A photograph of a lush green cornfield stretching to the horizon under a warm, orange-hued sunset sky. A small barn is visible in the distance on the left. A semi-transparent white box on the right side of the image contains the title and author information.

EMBRACING HEALTHIER EATING WITH MACHINE LEARNING TECHNOLOGY

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IST 736 – Text Mining – Final Project



Introduction

- Many people struggle to identify truly healthy recipes
- Importance of healthy eating is ever growing; demand for fresh, whole foods is at an all-time high
- Cuisine varies greatly across cultures, and this diversity presents both opportunities and challenges in making healthy food choices
- Significant opportunity for technology to play a transformative role in our dietary choices
 - Fueled by rising awareness of the links between diet and chronic diseases such as obesity, diabetes and heart disease
 - A healthy diet could prevent 80% of heart disease and 40% of cancer cases globally (WHO)
- Understanding the ingredients essential for maintaining a healthy lifestyle



Project Overview

- Prototype for classifying recipes as healthy or unhealthy using machine learning
 - Model considers key nutritional metrics: macronutrients (proteins, fats, carbohydrates), vitamins, and minerals.
- **Application and Benefits:**
 - Valuable for individuals and companies in the health and wellness industry.
 - Potential for integration into products and services, e.g., meal kit delivery services.
 - Helps customers make informed choices and supports health goals.
- **Impact:**
 - Enhances public health by bridging the gap between nutrition science and everyday eating habits.
 - Empowers individuals to make better dietary choices with a user-friendly model.
- **Data Preparation:**
 - Data sourced from two CSV files with healthy and unhealthy recipes; created through scraping the Spoonacular API and website.
 - Includes information on ingredients, calories, fat, protein, and carbs.



