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Research Article

Classification of the Condition of Cancer Patients Receiving Home Health Care with Machine Learning Methods

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Abstract

Determining the health status of cancer patients is of vital importance in the cancer treatment process. This process plays a critical role in assessing patients' quality of life and supporting the treatment process. We thought that the use of machine learning in the field of cancer treatment and patient care could contribute to better patient outcomes and increased quality of life. Evaluation results of cancer patients who received home health care from Amasya University and Research Hospital between January 2013 and August 2017 were discussed and 1000 patient files in home health service patient records were prospectively examined. In this article, cancer types were classified with machine learning methods using the Visual Analog Scale (VAS), Karnofsky performance scale, ECOG, Katz and Bartel scores to determine the quality of life of cancer patients receiving home health care. This study includes the evaluation results of 132 patients, 69 women (mean age 60.31±9.61) and 63 men (mean age 62.36±9.58). The DT classifier was noted to exhibit 83.3% accuracy and had the highest sensitivity in the lung cancer type, with a sensitivity of 88.9%. SVM classifier reached the highest accuracy compared to other classifiers with 90.2% accuracy. SVM has the highest sensitivity in lung cancers, with a sensitivity of 97.8%. The ANN classifier achieved 88.6% accuracy for all cancer types.The use of machine learning algorithms may provide a more sensitive and objective way to evaluate patients' response to treatment. Machine learning enables the classification of cancer types by analyzing feature spaces derived from VAS, Karnofsky performance scale, ECOG, Katz, and Bartel scores. This situation can also be constructed as an indicator in early diagnosis or risk group determination, and thus can contribute to improving home health services and increasing the quality of life of cancer patients. The results of this study may contribute to studies aimed at developing more effective strategies for the care and treatment of cancer patients.

Keywords: *Cancer, Deep learning, Machine learning, ANN, SVM, Decision process*

Evde Sağlık Hizmeti Alan Kanser Hastalarının Durumunun Makine Öğrenmesi Yöntemleri ile Sınıflandırılması

Özet

Kanser hastalarının sağlık durumlarının belirlenmesi, kanser tedavisi sürecinde hayati bir öneme sahiptir. Bu süreç, hastaların yaşam kalitesini değerlendirmek ve tedavi sürecini desteklemek için kritik bir rol oynamaktadır. Biz de makine öğrenmesinin kanser tedavisi ve hasta bakımı alanında kullanılmasının, daha iyi hasta sonuçlarına ve yaşam kalitesinin artırılmasına katkı sağlayabileceğini

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düşündük. Ocak 2013-Ağustos 2017 tarihleri arasında XXX Hastanesi'nden evde sağlık hizmeti alan kanser hastalarının değerlendirme sonuçları ele alındı ve Evde sağlık hizmeti alan hasta kayıtlarındaki 1000 hasta dosyası prospektif olarak incelendi. Bu makalede, evde sağlık hizmeti alan, kanser hastalarının yaşam kalitesini belirlemek için Visual Analog Scale (VAS), Karnofsky performans ölçeği, ECOG, Katz ve Bartel skorlarını kullanarak makine öğrenmesi yöntemleriyle kanser türleri sınıflandırıldı. Bu çalışma, 69'u kadın (ortalama yaş 60,31±9,61) ve 63 erkek (ortalama yaş 62,36±9,58) olmak üzere 132 hastanın değerlendirme sonuçlarını içermektedir. DT sınıflandırıcı %83,3 doğruluk sergilediği ve akciğer kanser türünde %88,9 duyarlılıkla en yüksek duyarlılığa sahip olduğu kaydedilmiştir. SVM sınıflandırıcı %90.2 doğruluk ile diğer sınıflandırıcılara göre en yüksek doğruluğa ulaşmıştır. SVM en fazla %97.8 duyarlılıkla akciğer kanserlerinde duyarlılığa sahiptir. ANN sınıflandırıcısı tüm kanser türleri için %88.6 doğruluk elde etmiştir. Makine öğrenmesi algoritmalarının kullanımı, hastaların tedaviye yanıtının değerlendirilmesinde daha hassas ve objektif bir yol sağlayabilir. Makine öğrenmesi modeli, VAS, Karnofsky performans ölçeği, ECOG, Katz ve Bartel skorlarına dayalı özellik uzayını kullanarak kanser türünün belirlenmesine olanak sağlamaktadır. Bu durum erken tanıda ya da risk grubu belirlemede bir gösterge olarak da kurgulanabilir ve böylelikle evde sağlık hizmetlerinin iyileştirilmesine ve kanser hastalarının yaşam kalitesinin artırılmasına katkıda bulunabilir. Bu çalışmanın sonuçları, kanser hastalarının bakımı ve tedavisi için daha etkili stratejiler geliştirmeye yönelik yürütülen çalışmalara katkı sağlayabilir.

