4.6, respectively, less than 90% of the notes.

The ratio of positive and negative adjectives used in both groups also varies (Table 4.9). Sick people used definitely more negative words, which reflects the ratio of positive to negative within the group and negative within both groups. In the research group the mean of negative adjective was 3.3 and positive only 0.8. These results cover the research assumptions of altered language in AN patients. No significant correlation between positive and negative adjectives in the control group was observed. They used more positive words towards their bodies, with the mean 2.8.

Tab. 4.8: Concept classes analysis for research and control group.

Concept Class	Research Group	Control Group
	Number of notes with the concept occurrence [%] / (average number/median of concept occurrences per note)	Number of notes with the concept occurrence [%] / (average number/median of concept occurrences per note)
Personal pronoun "I"	26.09% (1.83 / 2.00)	5.81% (1.20 / 1.00)
Verb "to be"	74.78% (3.07 / 2.00)	59.30% (1.98 / 2.00)
Noun Group	79.13% (3.14 / 3.00)	77.91% (3.21 / 3.00)
Verb "to be" in present form	65.22% (2.23 / 2.00)	59.30% (1.96 / 2.00)
Verb "to be" in past form	27.83% (2.66 / 2.00)	1.16% (1.00 / 1.00)
Verb "to be" in future form	6.96% (1.50 / 1.00)	0.00% (0.00 / 0.00)
Verbs in present form	93.04% (4.80 / 4.00)	70.93% (4.07 / 4.00)
Verbs in past form	43.48% (2.76 / 3.00)	6.98% (1.17 / 1.00)

Tab. 4.9: Average number of positive and negative adjectives occurrence in control and research group notes.

	Negative Adjectives	**Positive Adjectives**
Control Group	1.8	2.8
Research Group	3.3	0.8

In the case of nouns, in both groups, this part of speech was used most frequently, which is understandable considering its function. They appeared in practically one hundred per cent of the notes in the studied groups (Table 4.7). However, in this case, the results differ again, where for the research group, the average use of nouns was 8.18 and in the control group 6.42.

In the next studied class, the frequency of occurrences of the possessive pronoun was analyzed (Figure 4.6 and Table 4.7). In both groups, compared to other parts of speech, the use of the word "*My*", with its case declension was much less frequent, but the difference between the groups was small. In the group of sick people, the average number of occurrences was 1.99; in the healthy ones, it was 1.51.

The results of the analysis for the use of the personal pronoun "*I*", the verb "*to be*" and the frequency of occurrences of "*Noun Group*" are presented in the Figure 4.8 and Table 4.8.

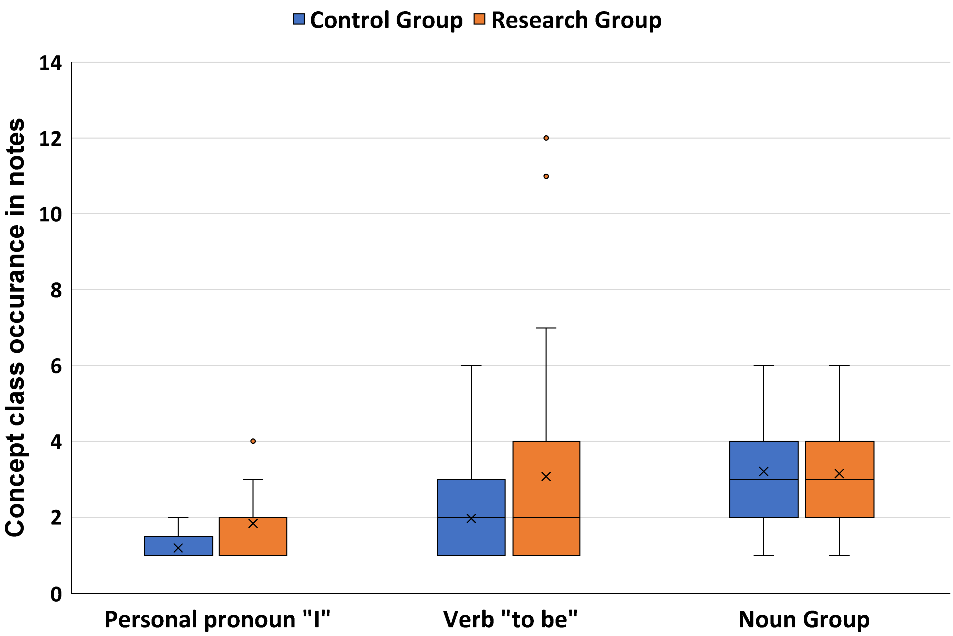

Fig. 4.8: Occurrence of concept class categories in control and research group notes.

According to the data, in the case of the pronoun "*I*", patients in the research group used it more often (average almost 2) than healthy people, with an average of 1.2. Although this difference is not significant, it is worth noting that in the research group, this part of speech appeared in over 26% of notes, and in the control group, only in 5.81%.

The following analysis results, namely of the verb "*to be*" showed a significant difference in its use in the studied groups. The notes of people with AN showed that the average match was 3.07, and in healthy people, it was 1.98. As part of the analysis of the verb form "*to be*", in over 65% of the notes of people with AN, it was shown that this verb was used in the present tense (average 2.23), over 27% in the past tense (average 2.66) and almost 7% in the future tense (average 1.50). However, the same analysis for healthy people revealed the presence of this verb in the present tense in almost 60% of notes (average 1.96) and the past tense only in 1.16% of notes with an average occurrence of 1.0. However, there were no references to the future tense.

Analysis results for *Noun Group* revealed that the mean of matches in both groups was similar and amounted to 3.1 and 3.2 for the research and control groups, respectively, in about 80% of notes.

4.3.2 Results of vocabulary statistics analysis for notes in HNC patients group

The analysis of notes for a dataset related to eating disorders due to HNC treatment concerned the same parts of speech. However, considering the different etiology and course, an additional measure was introduced for the frequency and form of the verb "*to be*" regarding future tense. The reason for this approach concerned the specificity of the disease and the desire to illustrate the patient's attitude depending on the phase of the disease.

According to the results presented in the Figure 4.9 and the Table 4.10 the average use of verbs was 4.09, this part of speech appeared in 92% of the notes. Research on the verb form gave the following results: the average use per note in the present tense was 3.50 and in the past tense 1.42, indicating that patients focus more on the present. In the case of adjectives, their average use per note was 3.98, they occurred in 96% of the notes.

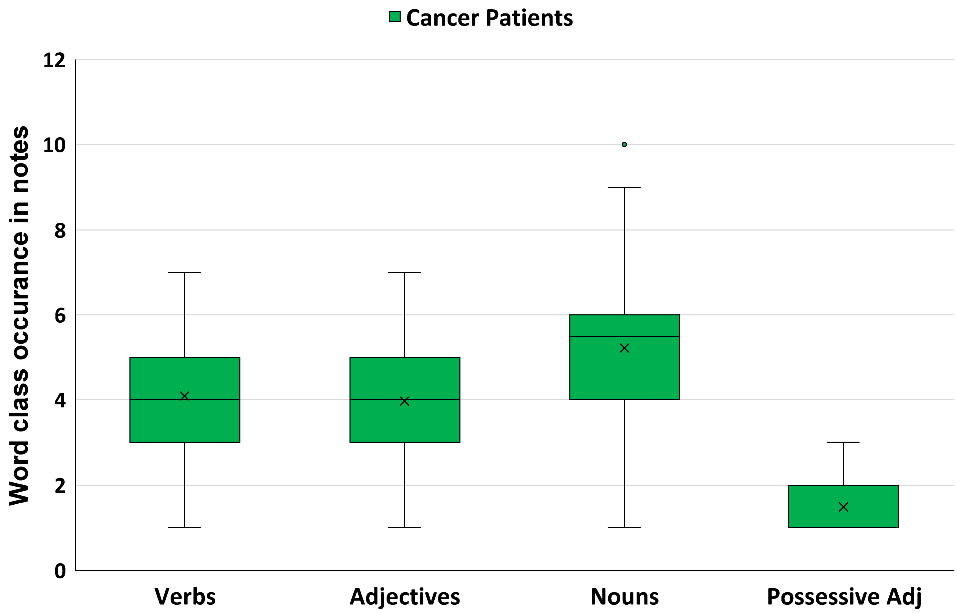

Fig. 4.9: Occurrence of word class categories in HNC patients notes.

