PATH40060 – PRECISION ONCOLOGY

BLUESKY PROJECT

DECISION SUPPORT TOOL FOR HEAD AND NECK CANCER

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DATASET:

Grossberg A, Mohamed A, Elhalawani H, Bennett W, Smith K, Nolan T, et al. (2017) ‘Data from Head and Neck Cancer CT Atlas’. The Cancer Imaging Archive. Available at: https://wiki.cancerimagingarchive.net/pages/viewpage.action?pageId=24281354#24281354da70bb0d8df4438b853b569c99a349ab.

Contents

1. CLINICAL DECISION-MAKING

a) History of clinical decision-making

Making medical decisions is a multi-faceted and complex process which has uncertainties in diagnostics and therapies (1). In particular, oncology decisions are not always evidence-based, but additionally require consideration of clinical experience and available research (1). Historically, the paternalistic model primarily governed medicine (2). Clinicians and their healthcare support teams were considered the sole decision makers and retained all medical knowledge (2). Therefore, under this model, clinicians bear the responsibility of deciding on screening, treatment and patient management without consulting patients or their relations (2). This approach has limitations relating to the restriction of patient autonomy.

Following the requirement of informed consent, there was an increased acknowledgment for providing patients with information about their medical care (2). Additionally, majority of patients have reportedly expected to contribute to the decisions made about their health as they feel accountable for their well-being. Another approach, the consumer model, employs clinicians to diagnose the health issue, provide treatment options, and give the patient substantial autonomy to make decisions (2). However, this can cause the patient great uncertainty and clinicians may not support the treatment plan chosen (i.e., natural remedies which are not supported by scientific evidence).

b) Shared decision-making

Clinicians and patients approach decision-making from different perspectives. Clinicians tend to plan treatment based on evidence (i.e., scientific research, symptoms, patient history, and objective tests) (1). However, patients may consider multiple psychological factors when making decisions about their healthcare, such as previous experiences, quality of life and life expectancy (1).

Shared decision making (SDM) allows patients and their clinicians to make mutually agreed healthcare decisions together based on currently available evidence (1-3). This approach encourages a patient-centric approach to treatment by highlighting the patient's informed values. SDM is not currently utilised and welcomed fully in clinical settings, however, there has been significant increase in its application (2, 3).

A challenge faced by SDM is decisional conflict where patients may experience uncertainty about which treatment path is best suited for them (1, 2). This may be especially prevalent

when there are competing options and they are required to evaluate risk, loss, regret and personal struggles (2). Consequently, patients are likely to delay making a decision, regret/change their choice, and blame their clinicians for negative outcomes (2). However, interventions can be established to facilitate patients in this decision-making process and clinicians should openly communicate with their patients to understand the level of involvement they wish to have in clinical decision making (2).

Patient decision-making aids can translate information into accessible forms to allow for understanding about; (i) disease prevalence and pathophysiology, (ii) risk factors, (iii) available treatments, (iv) benefits and risks, and (v) outcome probabilities (2). It has been reported that these tools can significantly reduce delusional conflict and provide patient-friendly information to aid informed consent (2). Studies have reported better adherence to treatment regimens and overall satisfaction of patients when they have been involved in decision-making (1). Ultimately, these tools allow for a patient-centric and preference-sensitive SDM approach which is vital in oncology patients (2).

2. HEAD AND NECK CANCER

a) Prevalence

Head and neck cancer (HNC) is currently the seventh most common cancer worldwide and is increasing in incidence (4). It is predicted that HNC incidence would have increased by 30% by 2030 (4). Squamous cell carcinoma accounts for 90% of head and neck cancers (i.e., emerging from the epithelial lining of the larynx, pharynx, and oral cavity) (4). Studies have shown that survival rates differ between geographical locations, tumour sites, and stage of diagnosis (4).

b) Risk factors

Smoking tobacco and drinking alcohol are key risk factors in HNC (4). A combination of these habits accounts for 72% of HNC cases (4). Within neck and head cancer it has been proven according to Park, Nam (5), regardless of whether they consume alcohol or use cigarettes, men are substantially more likely than women to develop head and neck cancer. The risk of head and neck cancer in men is two to three times higher than in women. But over the past few decades, women are developing head and neck cancer at a higher rate than men (6). Regarding the age risk factor, people who are over 40 years are more likely to develop head and neck cancer than others who are at an age less than 40.