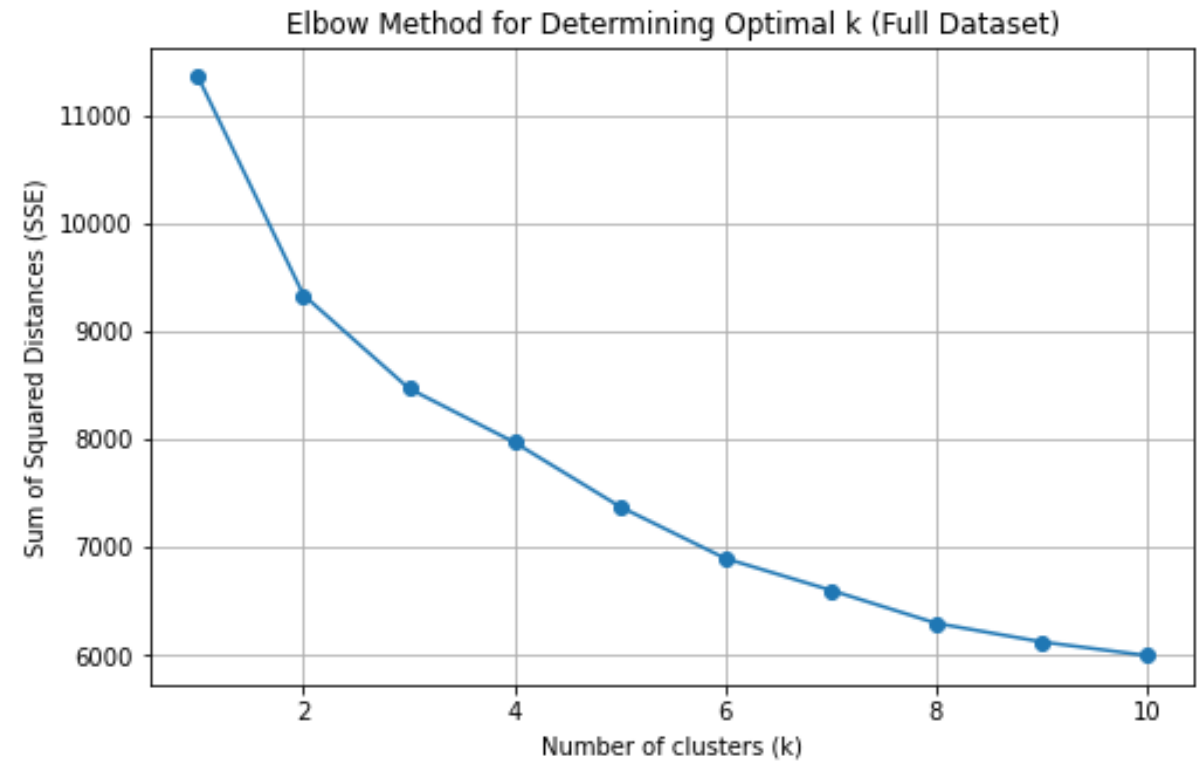
- # Healthy Recipes

[illegible]

EDA – Elbow Method



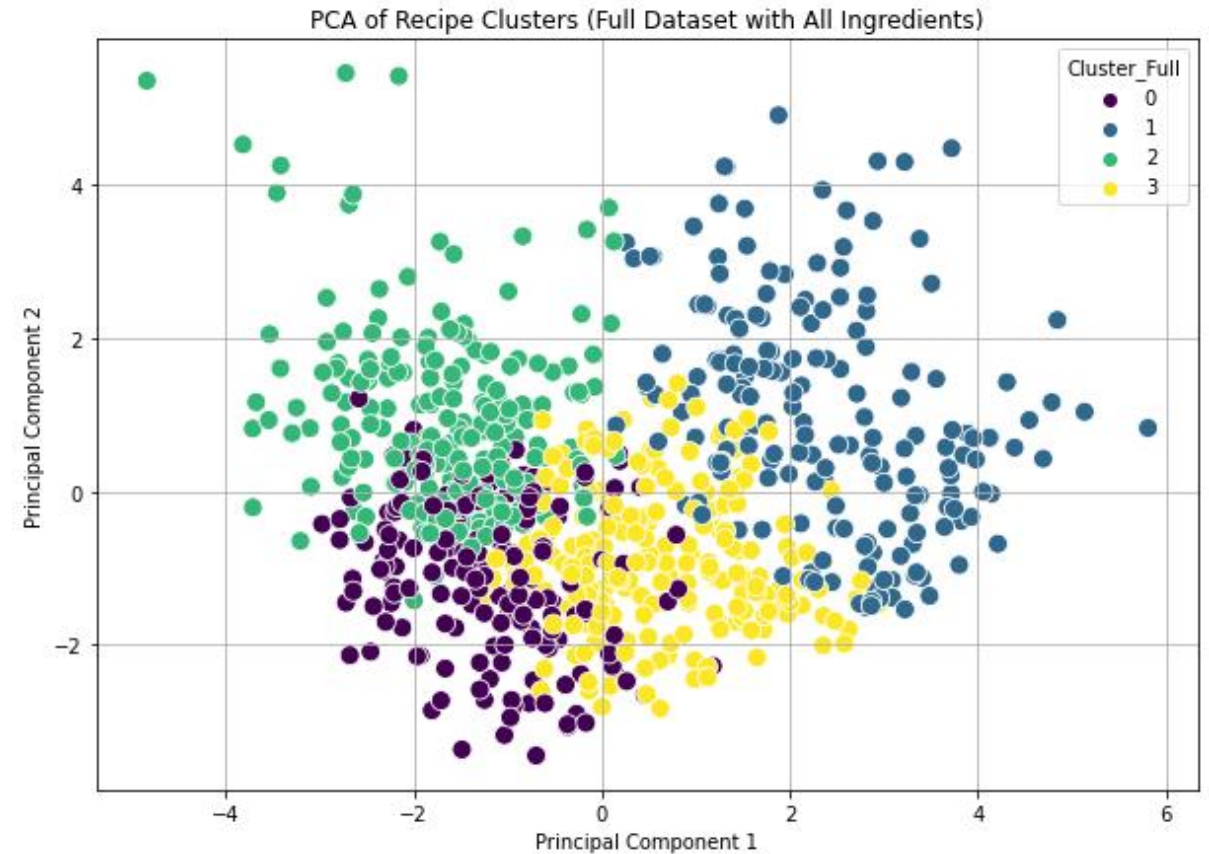
$k = 2$, After this point, the SSE value levels off or decreases more gradually.