Tab. 4.10: Word classes analysis for cancer patients.

Word Class	**Cancer Patients** Number of notes with the word class occurrence [%] / (average number/median of word class occurrences per note)
Verbs	92.00% (4.09 / 4.00)
Adjectives	96.00% (3.98 / 4.00)
Nouns	100.00% (5.22 / 5.50)
Possessive Adjectives	50.00% (1.48 / 1.00)

The results also focused on labelling adjectives as positive and negative at specific stages of treatment (Table 4.11). In phase I, an average of 14.45% negative adjectives and 1.83% positive adjectives were extracted. In the next phase, an increase in positive adjectives up to 4.30% and a simultaneous decrease in those with a negative polarity (6.81%) occurred. In phase III, the results revealed a renewed increase in negative words (11.65%), which was smaller than in phase I. On the contrary, in the case of positive words, the average percentage was 3.61, which was a better result compared to phase I. To sum up, the tests indicated that the most balanced results were for phase II because the difference between positive and negative results was 2.51%. The greatest difference in this respect was in phase I (difference of 12.62%) and in phase III (8.04% difference).

Tab. 4.11: Average percentage of positive and negative adjectives per patient note [143].

Phases of Treatment	Negative Adjectives	Positive Adjectives
Phase 1	14.45%	1.83%
Phase 2	6.81%	4.30%
Phase 3	11.65%	3.61%

The next stage of the research analysed the frequency of occurrences of the pronoun "*I*", the verb "*to be*" in various forms, and *Noun Group*. As the results in the Figure 4.10 and in the Table 4.12 show, only 6% of the notes contained the pronoun *I*, the average being 1.33.

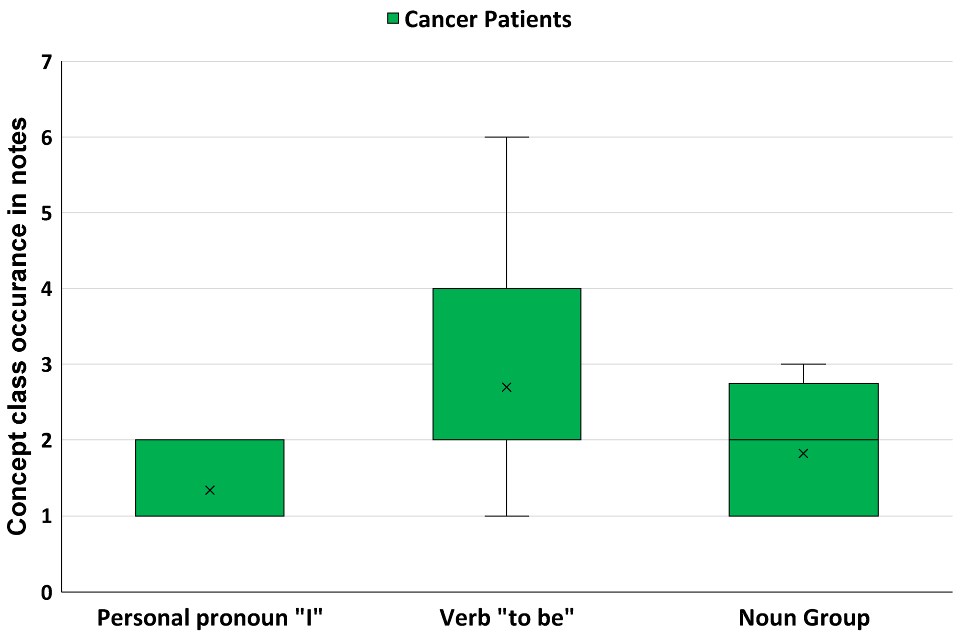

Fig. 4.10: Occurrence of concept class categories in HNC patients notes.

Tab. 4.12: Concept classes analysis for cancer patients.

Concept Class	Cancer Patients Number of notes with the concept occurrence [%] / (average number/median of concept occurrences per note)
Personal pronoun "I"	6.0% (1.33 / 1.00)
Verb "to be"	80.00% (2.70 / 2.00)
Noun Group	56.00% (1.82 / 2.00)
Verb "to be" in present form	80.0% (2.23 / 2.00)
Verb "to be" in past form	14.00% (1.29 / 1.00)
Verb "to be" in future form	20.00% (1.00 / 1.00)
Verbs in present form	92.00% (3.50 / 3.00)
Verbs in past form	70.93% (1.42 / 1.00)

The verb "*to be*" was detected in 80% of the notes, with an average of 2.70. Analysis of verb form (Figure 4.11) revealed the occurrence in 80% of the notes in the present tense (average 2.23), 14% (average 1.29) in the past tense, and future tense in 20% of the text, with an average use per note of 1.

The results confirmed that cancer patients focused mainly on the present condition. Within the Noun Group, an average of 1.82 was obtained, in 56% of notes in the group.

The sentiment analysis assumed three polarity references: positive (1), neutral (0), and negative (-1). The Figure 4.12 shows the percentage of notes in each stage with sentiment tagging. Based on the results, 9% of notes in the first stage were tagged as positive, 27% neutral, and 64% were negative. The second stage encompassed 32 notes, of which 29% were positive, 18% neutral, and 53% were negative. The palliative stage (stage III) assessed seven patients' notes, where 14% had a positive sentiment, 29% neutral, and 57% negative [143].

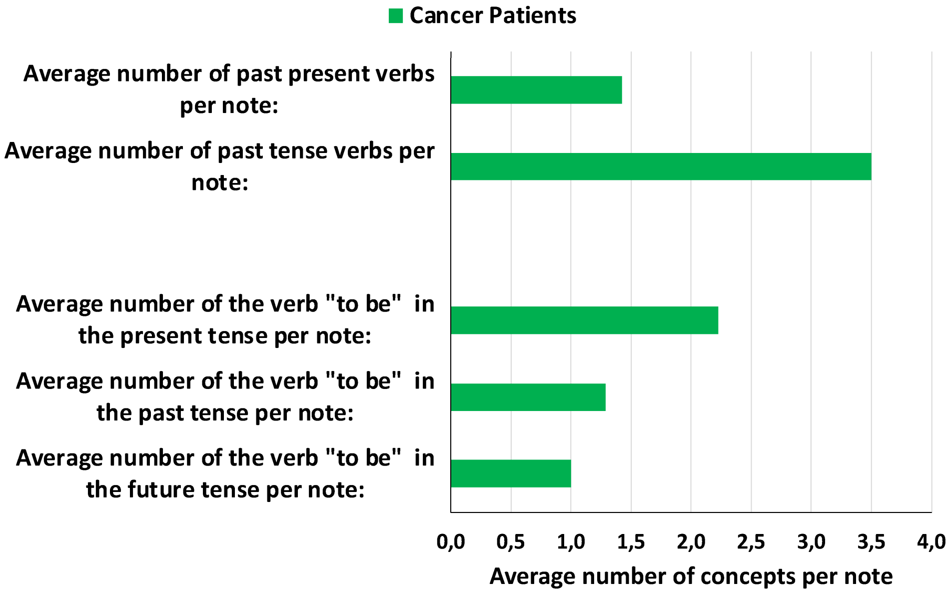

Fig. 4.11: Average number of concepts per note in HNC patients notes.

