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A Data-Driven Approach to Cancer Prognosis Using KNN Algorithm

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ABSTRACT

A vital component of medical research is cancer prognosis, which facilitates early diagnosis and efficient treatment planning. This study offers a data-driven method for accurately predicting the prognosis of cancer using the K-Nearest Neighbors (KNN) algorithm. With an overall accuracy of 94% after being trained and assessed on a structured dataset, the model proved to be dependable in categorization. Surgery had the best precision (0.97) of any class, showing a high capacity to accurately identify patients with few false positives. The model's efficacy was further confirmed by the classification report and confusion matrix, which displayed strong recall and F1-scores across many categories. According to these results, KNN may be a useful tool for helping medical practitioners make well-informed decisions about the prognosis of cancer. This study presents a novel application of the KNN algorithm for multi-modal cancer treatment prognosis, demonstrating high predictive accuracy and offering data-driven support for clinical decision-making. To further improve prediction performance, future research may concentrate on feature selection, hyperparameter tuning, and hybrid models. This study demonstrates the promise of machine learning in medical diagnostics by offering a successful and non-invasive method for predicting the prognosis of cancer.

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1. Introduction

About 10 million people die from cancer each year, making it one of the top causes of mortality globally [1].To enhance the patient survival rate and treatment result in cancer early and accurate prognosis required. In recent years ML techniques have produced strong instruments which have a great impact on medical sciences for evaluating and forecasting patient outcomes. To classify medical data there are many algorithms but KNN have drawn attention because of its ease of use, resilience and effectiveness [2]. For cancer diagnosis KNN is well suited because of non-parametric character and capacity. These characteristics use to categorize results according to their proximity to training data in a multidimensional feature space. The availability of high dimensional cancer datasets including gene expression profiles, histopathological images and clinical records have increased the new opportunities in oncology to use data driven approach. In such data where traditional statistical methods mostly struggling because of huge amount and complexity Machine learning algorithm KNN can efficiently handle such complex datasets and can uncover hidden patterns [3]. Doctors can utilize these patterns to identify patients who are more likely to experience negative outcomes and can make better judgments.

KNN which is supervised learning algorithm use similarities to classify new data points between old labeled data points. The algorithm measures the distance between ne data points and its neighbors in order to determine majority class label among the closest neighbors. The main benefit of KNN is to handle many medical data formats, including continuous, mixed and categorical. KNN does not need lengthy training period which makes it computationally efficient [4]. To get best result careful feature selection and parameter adjustment required because number of neighbors (K), distance measure and quality of input features have significant impact on KNN performance [5]. It is shown by many researcher that KNN is effective in cancer prognosis. For example KNN is used for breast cancer prognosis in a study to differentiate between benign and malignant tumors, KNN achieved excellent classification accuracy [6].

To predict the prognosis of other malignancies like prostate, liver and lung cancer KNN shown satisfied results [7]. According to these results when KNN paired with efficient feature selection and data preprocessing methods. For big datasets high computing cost and sensitivity to noisy input are the drawbacks of KNN. In high dimensional areas algorithm performance deteriorate because of the “Curse of dimensionality” which states that the distance between data points loses significance [8]. Weighted distance measurements, and the application of dimensionality reduction strategies like principal component Analysis (PCA) these are the enhancements which are suggested to address the drawbacks of KNN [9]. In this work using the KNN algorithm a data driven method for cancer prognosis is presented. By careful selection of features, parameters and managing unbalanced datasets it is analyzed that how KNN be optimized for medical applications.

The current study highlights the future research directions and recent advancements in KNN based cancer prognosis systems. Machine learning for cancer diagnosis and treatment prediction is explored by recent studies in which most focus on single models or limited datasets [31]. A comparative analysis is performed using KNN algorithm to evaluate the prognosis of five major cancer therapies which are chemotherapy, surgery, targeted therapy, Immunotherapy, radiotherapy. To the best of our knowledge, this study is among the first to present a unified and comparative KNN-based approach in this context, revealing surgery as the most accurately predictable treatment option. This contributes a new perspective to precision oncology and supports enhanced clinical decision-making.

This is how the rest of the paper is structured. A thorough explanation of the KNN technique and dataset is given in Section II. In section IV the technique for applying KNN to cancer prognosis, feature selection, data preparation, performance evaluation are covered. In section V analysis and results of experiments are presented and section VI is covered with result discussion and future research directions.