It is well-known that HPV plays a role in the development of head and neck cancer and is a significant risk factor, especially for oropharyngeal cancer (7). Throat and mouth infections from HPV can result in oropharyngeal cancer. Oropharyngeal is the tonsils and base of the tongue near the back of the throat. There are different subtypes of HPV. However, according to Kreimer, Clifford (8), the most frequent genotype for head and neck cancer is HPV16. In other words, one risk factor for several types of head and neck cancer, notably oropharyngeal malignancies, is oral cavity infection with cancer-causing HPV strains, especially HPV 16 (9).

c) Staging

Staging of HNC allows clinicians to assess the cancer status, prognosis, and patient management by subtyping tumours (10). The approach used for staging of HNC is the tumour, node, metastasis (TNM) staging system. T assesses the characteristics of the primary tumour (which is based on size and/or location), N defines the degree of regional lymph nodes involved, and M indicates the absence or presence of distant metastases.

Using the TNM status, the HNC is given a numerical stage status (i.e., I-II early-stage disease and III-IV advanced-stage disease) and subcategorised further for each stage (i.e., a-c). The AJCC tumour staging varies by site and therefore the defining categorisation varies between the types of head and neck cancer. The American Academy of Otolaryngology – Head and Neck Surgery Foundation has a reference guide to assist the staging of various types of HNC (see Deschler, Moore (10)).

d) Grade

When a cancer is in a particular stage, we can determine how big it is and whether it has spread. The cancer cells' appearance under a microscope determines their grade (11). There are 3 subtypes to indicate the grade of the cancer according to Macmillan (11):
Grade 1 (low grade): The cancer cells have a normal appearance and typically develop slowly.
Grade 2 and 3: Compared to normal cells, cancer cells have a distinct appearance and develop a little more quickly.
Grade 4 (high grade): The cancer cells may develop more quickly and have a drastically different appearance from normal cells.

3. AVAILABLE TREATMENTS

a) Oncology treatment overview

- Concurrent chemoradiation therapy (CCRT)
  - Cisplatin chemotherapy doses: high/weekly/2-3 cycles/switch to carboplatin/with taxol/with carboplatin AUC 2
  - Carboplatin/ carboplatin AUC 2 weekly
  - Carbolatin weekly
- Chemoradiotherapy (CRT)
- Oestrogen replacement therapy (ERT)
- Combined modality treatment (CMT)
- CCRT+Vandetanib
- ERT+Zactima
- ERT+Cettuximan
- CMT+Cetuximab
- Docetaxel + Erlotinib

Radiotherapy treatment approaches can take a duration of five days a week for up to 7-8 weeks of regimen. Each session would last up to 15 on the chosen treatment. The duration of radiotherapy treatments in the dataset ranged from 30 to 50 days of treatment; suggesting the duration the patient should expect.

b) Chemotherapy regimen options

Table 1: Chemotherapy approaches advised for head and neck cancer patients

Drug:	Delivery:	Potential side effects:
Cisplatin	Intravenous delivered infusion alkylating agent anti-cancer drug (12)	Nausea and vomiting Low blood cell count Kidney toxicity Hearing loss/ringing in ears Loss of appetite Hair loss
Docetaxel	Intravenous drip/central line delivered drug (13)	Risk of infection Breathlessness/looking pale Bruising/bleeding/ Nosebleeds Hair/appetite loss Diarrhoea/muscle pain
Carboplatin	Intravenous injections over at least 15 minutes (14)	Nausea/diarrhoea Constipation Mouth/throat sores Hands/feet/place of injection pain Weakness/hair loss

Taxol	Intravenous drip; plastic tube stays in chest during treatment course (e.g. Central line/portacath) (15)	Risk of infection Breathlessness/looking pale Bruising/bleeding Low blood pressure Hands/feet numbness/tingling Urinary tract infections

Various induction therapy options are usually advised in different combinations of aforementioned chemotherapy approaches prescribed at different cycles. These include:

- Carboplatin + 5-FU + Docetaxel
- Carboplatin + Docetaxel
- Cisplatin + 5-FU + Docetaxel
- Cisplatin + Docetaxel

Additionally, platinum-based chemotherapy approaches include cisplatin and carboplatin, and are generally known as non-selective chemotherapy approaches to treat cancers such as ovarian, breast and colorectal cancers (16).

c) Surgical interventions

Much like chemotherapy and radiotherapy approaches, surgery decisions can be made in combinations to fit the patient's cancer state. The following list describes potential surgery options that can either precede or follow chemotherapy or radiotherapy treatment:

- Neck dissection
- Neck node dissection
- Modified left radical neck dissection
- Tonsillectomy (removal of palatine tonsils)
- Tonsillectomy + radical neck dissection
- Tonsillectomy + neck node dissection
- Bilateral tonsillectomy
- Maxillectomy (removal of part of the upper jaw)
- S/p maxillectomy
- Total pharyngolaryngectomy (removal of voice box and back of of the throat and mouth)
- Excision (cutting of tissue in the neck) + neck node dissection
- Laryngectomy (removal of voice box) + neck node dissection
- Neck node dissection + salvage tonsillectomy
- Wide local excision + reconstruction + neck dissection
- Hemiglossectomy (removal of the lateral half of the tongue) + mandibulectomy (lower jaw removal) + neck node dissection
- Right total mandibulectomy + partial pharyngectomy + neck dissection
- Total glossectomy + total laryngectomy + reconstruction
- Thyroidectomy (removal of part/whole thyroid gland) + neck node dissection
- Total laryngectomy + neck node dissection
- Salvage tonsillectomy + neck node dissection

- Total laryngectomy + neck node dissection + thyroid lobectomy (removal of one thyroid lobe)

d) Additional treatment

Some HNC cases may require salvage surgeries or postoperative ERT treatment. The following table summarises the variety of treatment options for head and neck cases as reported in Grossberg, Mohamed (17).

Table 2: Summary of treatment options indicated for patients for each category of treatment approaches

Induction Chemotherapy	Chemotherapy Regimen	Platinum-based chemotherapy	CCRT chemotherapy Regimen	Surgery	Additional treatment
No	No	No	No	No	No
Carboplatin+ Taxol	Cisplatin q 3 weeks	Yes	Cisplatin high dose	Neck dissection	Salvage surgery
Carbo + Taxol x 2 cycles	Cisplatin weekly		Cisplatin weekly	Modified left radical neck dissection	Postoperative ERT
Carbo + Taxol x 4 cycles	Carbolatin weekly		Cisplatin high dose x 2 cycles	Tonsillectomy + Radical neck dissection	
Carbo + Taxol x 3 cycles	Cisplatin high does --> Carbo weekly		Carboplatin AUC 2 weekly	Neck node dissection	
Carboplatin + Taxol + Cetuximab	Docetaxel		Cisplatin x 1 cycle and cycle 2 switch to carboplatin	Right total mandibulectomy + Partial pharyngectomy + Neck dissection	
Carboplatin + Taxol + Ifosfamide x 3 cycles	Carboplatin + Taxol		Docetaxel + Erlotinib	Wide local excision + reconstruction + Neck dissection	
Cisplatin + Docetaxel x 2 cycles + Cetuximab	Carbolatin weekly		Cisplatin + Cetuximab	1) Tonsillectomy 2) Neck node dissection	
Cisplatin + Docetaxel x 3 cycles	Carboplatin + Taxol		Cisplatin high dose x 3 cycles	Tonsillectomy + Neck node dissection	
Cisplatin + 5-FU + Docetaxel x 4 cycles			Carboplatin + Taxol	Hemiglossectomy + Mandibulectomy + Neck node dissection	