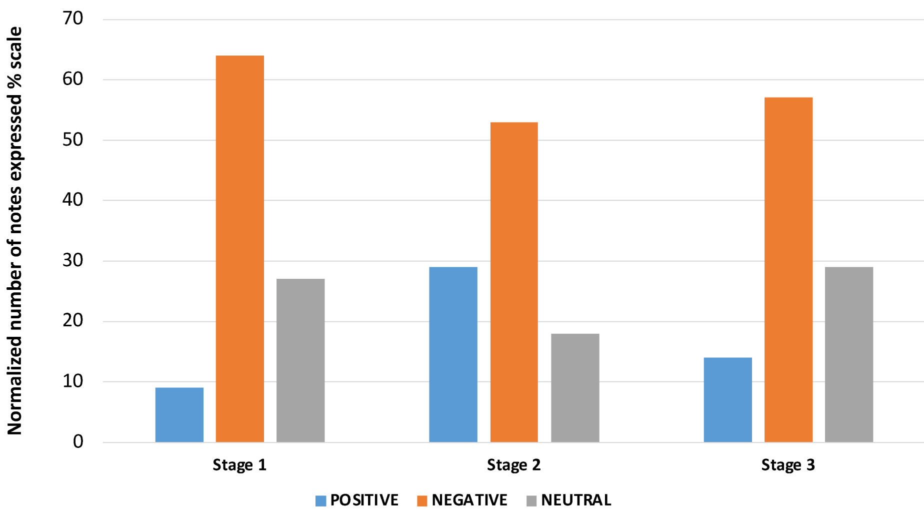

Fig. 4.12: Sentiment analysis in particular treatment stages of HNC patients notes [143].

4.3.3 Detailed lexical analysis

This part of the research comprises results received for specific terms among tested groups of participants. The first section provides findings for general keywords referring to the body. The further section depicts characteristic words or phrases related to specific body parts. The last part of this sub-chapter focuses on results regarding the occurrence of cognition words in all groups. The notes prepared by participants were in Polish language. Therefore, the figures in this section were purposely prepared in the Polish language to maintain the semantic originality of the notes.

Key terms and vocabulary associated to body image

Detailed text analysis among 3 different groups of participants allowed for extracting characteristic words, defined as general entries indicating a person's positive or negative relationship with their body. The findings for the research group are illustrated in Figure 4.13.

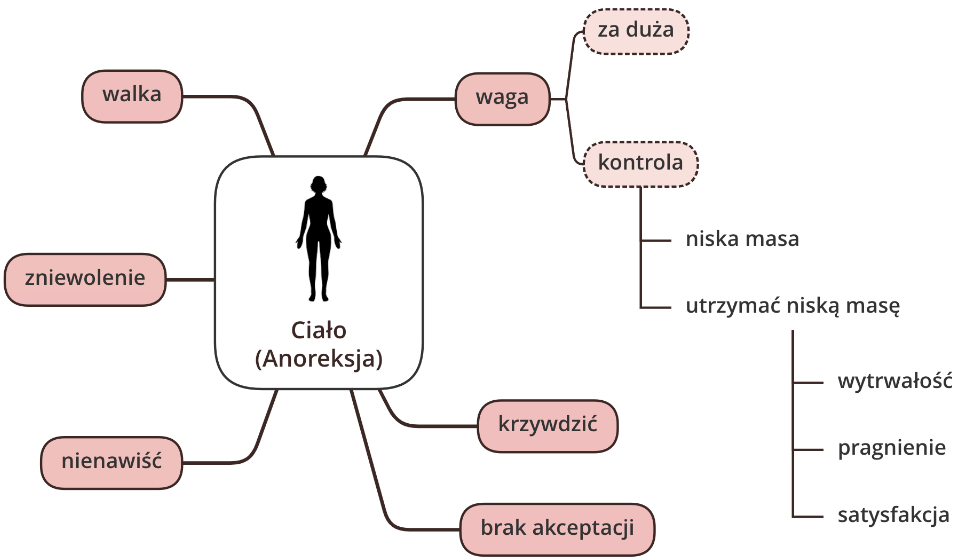

Fig. 4.13: Body key terms for anorexia patients.

The results suggest these relationships are negative and indicate the individual's struggle with his or her body. Among patients with anorexia, there is a noticeable fixation on weight, which is the epicentre that gives them some strength to act and satisfaction from achieving or maintaining a low body weight. The attached diagram also shows that, according to literature reports, the body is a source of strong, negative emotions and causes pain in the psychological sense. These people treat their bodies as an enemy; they feel disgust and hatred. The body image from the perspective of a person with AN differs from reality. Despite the extremely low body weight, the patient does not feel satisfied and constantly strives to achieve the result created in her consciousness.

The results obtained within the same category of tests for the control group, presented in Figure 4.14, clearly differ from those of sick people. The detected keywords indicate a serene attitude towards the body. The study participants spoke positively about their bodies, even though some statements contained negative comments. Healthy people were aware of their imperfections and treated their bodies as vital. The most important terms revealed by the analysis included distance from having an imperfect appearance, respect for themselves and their bodies, the desire to be healthy, and, most notably, for body image, acceptance.

The last group included notes from people suffering from HNC. The results, illustrated in Figure 4.15 showed that despite the great diversity of this group in terms of age, gender or phase of the disease, in general, they are balanced in terms of the polarity of notes.

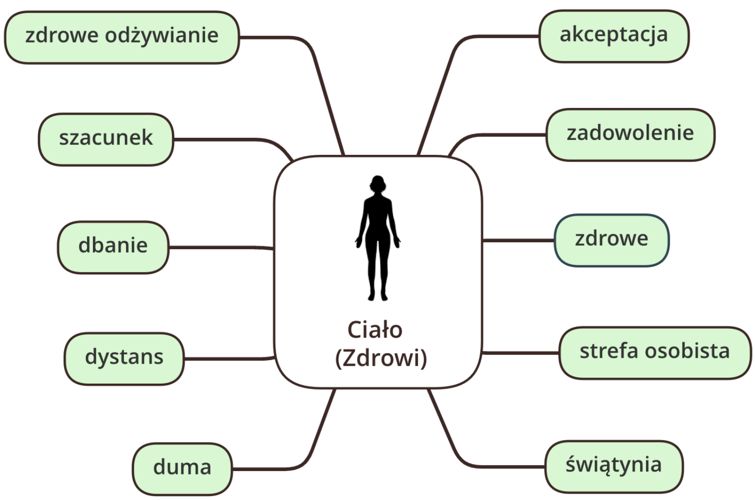

Fig. 4.14: Body key terms for health group.