EDA - PCA



- Principal Component 1 is plotted on the x-axis, ranging from -4 to 6
- Principal Component 2 is plotted on the y-axis, ranging from -2 to 4.
- The graph displays four distinct clusters
 - Some overlap between clusters
 - Visible outliers within the cluster



LOGISTIC REGRESSION



Evaluating classifier: Logistic Regression

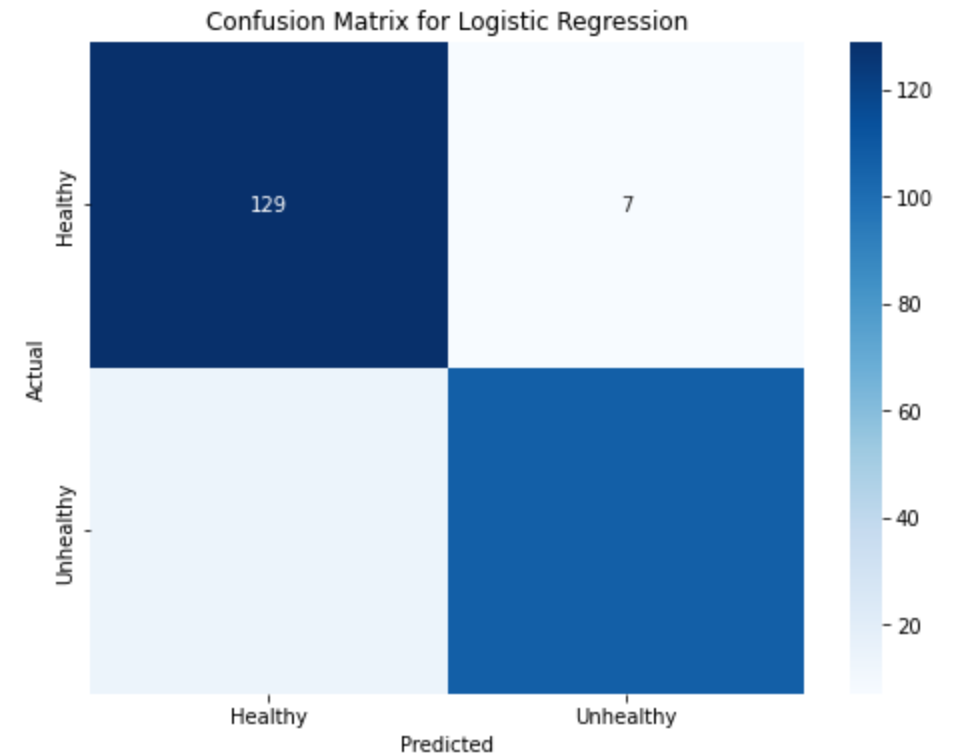
Cross-validation scores: [0.91747573 0.93170732 0.91219512
0.94634146 0.93170732]

Average cross-validation score: 0.927885389533507

Accuracy on test set: 0.9182879377431906

Classification report:

	precision	recall	f1-score	support
Healthy	0.90	0.95	0.92	136
Unhealthy	0.94	0.88	0.91	121
accuracy			0.92	257
macro avg	0.92	0.92	0.92	257
weighted avg	0.92	0.92	0.92	257