Anahtar Kelimeler: *Kanser; Derin öğrenme; Makine öğrenimi;YSA; DVM; Karar süreci*

I. INTRODUCTION

Cancer is one of the most complex and pervasive problems in medicine today. Affecting the lives of millions of people each year, it is a burden on health systems and societies. [1, 2]. The complex nature of cancer, combined with often debilitating treatments such as chemotherapy and radiation, presents a complex set of physical and psychosocial challenges for patients [3, 4]. In particular, people with advanced cancer experience problems with daily activities caused by diagnosis-specific symptoms and/or treatment-related side effects [5]. It is estimated that most of these individuals require palliative care [6, 7].

However, thanks to advances in screening and treatments, people are living longer and longer with the consequences of cancer and its treatment. Patients with cancer often report a constant symptom burden, exercise intolerance and loss of physical fitness, all of which can threaten a patient's daily independence [8]. Activities of daily living (ADLs) refer to essential tasks individuals must perform to maintain independent living in society [9]. In other words, the term GYA describes the practical daily tasks that need to be done at home in order to lead a manageable and worthwhile life [10].

Various tools developed to evaluate ADL problems have an important role in determining the quality of life of cancer patients. Among these tools, the Visual Analog Scale (VAS), Karnofsky performance scale, ECOG, Katz and Bartel scales stand out. While the Visual Analog Scale (VAS) allows patients to subjectively evaluate the symptoms they are experiencing or their quality of life, the Karnofsky performance scale and ECOG scales are used to objectively evaluate the patient's overall performance level and monitor the effectiveness of the treatment process. On the other hand, Katz and Bartel scales have an important role in evaluating independence and functional status in daily living activities. These evaluation criteria provide a solid basis for determining the quality of life of cancer patients, managing the treatment process, and creating personalized care plans. In this way, it is aimed to increase the quality of life of the patients and improve the treatment results by providing support in accordance with their needs.

Cancer treatment and patient care are increasingly complex processes and require a personalized approach for each patient. In this field, machine learning stands out as an important tool. By analyzing large amounts of patient data, machine learning algorithms make it possible to obtain valuable information about patients' diagnoses, response to treatment, and prognosis. Additionally, thanks to its

ability to detect complex relationships and patterns, machine learning can help personalize patients' treatment plans and determine the most effective treatment options. However, machine learning can also be used to analyze clinical assessment tools, such as scales used to determine patients' quality of life and monitor the treatment process. In this way, it may be possible to evaluate patients' conditions more accurately and direct treatment plans more effectively. Therefore, the use of machine learning in cancer treatment and patient care can contribute to better patient outcomes and improved quality of life.
Machine learning (ML) techniques have gained significant traction in healthcare over the past decade, particularly for disease diagnosis, prognosis, and treatment planning. Numerous studies have explored the effectiveness of ML models in classifying patient conditions across various medical domains, including oncology, cardiology, and neurology [11]. For instance, Esteva et al. (2017) demonstrated the success of deep learning in dermatology for the classification of skin lesions, achieving dermatologist-level accuracy [12]. Similarly, Che et al. (2017) applied recurrent neural networks (RNNs) to electronic health record data, showing the potential of ML in predicting patient outcomes across multiple chronic diseases, such as heart failure and chronic kidney disease [13]. These studies underscore the versatility and generalizability of ML models across different patient populations and medical conditions, which parallels the approach used in the current study for cancer classification.

This study contributes to the growing body of literature on the application of machine learning (ML) models in healthcare, with a specific focus on improving cancer care for home healthcare patients. While the effectiveness of ML models has been demonstrated extensively in clinical settings, their application in home healthcare remains relatively underexplored. By evaluating the classification performance of multiple ML techniques, including Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Decision Trees (DT), we provide valuable insights into the strengths and limitations of these models for classifying cancer patients based on quality-of-life measures. The relationship between the Visual Analog Scale (VAS), Karnofsky Performance Scale, ECOG, Katz, and Bartel scores, and cancer type is rigorously analyzed, allowing for a more nuanced understanding of patient outcomes. Through this comparative analysis, our study not only highlights the utility of these classifiers in personalized healthcare but also underscores their potential in enhancing patient monitoring and care delivery in non-clinical environments. Future research could extend this approach to other chronic diseases and healthcare contexts, thereby further contributing to the generalizability of ML in medical applications and aiding in the development of more effective health service planning and quality-of-life improvements for diverse patient populations.

II. MATERYAL METOD

Dataset:
This study was conducted between January 2013 and August 2017 by Amasya University Sabuncuoğlu Şerefeddin Education and Research Res. It includes the evaluation results of cancer patients who receive home health care from the hospital. Clarify that 1000 files were reviewed, but the final analysis focused on 132 patients Patient groups diagnosed with colorectal cancer, breast cancer and lung cancer were included in the study. Other cancer types were not included in the study because sufficient numbers could not be reached. Additionally, other patient groups receiving home health care were excluded from the study. The standard patient groups included in the study are patients between the ages of 18-90. This study includes the evaluation results of 132 patients, 69 women (mean age 60.31±9.61) and 63 men (mean age 62.36±9.58). Ethics committee approval for the study was received from Tokat Gaziosmanpaşa University Ethics Committee (2016/07). The demographic characteristics of the patients are given in Table 1.