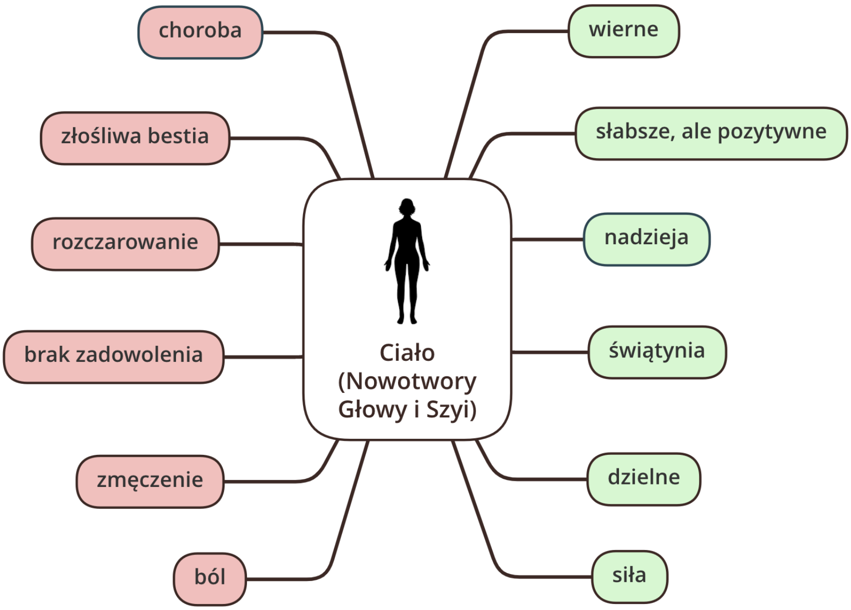

Fig. 4.15: Body key terms for HNC patients.

The analysis partially revealed words with a negative connotation among the characteristic keywords. However, the patients did not use them to express hatred or dissatisfaction with appearances that deviate from established beauty standards; rather, their use was understandably a result of the disease and its treatment. The most frequently occurring terms were illness, disappointment, dissatisfaction, fatigue, and pain. Some statements portrayed the disease as a beast or an adversary that had taken over their bodies, compelling them to engage in a relentless battle. On the contrary, their body, although weak and damaged, is a temple, a source of strength and hope, and a faithful companion.

The research findings presented above helped determine the key terms in each group of participants. The research tests highlighted significant differences among groups and a general conceptual framework to illustrate the differences in the approach to body image depending on the mental condition. The satisfactory results were consistent with the previous results. Therefore, a more detailed quantitative analysis of words was conducted to strengthen the study assumptions.

In this part of the research, notes were searched for matches of terms related to the word "*body*" (ciało) and its parts, such as legs, belly, and face.

According to the attached Figure 4.16, numerous matches to the body as a whole were found in the group of people with anorexia. Following the previous assumptions, the detected terms have a negative connotation. Those people are reserved towards their body size: ”*big*” (wielkie), ”*fat*” (grube), ”*plump*” (otyłe), attractiveness: ”*ugly*” (brzydkie), ”*unattractive*” (nieatrakcyjne), ”*needs improvement*” (do poprawy), or, having some awareness of the effects of the disease, they used descriptions of their actual physicality: ”*wasted*” (wyniszczone), ”*bony*” (kościste), ”*without muscles*” (bez mięśni). Interestingly, in the group of AN, there were many references to other parts of the body, which were the most problematic from the point of view of the disease. Most matches were found on the abdomen, legs, hair, skin, and face. Regarding legs, belly and fat tissue, the analysis mainly showed words such as: ”*obese*” (otyłe), ”*fat*” (grube), ”*hanging belly/fat*” (obwisły brzuch), and ”*fatty*” (otłuszczone). When referring to the face and skin, the patients used the terms: ”*dry*” (sucha), ”*with stretch marks*” (z rozstępami), ”*sagging*” (zwisająca), ”*emaciated face*” (wychudła), and ”*wrinkles*” (zmarszczki). These terms are also used negatively, but they show the consequences of the patients’ actions, which are also not satisfying for them.

It raises an interesting conclusion about a certain contradiction about one’s body. It seems that patients who want to achieve a slimmer body are not aware of the consequences of draconian diets. They are not aware that it primarily affects the appearance of the skin. A diet low in calories and the appropriate amount of nutrients leads to several disorders in the appearance of the skin, such as dryness, dehydration, difficulties in wound healing, and the formation of pigmentation lesions (Figure 4.16 – SKIN (SKÓRA)).

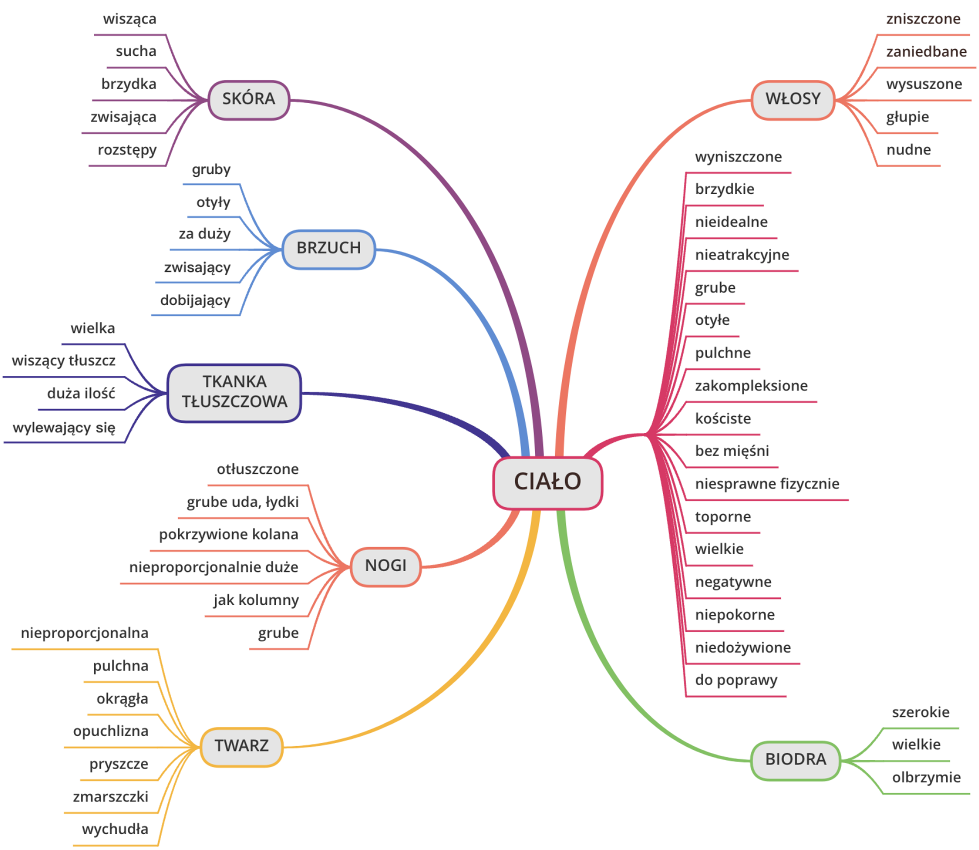

Fig. 4.16: Matched vocabulary related to body for anorexia patients.

The most remarkable conclusion to emerge from the results indicates a paradox in the behaviour of AN patients, contradictions between the subjective perception of one's own body and objective physical results. Moreover, the obtained results confirm perceptual and emotional disorders, indicating a disturbed body image, and emphasize the need for a holistic approach to the treatment, in particular therapy that rebuilds a positive perception of one's own body.

Vocabulary analysis of healthy people and people suffering from head and neck cancer showed that relationships with one's body are positive or very positive in the control group (Figure 4.17). The most frequent terms related to physicality included: "*athletic*" (wysportowane), "*muscular*" (umięśnione), "*slim*" (szczupłe), "*age of the body mature*" (dojrzałe), or those indicating the physiological state: ”*healthy*” (zdrowe), ”*full of energy*” (pełne energii). A common feature of all notes in the control group was the use of many concepts describing or intensifying the attractiveness of the body: ”*beautiful*” (piękne), ”*charming*” (powabne), ”*shapely*” (zgrabne), ”*great*” (super), ”*oasis of peace*” (oaza spokoju), ”*perfect*” (idealne), which clearly indicates the harmony and acceptance of the individual with the body. Healthy people differentiated their statements about the body by referring to their legs, belly, face and skin Figure 4.17 – SKIN (SKÓRA), LEGS (NOGI), FACE (TWARZ), BELLY (BRZUCH). In all these categories, terms indicating acceptance and satisfaction with one's body dominated.