2. Dataset description and KNN algorithm

There is a data collection center in England on systemic anticancer therapy name NHS England’s systemic Anticancer Therapy (SACT). This dataset offers a details information to support oncology treatment and research to enhance cancer care. The main characteristics of dataset are below:

3. Dataset Features

The dataset used in this study focuses on general cancer not specific like brain tumor, breast cancer or lung etc. This study covers the treatment strategy of all type of cancer to select the best strategy among various therapies which increase its versatility and applicability in wider range of clinical settings. The dataset have 4024 patients records and any missing value is handled using preprocessing. A subset of 565 was distributed in five classes 100,120, 110, 130 and 105 respectively to evaluate the model. For train test split data is divided in 86:14 having 565 samples for testing and remaining 3459 for training.

3.1 Age

At the time of diagnosis or at start of treatment a continuous variable is shown indicates patients age. Age is crucial variable which has much impact on treatment options, survival rates and cancer prognosis [10].

3.2 Martial Status

Data that is categorical and shows whether the patient is married, divorced, widowed, or single. Cancer patient survival rates may be impacted by psychological and social support, which has been connected to marital status [11].

3.3 Cancer Stages

An ordinal variable that indicates the cancer's stage at diagnosis (Stage I to Stage IV). Given that higher stages are linked to more advanced disease and worse outcomes, this is an essential trait for prognostic prediction [12].

3.4 Tumor Size

A constant that expresses the original tumor's size in millimeters or centimeters. One important measure of the aggressiveness and course of the disease is tumor size [13].

3.5 Therapy Type

Categorical information about the kind of systemic treatment that was administered (e.g., immunotherapy, chemotherapy, targeted therapy). Patient results can be greatly impacted by the therapeutic selection [14].

3.6 Survival Duration

The number of months that pass between a diagnosis or the start of treatment and the patient's passing or the last follow-up. In prognostic models and survival analysis, this is frequently the target variable [15].

3.7 Survival Status

To assess how well a treatment working binary variable survival status is observed which indicates whether a patient is dead (0) or alive (1). SACT dataset has useful use on cancer prognosis, treatment response and survival prediction. Machine learning algorithm such as KNN have been used along with SACT dataset to create successful predictive model for detecting high risk patients and improving treatment plans.

4. K-Nearest Neighbors (KNN) Algoritm

KNN is a supervised Machine learning algorithm has effective use in classification and regression problems. KNN use the technique of categorizing data points by measuring the distance and assigning to closest neighbors in multi-dimensional feature space. To make balance between bias and variance it is essential to choose an ideal K values using Minkowski distance and Euclidean distance for distance metrics in KNN [16]. KNN does not learns patterns explicitly because it is distance based algorithm. However, KNN is able to discover hidden patterns in the data through the proximity of data points in a multi-dimensional feature space. The "hidden patterns" emerge when similar data points (e.g., similar cancer profiles or treatment responses) are found close to each other in the feature space, and KNN identifies these patterns based on their nearest neighbors.

For instance, in cancer prognosis, KNN identifies patterns by analyzing the relationships between various features (such as tumor size, age, and treatment type) of patients and then classifies new instances based on the majority class of their neighbors. This approach allows KNN to implicitly capture complex relationships in the data. KNN performs well when the data has a geometric structure and relies on the distribution of data points for pattern discovery, particularly in problems with structured datasets where the relationships between features are already known or measurable[33].

Convolution neural networks (CNNs) are powerful for structured image data, KNN can outperform CNNs on tabular biomedical datasets where hidden patterns are irregular and data volume is moderate. KNN leverages local similarity without extensive training, making it less prone to overfitting in high-dimensional spaces, while CNNs may require large datasets and careful regularization [38], [39]. Therefore, for cancer prognosis tasks with limited samples and complex hidden patterns, KNN provides a simpler, more interpretable, and equally competitive alternative [40].

4.1 Feature Selection and Scaling

All input features need to be on the same scale because KNN depends on distance computations. Data preprocessing methods like normalization and standardization are frequently used [17].

4.2 Distance Metric

The algorithm's performance can be greatly impacted by the distance metric selection. Manhattan distance may be favored for high-dimensional datasets or when features have various distributions, but Euclidean distance is frequently the default option [18].

4.3 Computational Complexity

Because KNN needs to determine the distance between each data point in the training set and the query point, it is computationally costly, particularly for large datasets. Data reduction strategies or approximate closest neighbor algorithms can help to lessen this restriction [19].

4.4 Handling Imbalanced Datasets

When applied to imbalanced datasets, KNN may favor the majority class. Techniques such as oversampling the minority class or using weighted KNN, where closer neighbors are given more weight, can help address this issue [20].