Carboplatin + Docetaxol + 5-FU x 1 cycle			Cisplatin high dose x 2 cycles then carboplatin AUC 2 x 1 cycle	Bilateral tonsillectomy	
Carboplatin + Taxol x 6 cycles				Total glossectomy + Total laryngectomy + Reconstruction	
Cisplatin + Docetaxel				Thyroidectomy + Neck node dissection	
Cisplatin + 5-FU + Docetaxel x 1 cycle				Salvage tonsillectomy + Neck node dissection	
Cisplatin + 5-FU + Docetaxel x 3 cycles				Tonsillectomy	
Carboplatin + Taxol x 5 cycles				1)Neck node dissection 2) Salvage tonsillectomy	
Carboplatin + Docetaxel x 3 cycles				S/P Maxillectomy	
Carboplatin + Taxol x 5 cycles				1) Laryngectomy 2) Neck node dissection	
Carboplatin + Taxol x 6 cycles				Maxillectomy	
Carboplatin + 5-FU + Docetaxel x 3 cycles				Total pharyngolaryngectomy	
Carboplatin + Taxol weekly				Excision + Neck node dissection	
Carboplatin + Docetaxel				Total laryngectomy + Neck node dissection	
Cisplatin + Docetaxel x 3 cycles				Total laryngectomy + Neck node dissection + Thyroid lobectomy etc.	
Carboplatin + Docetaxel x 3 cycles					
Cisplatin + Docetaxel x 2 cycles					

Cisplatin + Docetaxel x 1 cycle then Carboplatin _ Taxol x 2 cycles					
Carboplatin + 5-FU + Docetaxel x 2 cycles --> Carboplatin + Docetaxel x 1 cycle					
Carboplatin + Taxol + Cetuximab					

4. DECISION SUPPORT TOOL

The aim of this decision support tool is to provide patients with a clearer understanding of their diagnosis which can aid shared decision-making. Using the dataset from Grossberg, Mohamed (17), patients can contextualise their presentation, diagnosis, and treatment options. This tool provides an accessible, visual overview of patients with head and neck cancer exhibiting similar presentations and diagnosis to current patients.

The Decision Support tool is built using R and R shiny programming, with the app hosted on shinyapps.io (which can be seen at this address https://emmetcampbell22.shinyapps.io/Cancer_Decision_Support_Tool/?_ga=2.230570521.487442132.1682971901-2067777840.1682971901). Python language was used for creating Machine Learning algorithms. We have created a cross-domain application where UI and Survival Analysis is done in R application and python machine learning scripts are imported in R environment to run the predictors. Github is being used for version control. Code is stored here: https://github.com/emmetcampbell/Cancer_Decision_Support_Tool.

The app contains 6 tabs, Front Page, Data Viewer, Demographics Plots, Patient Profile, Survival Analysis and Classifier. The Front page of the App provides and overview of the app. The Data Viewer displays a data table of the columns in the dataset and can be filtered. The demographics plots tab enables users to display various visualisations of filtered subgroups based on a factor. The plots available are 6 plots available barplot, scatterplot, histograms, waterfall plots, boxplot and violin plot. These plots are interactive. The patient profile tab displays a datatable of selected information for a selected patient. The survival analysis tab displays a kaplan-meier plot for filtered patients for selected outcomes. The outcomes available are Overall Survival in months and Disease-free interval months. Data Viewer, Demographics Plots, Patient Profile and Survival Analysis all have a print feature,

where the displayed output can be printed along with any filters used as footnotes. The classifier tab displays a prediction for patients and is discussed below. Using filters within the tool, patients can assess how various treatment options have influenced survival, recurrence, and treatment duration in other patients with similar head and neck cancer. Therefore, this tool encourages patients to communicate their concerns and preferences with clinicians. Patients can also be grouped based on categorical factors in the dataset and visualisations produced to be able to better interpret potential outcomes.

5. AI DATASET AND PRE-PROCESSING

We gathered a dataset from Grossberg, Mohamed (17) containing HNC patient data for 215 patients. This dataset comprised 112 feature points describing patient history, with most columns containing regular values. However, some columns had missing values. Although the number of features was sufficient for creating machine learning models, the limited patient count of 215 posed a challenge. After pre-processing, the number of patients might be further reduced, making it even more difficult to build a robust machine learning model.

Upon training our model with all the features and developing various classifiers, we observed overfitting. This issue stemmed from the excessive noise in the dataset and the inability of the model to fit all features, as the majority did not contribute to the model's prediction accuracy. To address these challenges, we initiated several data pre-processing techniques. For instance, columns such as "Surgery Summary," "Induction Chemotherapy," and "Site of recurrence (Distal/Local/Locoregional)" were restructured. These columns contained numerous categorical values, which we reduced to 3-4 after considering the trade-off between minimising the number of categories and retaining the necessary information for accurate modelling. We also Scaled our numerical features for the model training to ensure that all the features contribute equally to the model training process.