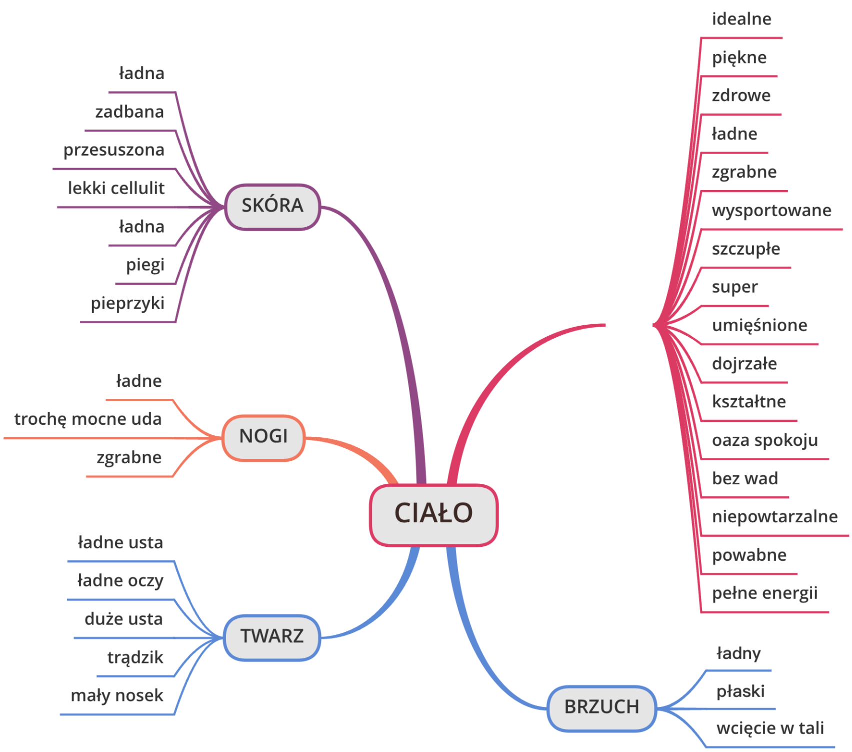

Fig. 4.17: Matched vocabulary related to body for health group.

In contrast, the results for HNC patients, presented in Figure 4.18 , showed that the only detailed references to other body parts concerned skin and hair.

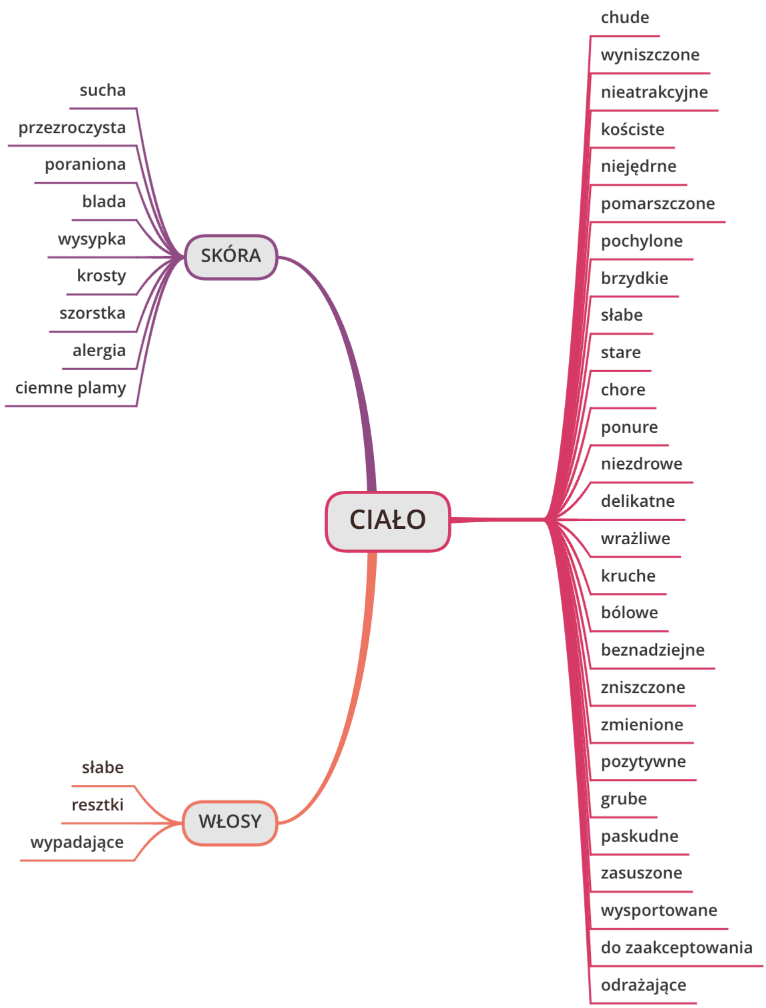

Fig. 4.18: Matched vocabulary related to body for head and neck cancer patients.

Patients complained about skin problems related to dryness, rashes, allergies, and spots. They used words such as: ”*pale*” (blada), ”*wounded*” (poraniona), ”*transparent*” (przezroczysta), and ”*rough*” (szorstka) skin in their statements. In turn, they described their hair as: ”*weak*” (słabe), ”*falling out*” (wypadające) and as ”*remnants due to chemotherapy*” (resztki po chemioterapii). The results regarding the body are characterised mainly by negative emotions. The body was often referred to as: "*weak*" (słabe), "*emaciated*" (wyniszczone), "*sick*" (chore), "*unhealthy*" (niezdrowe), "*painful*" (bólowe), "*dried*" (zasuszone) and "*nasty*" (paskudne). Other terms may indicate a strong empathy towards one's body and concern, as indicated by terms such as: "*delicate*" (delikatne), "*sensitive*" (wrażliwe), "*altered*" (zmienione), and "*fragile*" (kruche).

To summarize, the detailed analysis of vocabulary highlighted a strong negative emotion of body adjustment among patients with anorexia. In the control group, the same analysis provided opposite results. In this group, people are aware of their physical imperfections, but this does not distort their body image. On the contrary, being subjectively aware of their flaws, they balance them by exposing and focusing on other positive attributes, or try to deal with their imperfections in a responsible way. In the group of people with cancer, the analysis showed a balance between positive and negative words.

Moreover, these patients did not provide detailed descriptions of individual body parts in their statements, which is most visible in the group of AN patients. The vocabulary contained primarily deals with the body as a whole. Despite a similar negative narrative towards the body as in the case of the research group, dissatisfaction with appearance in the cancer group has a different context and psychological basis. To sum up, the results stand as a crucial guideline for the therapist, as they can help select the appropriate therapy that supports building good relationships within oneself.

Cognition words analysis

Cognitive words were another category considered in the study. Table 4.13, presents the obtained results. It has been proven that people with AN frequently used terms related to self-control and self-esteem, such as: "*control*" (kontrolować), "*be careful*" (być ostrożnym) and "*think*" (uważać). The notes also included words expressing emotional state. As expected, negative emotions and self-criticism predominated in this comparison, which demonstrated words such as: "*be ashamed*" (wstydzić sie), "*hate*" (nienawidzić), and "*worry*" (martwić się), "*dislike*" (nie lubić), or "*care*" (przejmmować się). This illustrates their dissatisfaction with their appearance and mental struggles. The analysis also revealed terms of how an individual thinks and processes information. The patients often used terms such as: "*perceive*" (postrzegać) and "*evaluate*" (oceniać), "*seem*" (wydawać się), and "*understand*" (rozumieć). It brought essential information about self-awareness of their feelings, thoughts, and even actions. However, referring to these terms towards the body may indicate focusing on analyzing and assessing oneself.