4.5 Advantages of KNN

- **Simplicity:** Easy to understand and implement
- **Versatility:** Can be applied to both classification and regression tasks.
- **No Assumption:** Does not assume any underlying data distribution.

4.6 Limitations of KNN

- **Computationally Intensive:** Requires recalculating distances for every query point.
- **Curse of Dimensionality:** Performance deteriorates with high-dimensional data.
- **Sensitive to Outliers:** Outliers can significantly affect the classification.

Notwithstanding these difficulties, KNN has been effectively used in cancer prognosis, especially in forecasting treatment response and survival outcomes in sizable datasets like the SACT dataset. KNN can produce accurate and reliable predictions when paired with feature selection and dimensionality reduction methods [21].

5. Related Work

Machine learning proven a massive grown in all fields specially in medical sciences and for diagnosis and prognosis of cancer. Machine learning efficiency is considered because traditional statistical techniques frequently struggle with the capacity and complexity of clinical context data. In recent years KNN becomes a dependable technique for cancer due to its ease of use, effectiveness and efficiency in high dimensional data contexts [22]. In this part of study KNN efficiency, comparison with other models for diagnosis and prognosis of cancer is discussed. Machine learning application in oncology is proven by accuracy of cancer prognosis, using KNN. Research has shown that for forecasting survival results and identifying high risk patients machine learning models are more effective than traditional statistical techniques. For managing interactions and nonlinear correlations between several prognostic factors Machine learning models like Support Vector Machine (SVM), Random forest (RF) and KNN are especially good [23].

KNN does not need explicit training process to generate predictions since frequently used by researchers however number of neighbors (K), feature selection methods and distance matric selection affect its performance [24]. KNN is used for various cancer types specifically prominent use for breast cancer using the clump thickness, cell size uniformity and mitosis [17] to differentiate between malignant and benign groups, where 95% accuracy showed that how useful may be KNN for clinical decision making. Similarly, for lung cancer survival prediction [26] used a dataset that contain clinical and pathological variables. The results proved that KNN can predict patient survival with high accuracy and low computing cost. Author emphasized the significance of choosing an ideal K value to avoid tradeoff between bias and variance.

Furthermore, weighted KNN is demonstrated which increase accuracy and priority to close neighbors. In different studies [27] use KNN for liver cancer and investigated its application. According to study KNN performed similarly to

other Machine learning algorithm including Decision tree, Support Vector Machine with an accuracy of 87.5 % in forecasting three-year survival outcomes. The preprocessing of data which included missing values and feature scaling are the secrets of KNN's excellent performance credited by authors. KNN have certain drawbacks along with efficacy such as sensitivity to high dimensional and noisy data. For example, as the number of dimensions increasing significance of distance between data points decreases potentially impairing KNN performance [28]. To cope up such issues researchers proposed PCA and LDA [29]. When compare to other models in terms of accuracy and resilience complex models like Random forest and Gradient Boosting Machines (GBM) surpass KNN, however due to low computations costs and ease of use KNN continues to useful baseline technique. In a study [30] GBM obtained greater accuracy in colorectal cancer but KNN Produced results that were equivalent with significantly less computing complexity.

Recent developments focuses on enhancing KNN accuracy and scalability using in cancer prognosis. The hybrid model of KNN with other Machine learning methods have been observed promising outcomes, specifically combining neural networks or Reinforcement learning techniques which can significantly improve algorithm performance [31]. In this field further research should be creation of automated system that use KNN for real time cancer prognosis. The system might use of patient specific data such as genetic information, and current clinical updates generate individuals forecast. Furthermore, combining KNN with cloud computing and big data analytics may open the door to the development of extensive, real-time cancer prediction systems that physicians throughout the globe can use.

6. Methodology

The study titled A data driven approach to cancer prognosis using the KNN algorithm's process starts with data gathering which is pertaining to cancer. A national dataset of United Kingdom systematic anti-cancer therapy (SACT) provides information of chemotherapy and other therapies given in England National Health Services (NHS). Its administrations in charge is National Disease Registration service (NDRS) a division of NHS. A wide and complete patient data is included like demographics, medical History, genetic markers, tumor features and survival rates. After data collection preprocessing of data set is performed which is essential for better performance. Imputation approaches such as mean, median or KNN based imputation is involved to ensure the avoidance of data loss and missing values. KNN depends on distance based metrics to minimize biases caused by different value ranges. Normalization approach is involved to guarantee consistency in feature distribution. After preprocessing train test split phase applied and data is divided in to 86:14. To avoid the bias prediction it is ensured that each subset has balanced class. The KNN is trained using various K values and training data to identify deal Hyperparameters configuration. The model is evaluated using performance indicators like accuracy, precision, recall, F1 score and confusion matrix. Once it reached a satisfactory level of accuracy model is then deployed. The final model deployment for practical application, hospital management and oncologists to make well informed data supported decision about treatment plans to enhance patient outcomes and survival rates. Utilizing machine learning to improve cancer prognosis accuracy while preserving interpretability and dependability in practical medical applications, the methodology takes a methodical, data-driven approach.