__Table 1.__ Demographic characteristics of the patients.

		Colorectal Cancer	Breast Cancer	Lung Cancer	Total
Gender	**Female**	18	40	34	92
	Male	24	5	11	40
Age	**Female**	65,57 ±14,25	54,22±5,43	61,15±9,15	60,31±9,61
	Male	64,50±12,30	63,90±4,75	58,70±11,70	62,36±9,58

There are many scales used to evaluate patients in palliative care. These scales are aimed at learning the patient's needs, identifying their severity and the difficulties they face. During the evaluation phase, data were collected from the patients via a survey. More than one scale was used to evaluate daily living activities in the patient groups included in the study. These scales used:

Visual Analog Scale (VAS)

Among the data collected, VAS scoring in the range of 0-10 was used to measure the pain intensity of the patients. VAS, which is an extremely simple, effective, repeatable measurement tool that requires minimal tools, is a one-dimensional scale frequently used in the measurement of subjective parameters. The scale consists of a 10 cm long line drawn vertically or horizontally. At either end of this line are the two extreme descriptive words of the subjective category (0 = "no pain at all", 10 = worst/unbearable pain"). The patient is told to make a mark on this line, appropriate to the intensity of pain, to intersect this line. The distance from the lowest VAS level to the patient's mark is measured with a ruler to obtain the numerical value of the patient's pain intensity in centimeters (cm) or millimeters (mm). [14, 15]. It has been shown that there is a good correlation between the horizontal and vertical plots of VAS, and it has been widely accepted in the world literature as a valid and reliable measurement tool in the evaluation of postoperative acute pain intensity. Most of the studies conducted to date indicate that VAS is a reliable tool that can be used to evaluate pain severity. The VAS score obtained from the collected data is shown in Figure 1.

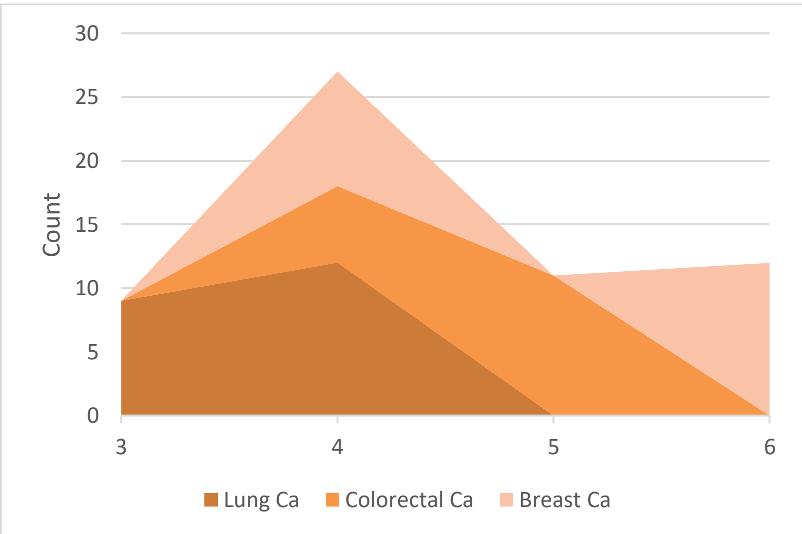


Figure 1. *VAS Score results*

Karnofsky Performance Scale

The scale was developed by Dr. Karnofsky in 1948 and was developed by Dr. Karnofsky in 1949. Burchenal and Dr. Remastered by Karnofsky [16]. The scale questions the patient's symptoms, ability to perform daily activities, addiction status, and need for medical care. While 100 points indicate normal health status, functions gradually deteriorate with ten-point decreases, and 0 points correspond to death. Patients are divided into 3 groups according to the evaluation results: Individuals in category A (80-100%) do not require special care, they can continue their normal activities and work; Individuals in category B (50-70%) can do personal care with assistance but cannot work; Individuals in category C (0-40%) cannot take care of themselves and the disease rapidly progresses towards death. The Karnofsky performance scale is shown in Table 1 [16]. The Karnofsky performance scale results obtained in the study are shown in Figure 2.