We further refined our feature engineering and feature selection processes by eliminating less important features and identifying the most informative ones. Features were selected based on clinical expertise and examining the dataset. In the end, we were able to shortlist 15 features, including "Sex", "Age", “Height (m)”, “BMI” "Diag," "Grade," "HPV status", "Induction Chemotherapy," "Chemotherapy Regimen," "Platinum-based chemotherapy", "Received Concurrent Chemoradiotherapy", "CCRT Chemotherapy Regime" "Surgery Summary", "Smoking History", "Current Smoker", and "Stage."

By focusing on these key features, our refined model better addressed the limited dataset size and reduced overfitting. The model's improved performance demonstrated the value of data pre-processing and feature selection in enhancing the accuracy and reliability of machine learning models, particularly when working with smaller datasets. We also tried experimenting with other machine learning techniques and their results are discussed in the “Machine Learning” section.

6. ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

We have created two classifier models, one which describes about the Response and Recurrence status of the patient and the other model which describes about the likability of the patient’s survival, i.e. weather patient will survive or not, the results achieved by the models were based on very fewer dataset, hence more patient’s data we could have achieved more accuracy. The accuracy and F1 score are two commonly used metrics for evaluating the performance of classification models, and for our models we have used these two only.

Accuracy: It measures the proportion of correctly classified instances over the total number of instances in the dataset. A higher accuracy indicates better performance of the model.

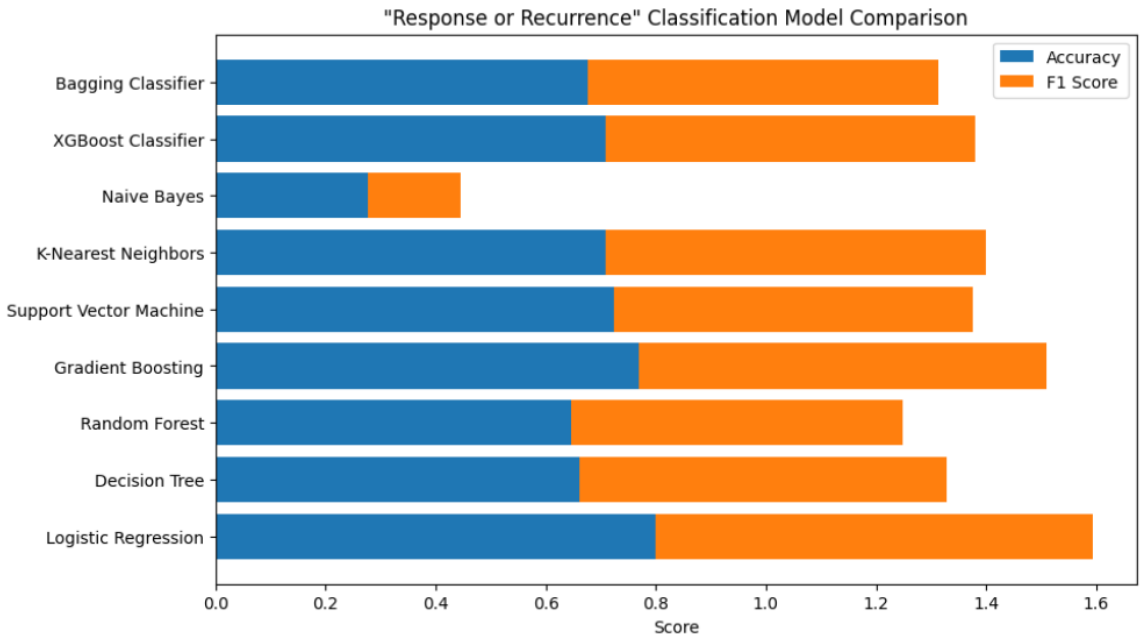
F1 Score: It is a weighted average of precision and recall, which balances the trade-off between them. It ranges between 0 and 1, where 1 indicates perfect precision and recall and 0 indicates the worst possible value.