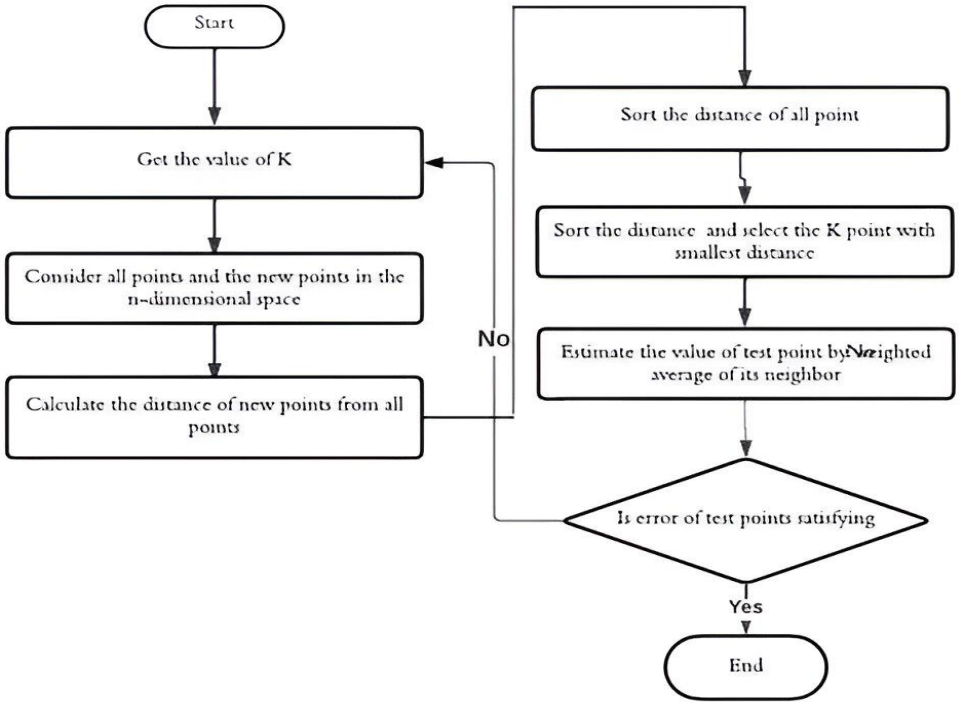

Figure. 1.

Flowchart of KNN

Figure. Shows the KNN algorithm working applied in a multidimensional space for cancer prognosis prediction. Initially a values is assign to K followed by considering all data pints with in n-dimensional feature space. Then distance is measured between new pints and existing points. After wards K-nearest neighbors with smallest distance is selected by sorting these distances using a weighted average the values of the test point is estimated. If the prediction error for

the new test points meets a predefined threshold, if not it re-evaluates. This iterative approach continuous to effectively handle medical datasets a suggested in recent studies and ensure improved accuracy and robustness in prediction outcomes [34], [35].

7. Results and Discussion

In this chapter KNN algorithm performance evaluated based on acquired dataset. To overcome the computational complexity and dimensionality problems irrelevant attributes are removed using feature selection techniques, while retaining clinically significant information. To improve accuracy and efficiency data is normalized to ensure all features contributed equally to distance calculation. The improved accuracy 0.94 becomes possible due to these strategies and individually surgery (0.97), chemotherapy (0.91), targeted therapy (0.94) immunotherapy (0.92), radio therapy (0.93) maintain high accuracies while model has ease of use and low computational cost..