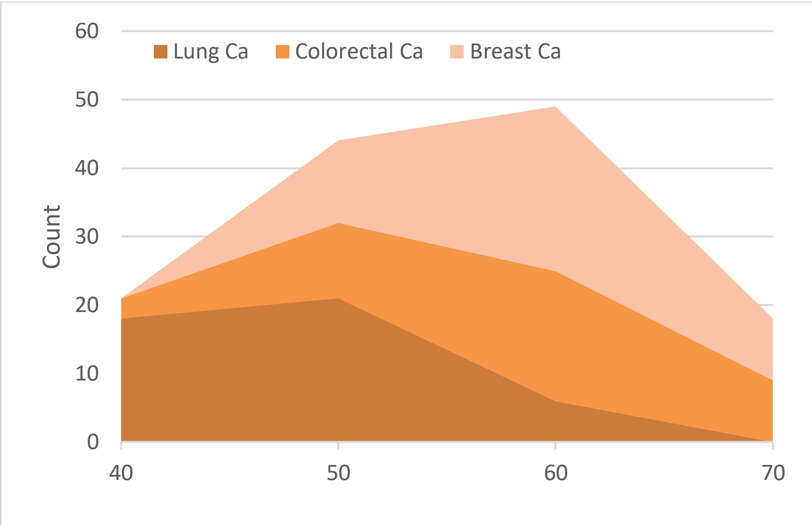


Figure 2. *Karnofsky performance scale results*

ECOG Performance Score

It consists of the initials of Eastern Cooperative Oncology Group. This performance score was developed and published in 1982 by the Eastern Cooperative Oncology Group (ECOG), part of the ECOG-ACRIN Cancer Research Group. The ECOG Performance Score is widely used to determine the functional status of cancer patients. The scale, also known as the WHO or Zubrod performance score, was developed in 1960. In the ECOG Performance Score: 0 indicates normal health and 5 indicates death. While low scores indicate good general condition, high scores indicate poor prognosis. ECOG Performance Score is shown in Table 2 [17]. The ECOG Performance Score results obtained in the study are shown in Figure 3.

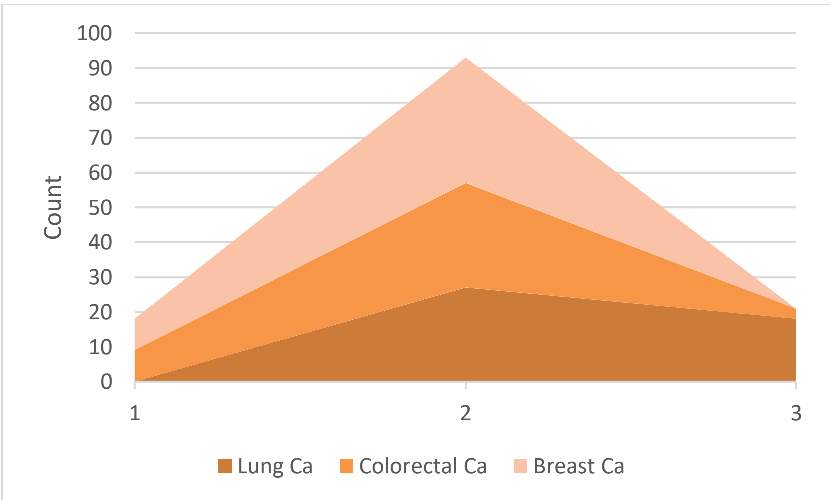


Figure 3. *ECOG Performance Score results*

Katz's Activities of Daily Living Index

It is a scale developed by Katz et al. in 1963. It consists of 6 questions regarding movement, nutrition, excretion, dressing, bathing and toilet functions, which evaluate whether the individual is dependent on other people to perform his daily life activities. If the individual can do each of these activities independently, 1 point is given, and if he cannot do it at all, 0 point is given. Functions performed with assistance receive 0 points, while functions performed independently receive 1 full point. A score of 6 indicates full function, a score of 4 indicates moderate function, and a score of 2 indicates less severe impairment. [18-21]. Katz's Activities of Daily Living results obtained in the study are shown in Figure 4.

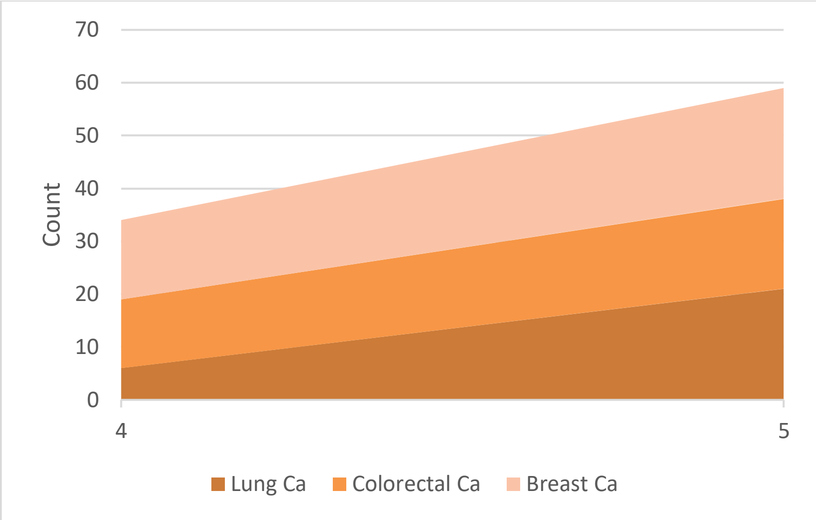


Figure 4. *Katz's Activities of Daily Living Score results*

Barthel Index-BI:
The index developed by Mahoney and Barthel in 1965 was modified by Shah et al. (1992). The Turkish version of the index was edited by Küçükdeveci et al. (2000) [22]. This scale evaluates mobility status and stair climbing functions such as feeding, washing, self-care, dressing, defecation control, urinary control, going to the toilet, ability to move from bed to wheelchair, walking or being dependent on a wheelchair, and stair climbing on a scale of 5-15 points (depending on the question). It consists of a total of 10 items that grade each other (0-15 points in 5-point increments). The main purpose of the evaluation made with this scale is to determine to what extent the patient performs these actions independently, without any physical or verbal assistance. It is not necessary to test the patient directly, but evaluation can be made in the light of direct observation, information obtained from the patient, the patient's relatives, or the caregiver or nurse involved in his/her care. In this scale, where the possible score ranges from 0 to 100, a higher score means that the patient is independent of other people and can run his own business. As a result of the scoring, 0-20 points are evaluated as fully dependent, 21-61 points as highly dependent, 62-90 points as moderately dependent, 91-99 points as mildly dependent, and 100 points as fully independent. [22]. The Bartel Index results obtained with the collected data are shown in Figure 5.