The analysis also showed the presence of words related to desires and beliefs, including: "*believe*" (wierzyć), "*want*" (chcieć), "*need*" (potrzebować), "*decide*" (decydować), and "*must*" (musieć). They indicate confidence in the success of the patient's actions and in achieving set goals. Term "*need*" may have two aspects; it may indicate a desire for acceptance or control, or it may mean a desire to change or improve one's condition and the willingness to undergo treatment.

In the category of healthy people, a positive attitude occurred through the use of words such as: "*enjoy*" (cieszyć się), "*like*" (lubić) and "*appreciate*" (doceniać), which indicates a generally positive and grateful approach to oneself and one's body. These people showed a balanced view and self-distance, as well as the ability to reflect, using terms like: "*think*" (myśleć) and "*accept*" (akceptować). In contrast, the study found much higher concern for health, uncertainty, and the fight against pain in the HNC group. Surprisingly, the patients simultaneously expressed hope using the words: "*believe*" (wierzyć) and "*hope*" (mieć nadzieję).

Overall, anorexia patients focused heavily on self-control and negative self-esteem, while cancer patients balanced their negative experiences with moments of hope and faith. The most visible difference in the results obtained in these two groups confirms the prior considerations confirmed by the results that the vocabulary with a negative connotation in AN involves internal self-assessment and self-control to achieve an unrealistic goal compared to the physical (external) fight for health in cancer patients. In comparison, healthy people demonstrate a balanced and positive approach to themselves.

Considering the results from all categories in vocabulary analysis (key terms, detailed vocabulary analysis, and cognitive words analysis), the research group (AN) obtained the most terms compared to the other groups. The same applies to the detailed description of the body, i.e., in their notes, AN patients paid more attention to particular parts of the body, toward which they felt negative emotions. In other groups, this tendency towards detailed descriptions decreased. The same observations apply to cognitive word occurrence.

Tab. 4.13: Results for cognition words analysis.

Anorexia patients	**Health group**	**Cancer patients**
akceptować	akceptować	akceptować
bać się	cieszyć się	bać się
być	czuć	boleć
cenić	decydować	być bez znaczenia
chcieć	koncentrować	być rozczarowany
cieszyć się	lubić	być zadowolony
czuć	mieć świadomość	chcieć
doceniać	myśleć	czuć się
kontrolować	nie lubić	czuć się świetnie
kwestionować	niepokoić się	krępować się
lubić	opinia	lubić
martwić się	percepcja siebie	mieć nadzieja
mieć	pogodziłam się	nie być pewnym
musieć	pokochać	opisać
myśleć	powinnam	postrzegać
nie lubić	starać się	trudno powiedzieć
nie podobać	umożliwiać	utracić
nienawidzić	uważać	wierzyć
oceniać	uważać iż	woleć
patrzeć	wiedzieć	
podobać się	wstydzić się	
postanowić	wybierać	
postrzegać	wyglądać	
potrzebować	zauważać	
prowadzić		
przejmować		
przyjąć		
rozumieć		
udawać się		
ukarać		
uważać		
uwierzyć		
wierzyć		
wpływać		
wstydzić się		
wydawać się		
zaakceptować		
zdrowieć		
zniewolić		
zrozumieć		

4.4 Assessment of the usefulness of developed methods of computer-aided diagnosis of eating disorders by specialists in eating disorders

The usefulness of the developed methods of computer-aided diagnosis of eating disorders was assessed in a survey by psychologists treating eating disorders (n=43). The factor analysis was carried out in 3 grouped issues: relationship with the patient, substantive aspects of diagnosis, and improvement of the psychologist's work comfort (see Chapter 3.5.1). Figure 4.19 and Table 4.14 present the results received from the questionnaire completed by psychologists, normalized to the percent scale.

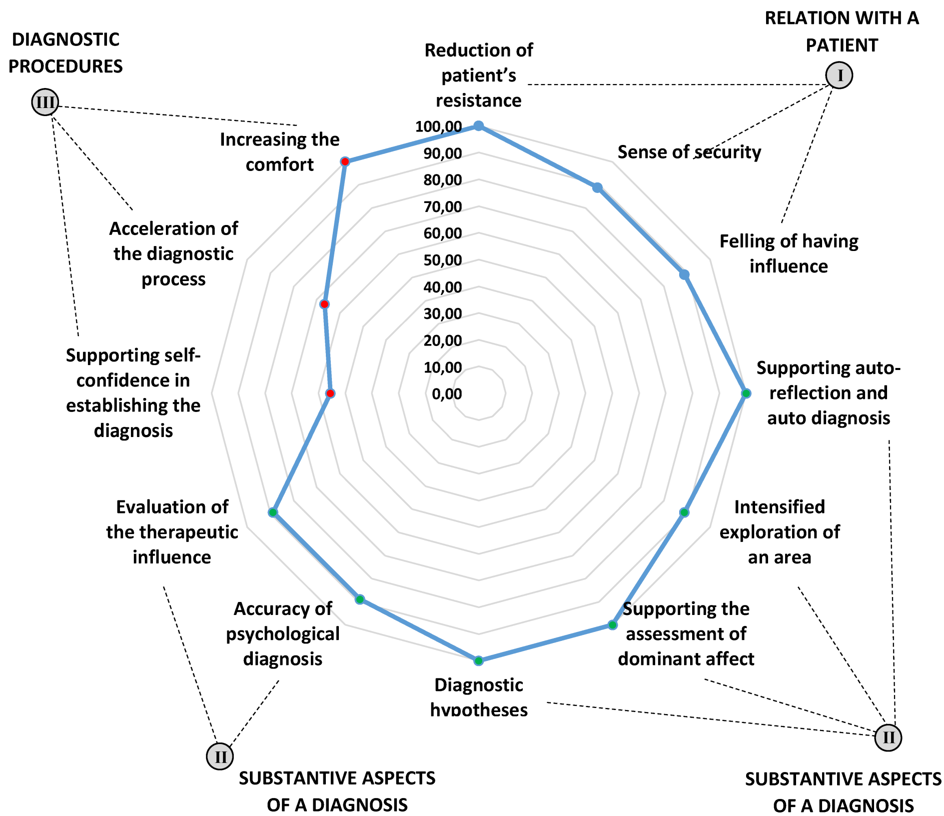

Fig. 4.19: Radar chart presents the results gathered in the particular three categories: relation with a patient, substantive aspects of a diagnosis, and diagnostic procedures (values are the percentage of yes marks) [141].

The study results showed that in the group regarded patient relationship factors (I) 95% of respondents indicated *improvement of the relationship with the patient*, mainly by reducing the patient's resistance. In the group *substantive aspects of diagnosis* (II), 97% of respondents indicated improvement in the aspect of formulating diagnostic hypotheses, which constitutes the main challenge, as it requires the necessary minimally invasiveness due to the severe condition of the patient. In the group of *diagnostic procedures* (III) 100% of respondents indicated improved work comfort, 70% faster diagnosis, and 55% greater confidence in making the diagnosis.

Tab. 4.14: Results received from the questionnaire completed by psychologists, normalized to the percent scale.