Statistic	Age	Tumor Size	Regional Node Examined	Regional Node Positive	Survival Months
Count	**4024.000000**	**0.000000**	**4024.000000**	**4024.000000**	**4024.000000**
Mean	**53.972167**	**NaN**	**30.473658**	**14.357107**	**71.297962**
Std (Standard Dev)	**8.963134**	**NaN**	**21.119966**	**8.099675**	**22.921430**
Min	**30.000000**	**NaN**	**1.000000**	**1.000000**	**1.000000**
25% (1st Quartile)	**47.000000**	**NaN**	**16.000000**	**1.000000**	**56.000000**
50% (Median)	**54.000000**	**NaN**	**30.000000**	**14.000000**	**73.000000**
75% (3rd Quartile)	**61.000000**	**NaN**	**38.000000**	**19.000000**	**90.000000**
Max	**69.000000**	**NaN**	**140.000000**	**61.000000**	**107.000000**

Table 1: Statistical Analysis of Dataset

To maintain numerical accuracy statistical lbrariees like pandas preserve full floating point precision during calculation as the data in Table1 includes six decimal places for survival months. The figure shows statistical overview of deataset with an emphasis on numerical properties like age, tuor size, Regionoal Node examined and survival months. The age of patients rang from 30 to 69 years old with mean age 53.97 years. The tumore size varies greatly suggesting a broad spectrum of disease progression having maximum 140 mm and average 30.47 mm tumor size. 14.35 is the number of average regional lymph nodes and 4.16 is average number of positive lymph nodes shows degree of cancer. Survival month indicates long follow up which vary from 1 to 107 months with 73 months median. The tumor size and survival length appear to vary moderately, based on the standard deviation data. Furthermore, the "Unnamed: 3" column is probably superfluous and has no values (NaN). All things considered, the dataset offers important information about patient characteristics, the course of the cancer, and survival rates, which makes it a useful tool for predictive modeling with machine learning methods like KNN.

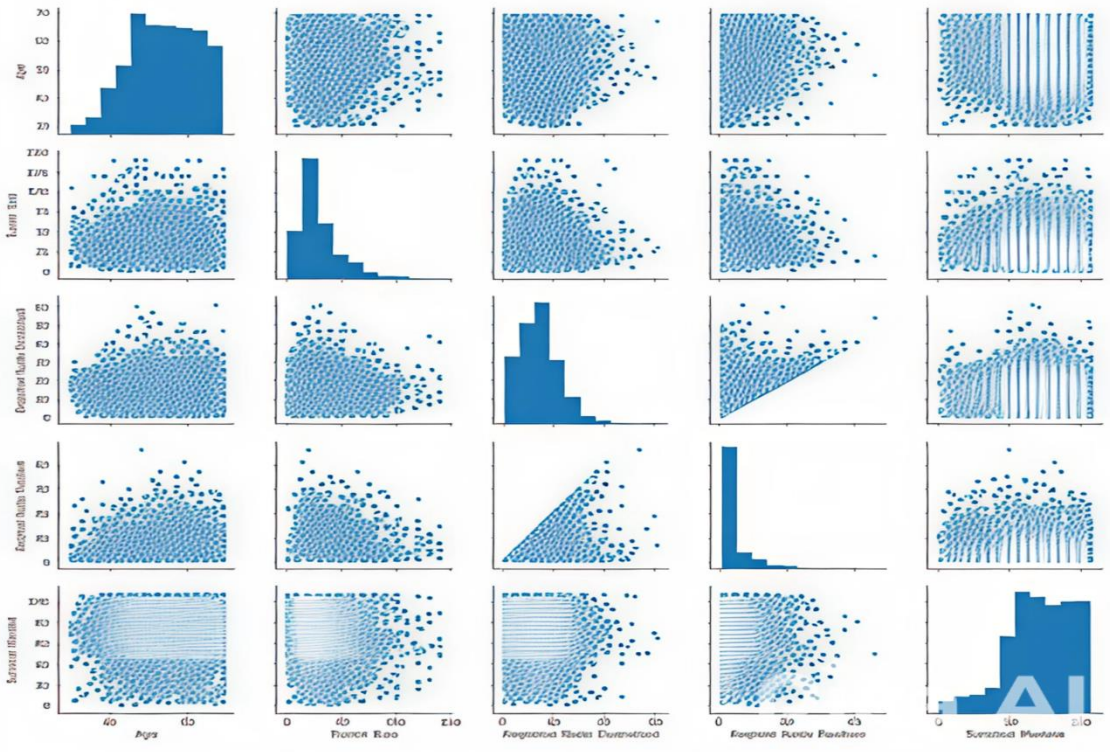

Figure 2: Pairplot of Dataset

Histogram and scatter plots of variable and feature distributions presents pair plot visualization of numerical variables from a cancer prognostic dataset. Age distribution is between 40 and 70 and tumor size show a broad range suggesting possible outliers. There is positive connection between regional node examined and regional node positive as anticipated in cancer staging. In survival months a tight cluster raises the possibility of distinct survival periods in the data. According to scatter plots most variables have poor linear correlations suggesting that feature engineering or nonlinear models could improve prediction accuracy All things considered, this representation aids in comprehending data distributions, trends, and possible relationships among important indicators of cancer prognosis.