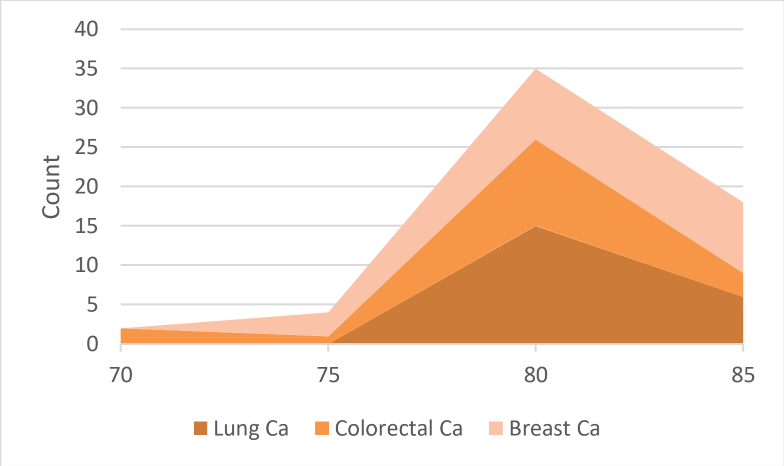


Figure 5. *Barthel Index results*

Classification model

Classification in data mining is commonly performed to discover hidden patterns in large-scale data sets. A pattern represents information that is observable, measurable, and repeatable. Classification algorithms are designed to separate data into specific groups (classes) to obtain specific target information. At this stage, feature extraction plays an important role. Feature extraction is the most suitable Torre in the classification process. This method is used for classification and pattern recognition problems in many different fields, such as medicine and signal processing. [23]. While support vector machines (SVM) are preferred for their classification performance and accuracy in predictions, they are also effective for classifying non-linear data sets. They offer a versatile solution when used in conjunction with other algorithms such as decision trees. Therefore, support vector machines are considered an important tool for extracting and classifying patterns in complex data sets. Figure 6 shows the general structure of SVM.

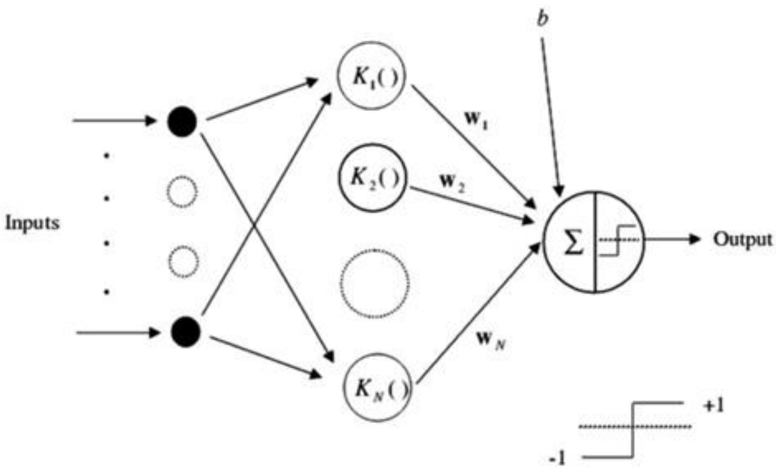


Figure 6. *Support vector machines network structure*

Artificial Neural Network (ANN)

ANN is a complex and multi-layered artificial learning model inspired by the functioning of the human brain. [24]. ANNs consist of neurons arranged in a manner similar to biological neural networks and use connections between these neurons to process information. [25]. ANNs generally have a double-layer and feed-forward structure, which allows data to be transferred in a single direction from input to output. Additionally, ANNs have the flexibility to work with numerical and categorical data and can solve a variety of complex problems. The learning process of ANNs is based on recognizing patterns in the data set and creating models through learning. In real-life applications, ANN is used in many different fields such as medicine, finance, industry and image recognition. [26, 27]. In particular, they provide successful results in tasks such as classification, regression and pattern recognition on complex data sets. ANNs are now considered an important machine learning tool because they have high processing power and a wide range of applications. The structure of the ANN is shown below in Figure 7 [25],