		YES	NO	NOT SURE
RELATION WITH A PATIENT	**Reduction of patient's resistance**	100.00	0.00	0.00
	Sense of security	88.89	0.00	11.11
	Felling of having influence	88.89	0.00	11.11
SUBSTANTIVE ASPECTS OF A DIAGNOSIS	**Supporting auto-reflection and auto diagnosis**	100.00	0.00	0.00
	Intensified exploration of an area	88.89	0.00	11.11
	Supporting the assessment of dominant affect	100.00	0.00	0.00
	Diagnostic hypotheses	97.00	0.00	0.00
	Accuracy of psychological diagnosis	88.89	0.00	11.11
	Evaluation of the therapeutic influence	88.89	0.00	11.11
DIAGNOSTIC PROCEDURES	**Supporting self-confidence in establishing the diagnosis**	55.56	0.00	44.44
	Acceleration of the diagnostic process	66.67	000	33.33
	Increasing the comfort	100.00	0.00	0.00

Figure 4.20 shows the evaluation of the proposed methods (see Chapter 3.5.2) by first-contact staff, consisting of psychologists specializing in diagnosing and treating eating disorders, school psychologists and nurses. Detailed results are presented in Table 4.15. Expert Psychologists rated this question at 4.4, highlighting the tool's usefulness in screening studies. The results for

School Counselors/Psychologists were slightly lower, at 3.93, while First Contact Staff (Nurses) were at 3.88, showing general agreement but with slightly less enthusiasm. In the second question, Expert Psychologists and School Counselors/Psychologists provided a very high rating of 4.7 and 4.5, respectively. They suggested strong agreement on the usefulness of sentiment towards the body as an informational metric. First Contact Staff (Nurses) gave it a significantly lower rating of 3.25, indicating some discrepancy in perceived usefulness between different groups. Irony (question 3) was helpful information for the two interviewed groups. The study revealed high ratings among Expert Psychologists (4.4) and School Counselors/Psychologists (4.36). Again, First Contact Staff (Nurses) showed divergence in this issue, with a low rate of 2.88. Slightly worse results were obtained for past tense information (question 4). Experts rated the usefulness of this information at 4.1 and school psychologists at 3.93. The lowest rate was received from nurses who did not perceive the past tense as a helpful category. Category Healthy/Sick (question 5) received the highest ratings overall, with Expert Psychologists at 4.9, School Counselors/Psychologists at 4.86, and First Contact Staff (Nurses) at 4.5. This consensus suggests the high importance of the Healthy/Sick tag among all groups. Similarly, for the last question, ratings were consistent across all groups. Expert Psychologists rated it at 4.4, School Counselors/Psychologists at 4.21, and First Contact Staff (Nurses) at 4.13. It also proved the importance of the research towards assessing a person's condition based on vocabulary assessment.

Tab. 4.15: The results of the feedback from specialists shown according to the Likert scale [100].

Question Number	**Expert Psychologists**	**School Counselors/Psychologists**	**First Contract Staff (Nurses)**
1	4.4	3.93	3.88
2	4.7	4.5	3.25
3	4.4	4.36	2.88
4	4.1	3.93	3.0
5	4.9	4.86	4.5
6	4.4	4.21	4.13

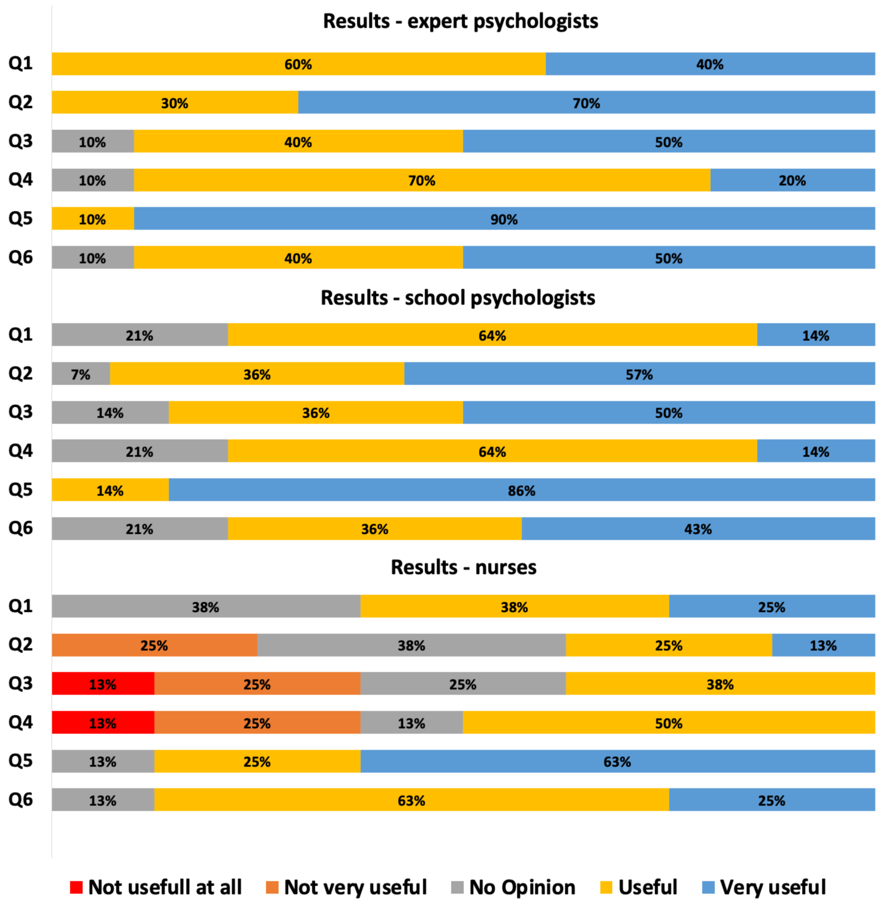

Fig. 4.20: The results of the questionnaire according to the Likert scale [100].

The results highlight generally positive feedback from Expert Psychologists through all questions, with consistently high ratings. The method also received positive feedback from School Counselors/Psychologists, though with slightly lower ratings. On the other hand, First Contact Staff (Nurses) showed more variability in their responses, particularly with lower ratings on Questions 2–4, where their opinions varied from the other groups.

5. Discussion and conclusion

The research subject presented in the doctoral thesis concerned the analysis of medical notes using the projective method. The method was developed with the help of the specialist in eating disorders. The method assumptions were based on open-ended written notes about the attitude towards one's body. The research involved a group of female individuals diagnosed with anorexia, aged 12-19, and a group of potentially healthy students of the same age, meeting the requirements detailed in Chapter 3. Additional group were patients with head and neck cancers in different treatment stages. So far, the considerations indicate a need to develop an automatic tool to support anorexia diagnosis not only for experts but also for first-contact staff. The research confirmed that the proposed method can contribute to understanding the patient better and responding quickly to specific characteristic symptoms. Such a solution would also, as the educators and school psychologists confirmed, have a valuable screening aspect.

Within the research regarding NLP in the context of diagnosing eating disorders, classification methods of notes were proposed. The research used deep recurrent networks and dictionary-based methods (which included all other methods). The classifiers developed for automatic classification in the proposed approach were an initial screening method identifying people at risk of eating disorders.