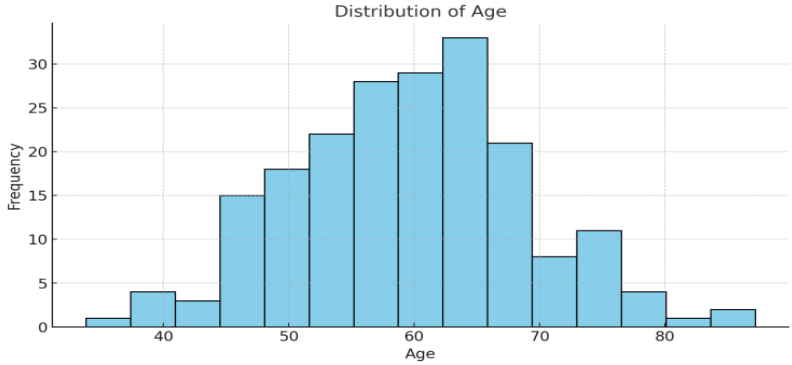

Figure 3: Age Distribution of Patients

Figure 3 represents the age distribution of patients where most cases occur between 50 and 70 years with maximum around 60-65 years. The frequency raises from around 40 years, reaches its highest point in the early 60s, and then declines after 70 years. The overall distribution shows that cancer is more common in older ages comared to age below 40 years and above 80 years**.**

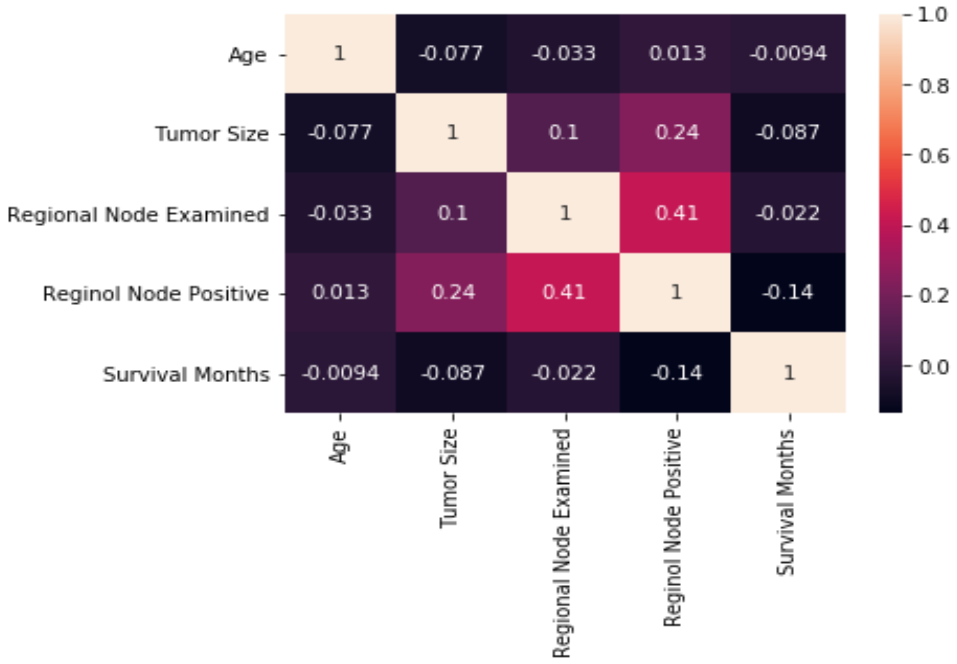

Figure 4: Correlation analysis of Dataset

The picture shows the direction and degree of links between features by displaying a correlation heatmap for important numerical variables in the cancer prognostic dataset. Correlation values, which range from -1 (strong negative correlation) to 1 (strong positive correlation), are represented by the color gradient. As would be expected given that a higher number of investigated nodes frequently correlates with a higher count of positive nodes, the most noticeable positive correlation is found between Regional Node investigated and Regional Node Positive (0.41). Additionally, there is a weak positive connection (0.24) between tumor size and regional node positivity, indicating that lymph nodes are more likely to be affected by larger tumors. However, there are minor negative relationships between Survival Months and Regional Node Positive (-0.14) and Tumor Size (-0.087), suggesting that longer survival times may be somewhat shortened by larger tumors and higher node positivity. Other factors, like age, have little association with indications of cancer progression or survival, indicating that they might not be reliable predictors on their own. In order to improve machine learning models for cancer prognosis, this heatmap aids in feature selection and the comprehension of variable dependencies.