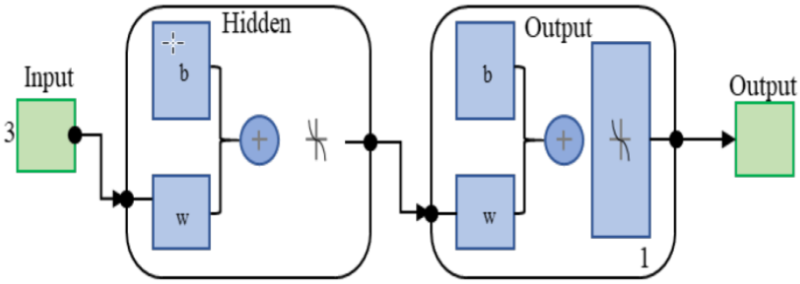


Figure 7. *Schematic ANN diagram [25]*

Decision Tree (DT)
A Decision Tree is a simple yet powerful classification and regression model that splits the dataset into branches based on certain decision criteria. Each internal node in a decision tree represents a feature (or attribute), each branch represents a decision rule, and each leaf node represents the outcome or class label. DTs are particularly valued for their interpretability, as they allow the user to easily understand and visualize the decision-making process. They work well on both numerical and categorical data and are capable of handling datasets with missing values. However, decision trees are prone to overfitting, especially with small datasets or when the tree becomes too deep, leading to high variance. To mitigate this, techniques like pruning or using ensemble methods (such as Random Forest or Gradient Boosting) are often applied to improve generalization. Despite these limitations, DTs are widely used in medical decision-making due to their ease of implementation and transparency in how they classify data.

The main purpose of choosing SVM, ANN and DT in this study is that each algorithm offers different advantages when considering the size and complexity of the data. While SVM shows strong performance especially in nonlinear relationships; ANN offers the capacity to learn deeper patterns in large data sets. DT is valuable in terms of fast decision making and model explainability. Therefore, the combination of these algorithms provided the most suitable solutions for this study, which evaluates and classifies the quality of life of cancer patients.

III. RESULTS

Confusion matrices of the classification results for the 5-dimensional feature space obtained as a result of the survey are given in Tables 3, 4 and 5. The Decision Tree (DT) model (Table 2) appears to have a strong performance, especially in classifying Lung Cancer with remarkable precision.

Table 2 DT Classification result.

DT		**Predicted Class**		
		Lung cancer	Lung cancer	Lung cancer
True Class	Lung cancer	40	2	3
	Colorectal Cancer	4	30	8
	Breast Cancer		5	40

The SVM model (Table 3) exhibited higher accuracy performance in all cancer types. Additionally, this model has been shown to show lower misclassification rates compared to the DT model in distinguishing Colorectal Cancer from breast cancer.

Table 3 SVM classification result.

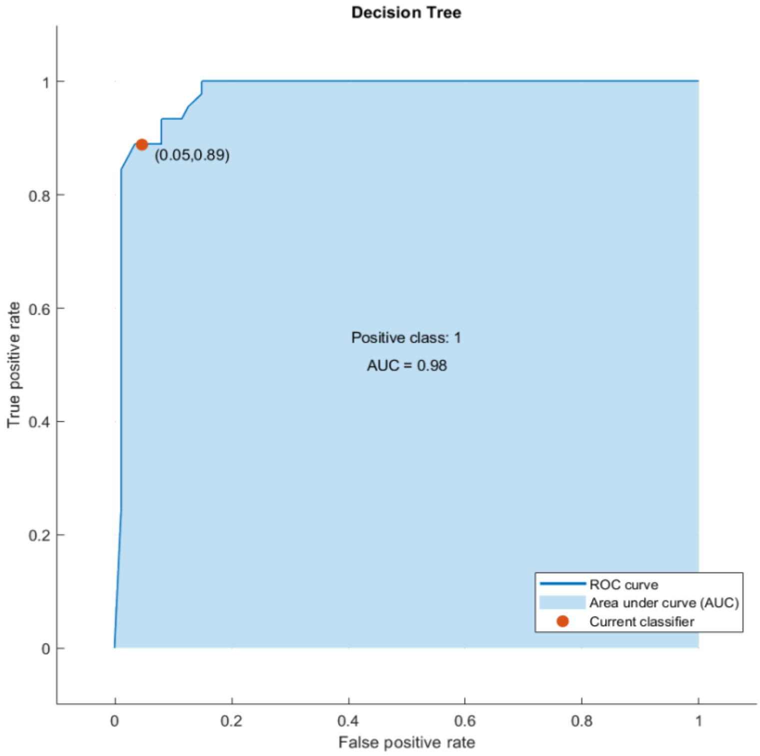
	SVM	Predicted Class		
		Lung cancer	**Lung cancer**	**Lung cancer**
True Class	**Lung cancer**	44	1	
	Colorectal Cancer	4	35	3
	Breast Cancer	2	3	40

The ANN model (Table 4) showed similar high performance to the SVM model, with better discrimination between Lung Cancer and other types of cancer. However, the ANN model noted some misclassifications between Colorectal Cancer and Breast Cancer, although to a lesser extent than the DT model.