In the case of classification methods used, deep recurrent networks are referred to as black-box models, which means that it is impossible to interpret how the input data is modified/processed by the model [3, 146]. The proposed approach did not extend the methods for interpreting the results using explainable AI methods, which include the following explanation methods in the field of recurrent networks: gradients-based methods [118], the attention mechanism, layer-wise relevance propagation (LRP) [3, 14, 114, 149], or the SHapley Additive exPlanations (SHAP) [119, 120]. Two important reasons were considered in this approach. The first is the ambiguity of words used by the research participants, where almost every word has many meanings, and the patient selects vocabulary quite subjectively in free speech using the proposed projective method. For example, in the commonly used SHAP method, it is possible to indicate the importance of individual tokens of the input sequence on the decision made by the classifier. Due to the previously mentioned freedom in using vocabulary by the respondents, the research neglected to explore this issue in depth. Moreover, the textual analysis showed that a given word may have a different connotation and meaning depending on the context used. For example, the word "*fat*" may not have a pejorative connotation in every use case. Moreover, the analysis showed that words with a negative connotation were mainly used by sick people, e.g. fat legs and sagging skin. However, in the control group, the same words were used in a different context, which did not indicate the low self-esteem of the examined person. The second reason was the parallel use of dictionary methods, which aimed to determine the characteristic linguistic profile of a person from the eating disorders' perspective. They served as an additional supplement to the research and a deeper explanation of the participant's condition than the use of explainable AI methods. The use of dictionary methods to analyze the vocabulary, word statistics, the diversity of lexical indexes, the length of sentences, or the frequency of occurrence of given words is an increasingly popular object of research to demonstrate changes in the natural language used by people with anorexia. The authors of the work [37] demonstrated significant linguistic differences in a group of people with anorexia who were asked to create a complex description of a standardized illustration depicting an everyday situation related to eating. When describing the illustration mentioned above, sick people used a richer vocabulary for elements of the illustration unrelated to nutrition compared to healthy study participants. They also showed less use of personal pronouns, conjunctions and adverbs. Moreover, their descriptions contained simpler sentence structures.

The classifiers proposed in this work achieved different classification effectiveness depending on the examined category determined by the expert (healthy/sick, past tense, irony, sentiment). The classification error values oscillated at: 3.5% , 10%, 18.3%, 38.3% for irony, past tense, healthy/sick and sentiment, respectively and due to the small dataset size (approximately 200 written notes) serve as empirical results. They generally indicate the possibility of applying the selected classifier architecture, except sentiment analysis. The limitations posed by the small dataset justified the author's decision not to use complex language models, including those with attention mechanisms. The slightly disappointing results for the sentiment category were supplemented with the results obtained with the dictionary method, which generally yielded an error below 13% - see Figure 4.5 and Table 4.6 for the results of the sentiment dictionary method. Comparing the obtained results to the findings achieved by the authors in the work [69], we can conclude that automatic sentiment analysis of documentation of patients with eating disorders gives less satisfactory results than the analysis carried out by specialists. As the authors of the mentioned work point out, the automated form of sentiment analysis is not adapted to the specificity of eating disorders, and it is uncertain whether it will be reliable. Despite the great popularity of sentiment analysis in NLP methods, its use in clinical practice is not common, and such research would require additional verification.

Another point in the research included analysis of the grammatical tense used in the statement. This approach was due to challenges in NLP resulting from the terms' ambiguity. In the context of eating disorders, assessing the current attitude towards one's body is crucial. Hence, the research distinguished various verb forms, focusing on present form as the main point of interest. Furthermore, the study also examined positive references towards the body among AN patients but related to the period before the disease. The findings received were excluded from the established research procedure, though they underlined the importance of further research and provided valuable evidence.

Speaking in more detail, from a psychological point of view, interpreting a patient's current references to the past with a positive connotation is a way of dealing with the costs of the illness and the subconscious desire to return to well-being before the illness. Therefore, such an analysis may help search for appropriate therapy and build appropriate motivation for the patient [62, 150].

Regarding dictionary methods, individuals with anorexia nervosa exhibited a higher frequency of verbs (primarily in the present tense), more negative adjectives, and frequent use of the possessive pronoun "*My*". In contrast, patients with eating disorders resulting from HNC displayed a noticeable dominance of present-tense verbs, with the verb "*to be*" notably prevalent in this form. This group also showed a predominance of adjectives with negative polarity and frequent use of the pronoun "*My*". The vocabulary analysis was further divided into three disease stages for HNC patients: diagnosis, treatment, and palliative. During the diagnosis stage, negative adjectives were concentrated, reflecting an overall negative sentiment. In the treatment stage, patients generally adapted to the disease, leading to a significant reduction in negative attitudes. However, in the palliative stage, negative vocabulary increased once more, attributed to the impossibility of complete recovery.

Psychological diagnosis of individuals suffering from eating disorders, including AN, poses a significant challenge due to its minimally invasive nature, as per the treatment criteria established by the APA [158]. The designed method, developed in collaboration with dr n. med. Katarzyna Rojewska, from the Medical University of Silesia, is a projective method that enables therapists to uncover certain diagnostically valuable areas that the patient may be unaware of, potentially bypassing the patient's control mechanisms [151].

As state-of-the-art in the field of eating disorders points out, the etiology of anorexia and other eating disorders is not fully explored. Current trends highlighted that the prevalence of eating disorders is prevailed by biological factors, while social factors, in particular family relationships, are decreasing in significance. Currently, the family is becoming an ally of the therapist, playing an increasingly important role in the therapy process and taking over the role of restoring standard eating patterns and body weight in the sick adolescent. [90].

All things considered, the research methodology applied elements of NLP to computer-aid the diagnosis of eating disorders, in particular of anorexia and patients in different stages of head and neck cancer. The research chose the projective method for obtaining data about a person's condition, designing an automatic method of classifying notes using RNN, and dictionary methods aimed at eliciting the characteristic patterns of a language conveyed by people with eating disorders.

The following are considered original elements of the work:

1. Establishing the research goals and planning the scope of research based on interviews with psychologists regarding the tools using elements of NLP for computer-aided therapeutic diagnosis of anorexia, obtaining the consent of the Bioethics Committee and compiling a dataset in the research and control groups.

2. Specifying the categories for notes assignment, developing an automatic classification method based on deep recurrent networks and the dictionary-based method.

3. Developing vocabulary analysis methods using POS statistics and detailed linguistic rules to examine and determine the linguistic profile of a person under the research.

4. Analyzing the feedback of the proposed approach among first-contact staff and specialists in eating disorders.

The scope of the completed work and the results of the experiments presented above confirmed the research thesis proposed at the beginning of the dissertation:

The use of elements of natural language processing in participants' written statements about their body image enables computer-aided psychological diagnosis of eating disorders.

5.1 Future work

The research results are encouraging, and in the author's opinion, they are worth validating with a larger sample size. As part of planned further research works, several aspects should be addressed. In the early phase of the research, the study considered the possibility of recording the patient's oral statements, which would have provided additional features on language patterns. Such an examination would include the following features: intonation, speed of speech, tone of voice (vocal tremors, monotony, pitch) and accompanying emotions. Ultimately, after consultation, this idea was abandoned due to greater social exposure and awareness of being watched and recorded, which could result in increased control over a person's speech. Moreover, the consent of the Bioethics Committee regarded only the collection of research material - notes, in written form.

The course of the disease in the group of eating disorders depends on the personality organization of the affected individual. The conducted studies did not account for the influence of this factor due to the lack of such information about the patients. However, in future research, it would be beneficial to determine this characteristic and examine the variation in disease progression by dividing patients into subgroups based on this criterion. The literature indicates that specialists distinguish significant types of personality organization with regard to eating disorders [74].

Extending the dataset for further research will allow the author to apply more complex language models, leveraging attention mechanisms. It may, in turn, facilitate interpreting the results of these complex models.

Referring to the survey results, the proposed method received positive feedback among different groups of professionals. The divergence concerning the irony and past tense information, especially low rating among first-contact staff (nurses) underline the need to enhance understanding and training for nurses on how to interpret sentiment and irony in eating disorders diagnosis. On the other hand, further research should be done toward the method customization for better suit practical needs. Additionally, studies on exploring the specific preferences of different user groups seem crucial to tailor the tool more effectively.

To summarize the entirety of the research work, the satisfying results have encouraged the author to extend future research to other eating disorders, such as bulimia and orthorexia. Considering the diverse nature of these conditions, further developing the current methods will be challenging. However, it is essential to strive towards enhancing these approaches to serve utilitarian purposes and as applicable medical tool.

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