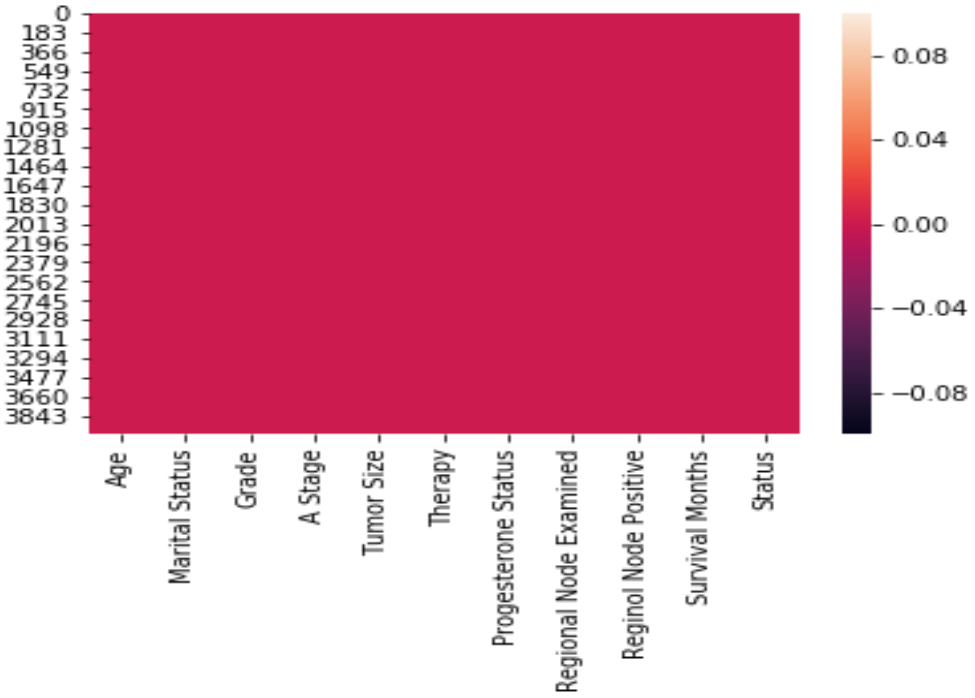

Figure 5: Heatmap of cleaning from missing values

Following data cleaning, the graphic depicts a heatmap of missing values; the consistent hue of each cell shows that there are no more missing values in the dataset. The dataset has been completely refined after applying data cleaning procedures including imputation, removal, or replacement with acceptable values, which may have previously included missing values in one or more attributes. This guarantees that the dataset is now complete and prepared for feature selection, additional preprocessing, and model training. A thoroughly cleaned dataset lowers biases, guards against mistakes in machine learning models, and improves the precision of KNN algorithm-based cancer prognosis forecasts.

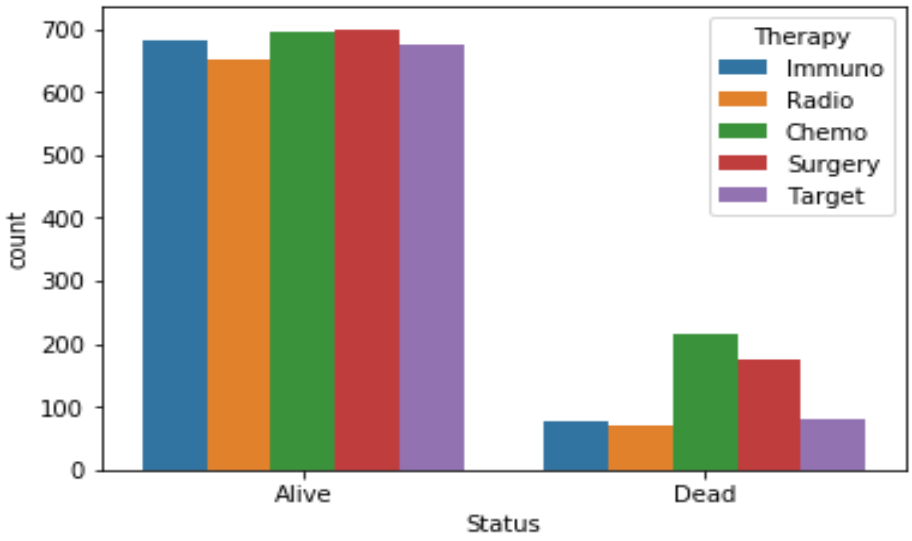

Figure 6: Bar chart of Alive vs Dead

Figure 6 bar chart shows the survival status (alive vs dead) against each therapy (Chemotherapy, radiotherapy, Immunotherapy, surgery and targeted therapy). These treatments are successful because alive group comprises the majority cases across all therapy. The patients who received chemotherapy had late stage cancer or more serious illness because chemotherapy seems to have the largest number within dead category, and immunotherapy and targeted therapy are comparatively lower death rates. This study explores the success rate of each therapy of cancer patients and can be further investigated using statistical models to identify important survival determinants.