Hyperparameter tuning: is the process of selecting the best set of hyperparameters for a machine learning algorithm in order to optimize its performance on a given dataset.

Classifier 1 - Complete Response or Recurrence

Results:

```
Logistic Regression: Accuracy = 0.80, F1 Score = 0.79
Decision Tree: Accuracy = 0.66, F1 Score = 0.67
Random Forest: Accuracy = 0.65, F1 Score = 0.60
Gradient Boosting: Accuracy = 0.77, F1 Score = 0.74
Support Vector Machine: Accuracy = 0.72, F1 Score = 0.65
K-Nearest Neighbors: Accuracy = 0.71, F1 Score = 0.69
Naive Bayes: Accuracy = 0.28, F1 Score = 0.17
XGBoost Classifier: Accuracy = 0.71, F1 Score = 0.67
Bagging Classifier: Accuracy = 0.68, F1 Score = 0.64
```



The results represent the performance of different classifiers on the HCN dataset. From the results, we can see that Logistic Regression performed the best with an accuracy of 0.8 and an F1 score of 0.79. This indicates that the model has a good overall performance in correctly classifying the samples. Gradient Boosting also performed well with an accuracy of 0.77 and an F1 score of 0.74.

On the other hand, Naive Bayes had a very low accuracy of 0.28 and an F1 score of 0.17, indicating poor performance. Random Forest and Support Vector Machine also did not perform well, with accuracy scores of 0.65 and 0.72, respectively.

We also tried Hyper Parameter Tuning for increasing the efficiency of the model, but the results were somewhat similar to what we achieved from the original models. Below mentioned are the results obtained.

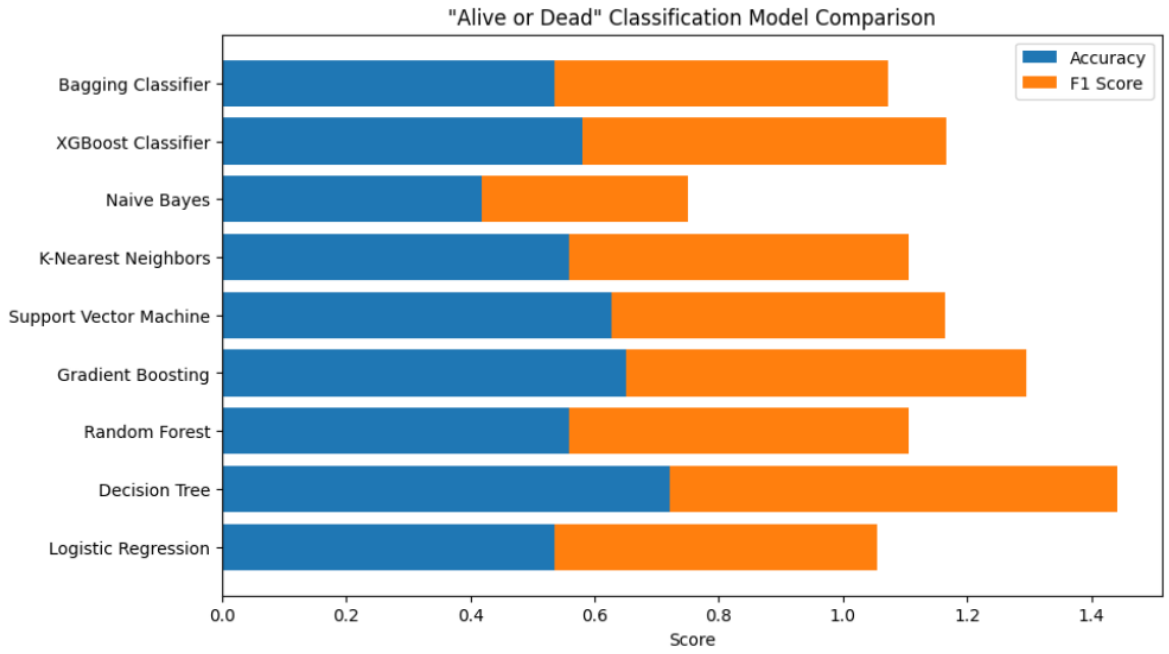
```
Logistic Regression: Accuracy = 0.75, F1 Score = 0.74
Gradient Boosting: Accuracy = 0.72, F1 Score = 0.61
```

Hence, after analysing the results of all the models, the Logistic Regression model was selected for the deployment on our application.