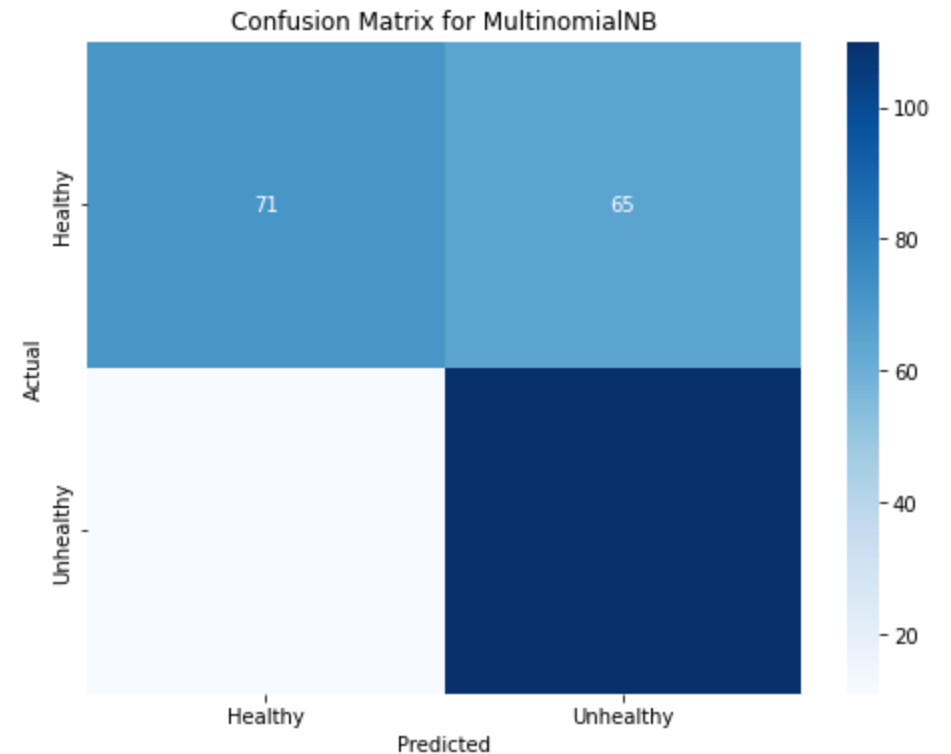


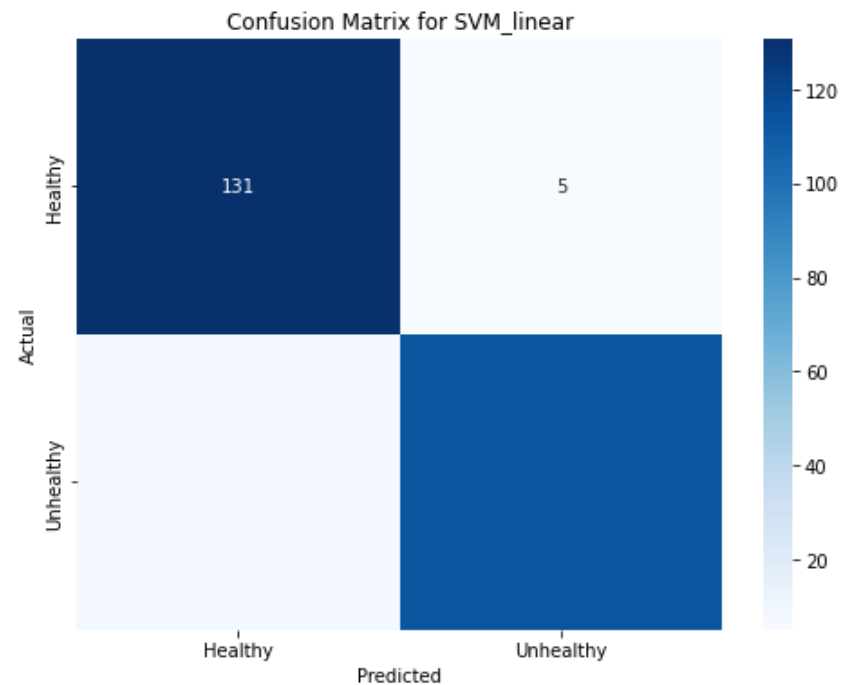
NAÏVE BAYES

Multinomial and Gaussian NB
Best performer: Multinomial



```
Evaluating classifier: MultinomialNB  
  
Cross-validation scores: [0.65048544 0.69268293 0.62439024  
0.65365854 0.71219512]  
Average cross-validation score: 0.6666824532322992  
Accuracy on test set: 0.7042801556420234  
Classification report:  
              precision    recall  f1-score   support  
  
   Healthy       0.87        0.52        0.65        136  
  Unhealthy       0.63        0.91        0.74        121  
  
   accuracy              0.70        0.70        0.70        257  
  macro avg              0.75        0.72        0.70        257  
 weighted avg              0.75        0.70        0.69        257  
  
-----
```





```
Evaluating classifier: SVM_linear