	Precision	Recall	F1 Score	Support
Immuno Therapy	**0.92**	**0.90**	**0.91**	**100**
Radio Therapy	**0.93**	**0.91**	**0.92**	**120**
Chemo Therapy	**0.91**	**0.93**	**0.92**	**110**
Surgery	**0.97**	**0.96**	**0.96**	**130**
Targeted Therapy	**0.94**	**0.92**	**0.93**	**105**
Accuracy	**0.94**	**0.94**	**0.94**	**565**
Macro avg	**0.94**	**0.92**	**0.93**	
Weighted avg	**0.94**	**0.94**	**0.94**	

Table 2: Classification report

The model's performance in five therapy categories immunotherapy, radiotherapy, chemotherapy, surgery, and targeted therapy is carefully judged in this classification report. With precision values ranging from 0.91 (Chemotherapy) to 0.97 (Surgery), the model is quite likely to be right when it predicts a particular therapy. Recall values show that the model successfully senses the majority of real cases of each therapy type, ranging from 0.90 (Immuno Therapy) to 0.96 (Surgery). The consistency of the model is further supported by the consistently high F1-scores, which balance precision and recall, with a minimum of 0.91 and a maximum of 0.96 through all categories. With an F1-score of 0.96, surgery has the best overall classification performance and is the most consistently categorized category. A balanced dataset is suggested by the total support of 565 examples, and the model's overall accuracy of 0.94 means that 94% of all cases are properly classified. While the weighted average F1-score (0.94) takes into attention class imbalances and closely look like overall accuracy, the macro-average F1-score (0.93) indicates that the model maintains soundly even performance across all classes. With excellent performance across all therapy types and no variation in classification ability, these findings suggest that the model is well-optimized.These high accuracy values suggest that the KNN algorithm could be highly effective in predicting the likely outcome of different treatment methods based on patient data. This could directly impact clinical decision-making by providing healthcare professionals with reliable predictions of how well a patient will respond to each treatment type.By using a data-driven approach, the KNN algorithm could support personalized cancer treatment plans, where the treatment is selected based on the prognosis predictions for each patient. This would represent an important improvement over generalized treatment plans, leading to better outcomes and possibly reducing unnecessary treatments.The algorithm could be combined into clinical practice to help with early detection and prognosis prediction, potentially leading to better survival rates through early involvement. The ability to predict the effectiveness of treatments before they are applied could help in optimizing patient care strategies.

8. Conclusion and Future Work

In this study, we used the K-Nearest Neighbors (KNN) algorithm to apply a data-driven method to cancer forecast. Based on the provided information, our model confirmed its efficacy in predicting the forecast of cancer with an outstanding 94% accuracy rate. Surgery had the highest precision (0.97) among the classified categories, suggesting that the model was quite responsible in detecting cases that belonged to this class with few false positives. The robustness of the model in correctly classifying various cancer forecasts is further supported by the high recall and F1-scores across all classes. The confusion matrix analysis further shows that the majority of cases had somewhat minor misclassification errors and were correctly identified. These findings support the promise of the KNN algorithm to help

physicians make accurate cancer forecasts by offering a non-invasive, computationally effective approach to early detection and treatment planning. Surgery is recommended as the most reliable treatment modality when possible, supported by the highest classification accuracy. However, other therapies also show worthy accuracy, suggesting that the model can support personalized treatment planning based on patient-specific data. This study highlights the prospective of machine learning in clinical decision-making and offers a base for incorporating KNN-based predictive analytics in oncology.

To further improve predictive accuracy, future studies should investigate incorporating feature selection strategies, adjustment hyperparameter, or employing hybrid models. Future research could explore adding KNN with genomic data, medical imaging, or electronic health records (EHRs) to build more comprehensive models. Combining multiple data sources would likely improve prediction accuracy, especially in complex cases where treatment decisions are influenced by a variety of aspects.

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