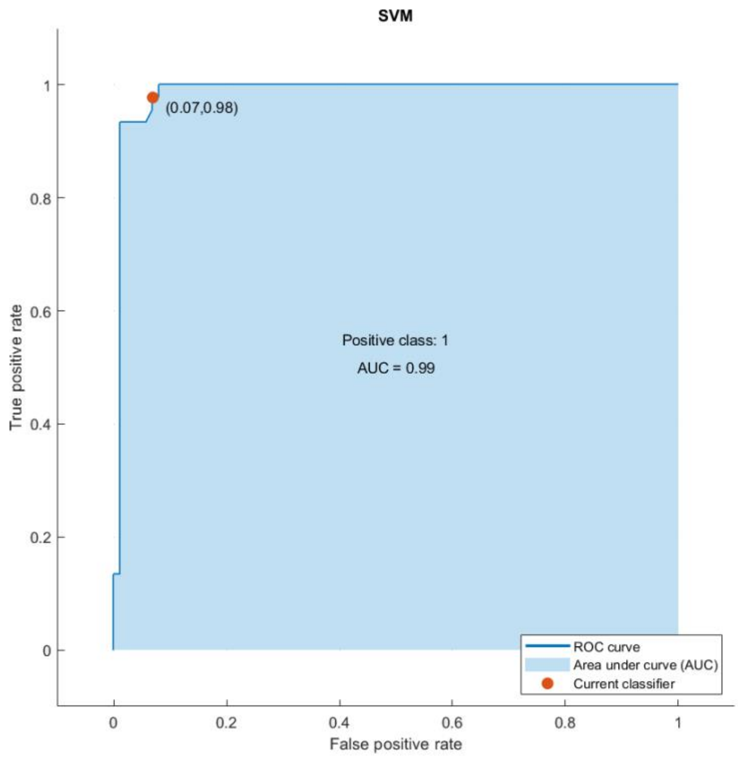
Table 4 ANN classification result.

	ANN	Predicted Class		
		Lung cancer	**Lung cancer**	**Lung cancer**
True Class	**Lung cancer**	**42**	**3**	
	Colorectal Cancer	**1**	**36**	**5**
	Breast Cancer		**6**	**39**

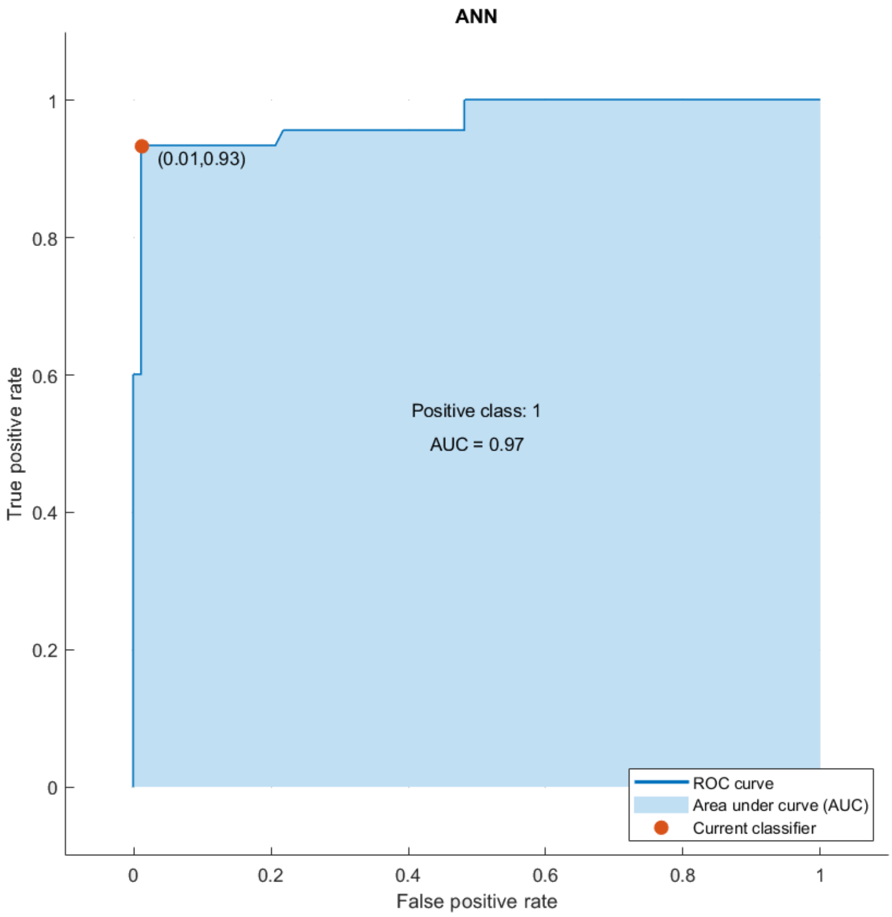
Figure 8 shows the ROC curves of the health scores of cancer patients receiving home healthcare services obtained by DT, SVM and ANN models. Examining the ROC curves, the high AUC values in all models indicate that machine learning can serve as a powerful adjunct to traditional statistical methods and provide clinicians with more detailed and data-driven tools to inform their decisions.