Classifier 2 - Alive or Dead

Results:

```
Logistic Regression: Accuracy = 0.53, F1 Score = 0.52
Decision Tree: Accuracy = 0.72, F1 Score = 0.72
Random Forest: Accuracy = 0.56, F1 Score = 0.55
Gradient Boosting: Accuracy = 0.65, F1 Score = 0.64
Support Vector Machine: Accuracy = 0.63, F1 Score = 0.54
K-Nearest Neighbors: Accuracy = 0.56, F1 Score = 0.55
Naive Bayes: Accuracy = 0.42, F1 Score = 0.33
XGBoost Classifier: Accuracy = 0.58, F1 Score = 0.59
Bagging Classifier: Accuracy = 0.53, F1 Score = 0.54
```



Based on the results achieved, the performance of the classification models varies. The Decision Tree Classifier appears to perform the best, with the highest accuracy (0.72) and F1 score (0.72). While an accuracy of 0.72 is not perfect, it is a good start, and the model could potentially be improved further by increasing more data or maybe by adding more features could have been a plus point too. We also did Hyperparameter Tuning for the classification and results are mentioned below and the end Decision Tree Classifier was selected for the “Alive or Dead” Model.

```
K-Nearest Neighbours: Accuracy = 0.65, F1 Score = 0.63
Gradient Boosting: Accuracy = 0.68, F1 Score = 0.66
```

```
Decision Tree: Accuracy = 0.65, F1 Score = 0.63
```

Regression Models

We have created two regression models one for predicting the average survival days for a patient who undergoes HCN treatment and the other one predicts the Total RT treatment time for patients. These models were created with very few dataset, larger dataset would have definitely boosted up the algorithms. Also adding more numerical features like information of pre and post RTs or more description about the x ray images would have helped in getting better results. But we were trying to build a simple application and wanted to innvolve less features so that, it can be easily used by the wider public.

Regressor 1

Original models

```
Linear Regression: Mean Squared Error = 796926069601964749131612l6.00, R^2 Score = -1052901950234667264245 76.00

Ridge: Mean Squared Error = 710.52, R^2 Score = 0.06

Lasso: Mean Squared Error = 650.20, R^2 Score = 0.14

ElasticNet: Mean Squared Error = 691.71, R^2 Score = 0.09

LightGBM: Mean Squared Error = 746.28, R^2 Score = 0.01

CatBoost: Mean Squared Error = 658.04, R^2 Score = 0.13

Decision Tree: Mean Squared Error = 1626.65, R^2 Score = -1.15

Random Forest: Mean Squared Error = 704.89, R^2 Score = 0.07

Gradient Boosting: Mean Squared Error = 795.94, R^2 Score = -0.05

Support Vector Machine: Mean Squared Error = 834.47, R^2 Score = -0.10
```

Based on the results of the basic regression models, we can see that Linear Regression, Decision Tree, Random Forest, Gradient Boosting, and Support Vector Machine have poor performance in terms of Mean Squared Error and R^2 Score. Lasso and CatBoost have a decent R^2 score of 0.14 and 0.13, respectively, but their Mean Squared Error could be improved.

Models after tuning hyperparameters

```
Ridge: Mean Squared Error = 683.27, R^2 Score = 0.10
```

```
Lasso: Mean Squared Error = 650.20, R^2 Score = 0.14
ElasticNet: Mean Squared Error = 681.84, R^2 Score = 0.10
LightGBM: Mean Squared Error = 629.72, R^2 Score = 0.17
CatBoost: Mean Squared Error = 689.70, R^2 Score = 0.09
```

The Hyperparameter tuning improved the performance of all the models, and the LightGBM model performed the best with a Mean Squared Error of 629.72 and an R^2 Score of 0.17. This suggests that LightGBM is the best model out of the basic and tuned models and can be used for deployment. The **LightGBM model** is a gradient boosting framework that uses tree-based learning algorithms. It has high accuracy and a fast-processing speed, making it suitable for large datasets. Its superior performance in this case could be attributed to its ability to manage complex features and interactions among variables. With a Mean Squared Error of 629.72 and an R^2 Score of 0.17, the LightGBM model can provide reliable predictions for the target variable.