Decision Tree
(0.05,0.89)
Positive class: 1
AUC = 0.98
ROC curve
Area under curve (AUC)
Current classifier
True positive rate
False positive rate
0
0.2
0.4
0.6
0.8
1

a)


SVM
(0.07,0.98)
Positive class: 1
AUC = 0.99
ROC curve
Area under curve (AUC)
Current classifier
True positive rate
False positive rate
0
0.2
0.4
0.6
0.8
1

b)



c)

Figure 8: *ROC Curves* ***a)*** *DT* ***b)*** *SVM* ***c)*** *ANN*

The accuracies and sensitivities obtained during the classification process are given in Table 5. When the table was examined, it was noted that the DT classifier exhibited 83.3% accuracy and had the highest sensitivity in the lung cancer type with 88.9% sensitivity. SVM classifier reached the highest accuracy compared to other classifiers with 90.2% accuracy. SVM has the highest sensitivity in lung cancers, with a sensitivity of 97.8%. The ANN classifier achieved an overall accuracy of 88.6%, with varying performance across different cancer types.

Table 5: *Precision and Accuracy for Each Classifier.*

		Precision (%)			Accuracies (%)
		Lung cancer	**Lung cancer**	**Lung cancer**	
Classifier	**DT**	88,9	71,4	88,9	83,3
	SVM	97,8	83,3	88,9	90,2
	ANN	93,3	85,7	86,7	88,6

When examining Table 5, DT model, while offering the lowest overall accuracy (83.3%), stood out for its interpretability, making it particularly valuable in clinical settings where transparent decision-making is essential. Although the ANN demonstrated slightly lower accuracy, it excelled in identifying complex patterns, especially in distinguishing cancer types with overlapping symptoms. ANN's ability to capture deep, non-linear relationships in the data makes it well-suited for more intricate and larger datasets. On the other hand, SVM showed the highest performance across all cancer types, particularly excelling in non-linear classification tasks such as lung cancer differentiation. SVM's strength lies in its ability to handle high-dimensional data and complex patterns, making it a robust choice for datasets with significant variability, including those with multiple medical variables.

IV. DISCUSSION

In this study, Visual Analog Scale (VAS), Karnofsky performance scale, ECOG, Katz and Barthel Index scores were used to classify cancer patients receiving home health care. The machine learning methods used provided an effective way to classify patients into quality of life categories. The results of our study show that the classification performance of machine learning models, especially Decision Trees (DT), Support Vector Machines (SVM) and Artificial Neural Networks (ANN), make an important contribution to the detection of cancer patients.

The use of Decision Trees, Support Vector Machines and Artificial Neural Networks is a common approach in the literature for the management of cancer patients and quality of life assessment. [24, 29]. The findings of this study demonstrate the capacity of these algorithms to handle complex patient data and effectively classify various types of cancer. In particular, the SVM model exhibited highly accurate classification performance for all cancer types, confirming the strong classification ability of SVM observed in previous studies. [23, 30].

The Artificial Neural Network model showed similarly high performance and provided particularly good discrimination between 'Lung Cancer' and other cancer types. This finding shows that ANN is effective in complex classification problems and has a wide range of applications in real-world applications. [26, 27].

From a clinical perspective, the implementation of machine learning models like SVM and ANN can offer significant improvements in the management of cancer patients receiving home health care. These models could assist clinicians by providing data-driven predictions regarding patient outcomes and helping identify patients who may benefit from early intervention or specialized treatment plans [31]. The integration of such models into healthcare systems could also facilitate the early detection of cancer progression and improve the quality of life of patients by enabling more personalized and timely interventions [32].

The results of this study show that as an alternative to traditional statistical methods, machine learning can provide clinicians with more detailed and data-driven decision-making tools. In particular, the high AUC values observed in the ROC curves emphasize the usability of machine learning models in classifying cancer patients. These results are in line with the findings of Torre et al. (2016) and Coleman et al. (2008) and support the potential of machine learning in improving the management and treatment of cancer patients. [1, 2].

The study has limitations. The small sample size and limited cancer types (lung, colorectal, and breast) analyzed may restrict the generalizability of the findings. In addition, the lack of cross-validation raises concerns about model overfitting. Incorporating advanced validation techniques in future work would enhance the robustness and reliability of the results.

IV. CONCLUSİON

In this study, Visual Analog Scale (VAS), Karnofsky performance scale, ECOG, Katz and Barthel Index-BI scores were used to classify cancer patients receiving home health care services. The scores obtained were found to be an effective feature to accurately classify cancer types, with each of the Decision Tree (DT), Support Vector Machine (SVM) and Artificial Neural Network (ANN) classifiers, along with some models exhibiting higher efficiency for specific cancers. In conclusion, this study shows that machine learning models have the potential to provide benefits in identifying cancer risk and early diagnosis of elderly people receiving home health care services. This will enable the design of systems that can assist clinicians.

The analysis shows that the SVM classifier is the best performing classifier with the highest accuracy of 90.2%. In particular, it showed a sensitivity of 97.8% for lung cancer, suggesting that it is highly reliable in detecting and differentiating lung cancer cases. The ANN classifier showed high accuracy for all cancer types. It was noted that the DT and SVM classifier achieved a sensitivity of 88.9% in the diagnosis of lung cancers.

These results suggest that different machine learning models may be superior in different areas. For lung cancer, both SVM and DT classifiers stand out and have high sensitivity rates that can be used in clinical settings for early detection.

V. REFERENCES

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