Regressor 2

Original models

```
Linear Regression: Mean Squared Error = 2455194012523427203645 44.00, R^2 Score = -9232028447198949670912.00
Ridge: Mean Squared Error = 26.82, R^2 Score = -0.01
Lasso: Mean Squared Error = 27.09, R^2 Score = -0.02
ElasticNet: Mean Squared Error = 27.11, R^2 Score = -0.02
LightGBM: Mean Squared Error = 30.25, R^2 Score = -0.14
CatBoost: Mean Squared Error = 29.04, R^2 Score = -0.09
Decision Tree: Mean Squared Error = 29.91, R^2 Score = -0.12
Random Forest: Mean Squared Error = 26.22, R^2 Score = 0.01
Gradient Boosting: Mean Squared Error = 25.91, R^2 Score = 0.03
Support Vector Machine: Mean Squared Error = 28.58, R^2 Score = -0.07
```

Hyperparameter model

```
Ridge: Mean Squared Error = 25.68, R^2 Score = 0.03
Lasso: Mean Squared Error = 27.09, R^2 Score = -0.02
```

```
ElasticNet: Mean Squared Error = 27.09, R^2 Score = -0.02
LightGBM: Mean Squared Error = 27.10, R^2 Score = -0.02
CatBoost: Mean Squared Error = 27.18, R^2 Score = -0.02
```

Based on the mean squared error and R^2 score, it appears that the linear regression, ridge regression, and Lasso regression models are not performing well, with negative R^2 scores indicating that they are performing worse than a horizontal line.

The ElasticNet model is also not performing well with a negative R^2 score. On the other hand, the LightGBM, CatBoost, Random Forest, and Gradient Boosting models are performing better with positive R^2 scores, indicating that they are performing better than a horizontal line. After hyperparameter tuning, the Ridge, Lasso, ElasticNet, and CatBoost models show no improvement in performance compared to their basic versions. The LightGBM model shows slight improvement in performance, while the tuned Ridge model performs slightly better than the basic Ridge model. Based on these results, the LightGBM model was selected as the best choice for deployment, as it has the lowest mean squared error and the highest R^2 score among the basic models.

Conclusion

As per the results obtained by our classifiers and regressors, results were satisfactory. However, it is important to note that the R^2 score is still relatively low, indicating that there may be other factors that are not accounted for in the model. Further analysis and feature engineering may be necessary to improve the model's performance.

Before deployment, the model should be thoroughly tested and validated to ensure its accuracy and reliability. Additionally, it is important to monitor the performance of the deployed model and update it regularly to ensure its continued accuracy.

7. LIMITATIONS AND FUTURE APPLICATIONS

A much larger, more diverse dataset should be used to inform the AI of this tool. Additionally, this tool would be significantly strengthened if the dataset included detailed HPV subtype, genetic and epigenetic analysis, available imaging analysis results, and family history data from previous patients. Seven unique loci have been linked to the genetic susceptibility to HNC using GWAS (4). For example, GWAS analysis of oropharyngeal subgroups reported a strong protective association at variant rs3828805 (mapped within the human leukocyte antigen Class II region). Additionally, increased HNC risk is linked to variations in alcohol-metabolising genes (e.g., alcohol dehydrogenase). Therefore, including genomic risk factors such as these will likely strengthen the predictive ability of the tool.

Although the model designed here is limited by the current dataset, there is great potential to improve the accuracy required to provide patients with accessible information. Additionally, there may be other treatment options which interest patients that are not included in the dataset. For example, herbal/natural alternatives or other pharmaceutical compounds. Therefore, this somewhat restricts the applicability of this tool.

Future applications of this tool should take the above missing features into account. With substantial development, this tool has the potential to be applied to various cancers in addition to HCN. Other applications of this tool could include an online Q&A session for patients to actively interact with medical professionals when viewing this information as well as hyperlinks to available patient-centric websites and available clinical trials.

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