Cross-validation scores: [0.9368932  0.93658537 0.95121951
0.96585366 0.94634146]
Average cross-validation score: 0.9473786407766991
Accuracy on test set: 0.9494163424124513
Classification report:
      precision    recall  f1-score   support

 Healthy      0.94      0.96      0.95        136
Unhealthy      0.96      0.93      0.95        121

 accuracy      0.95
 macro avg      0.95      0.95      0.95        257
weighted avg      0.95      0.95      0.95        257
```

SUPPORT VECTOR MACHINES



Kernels ran: Linear, Polynomial,
Radial Basis Function

Best performer: Linear Kernel

RANDOM FOREST



Evaluating classifier: Random Forest

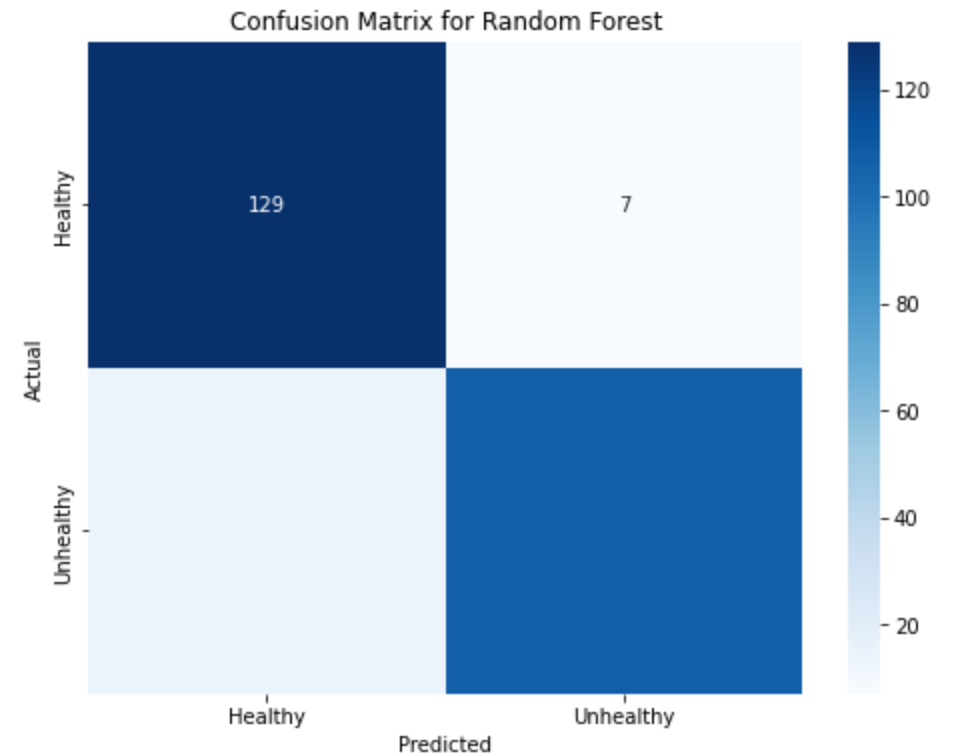
Cross-validation scores: [0.94660194 0.92195122 0.89268293
0.92195122 0.93170732]

Average cross-validation score: 0.9229789249348805

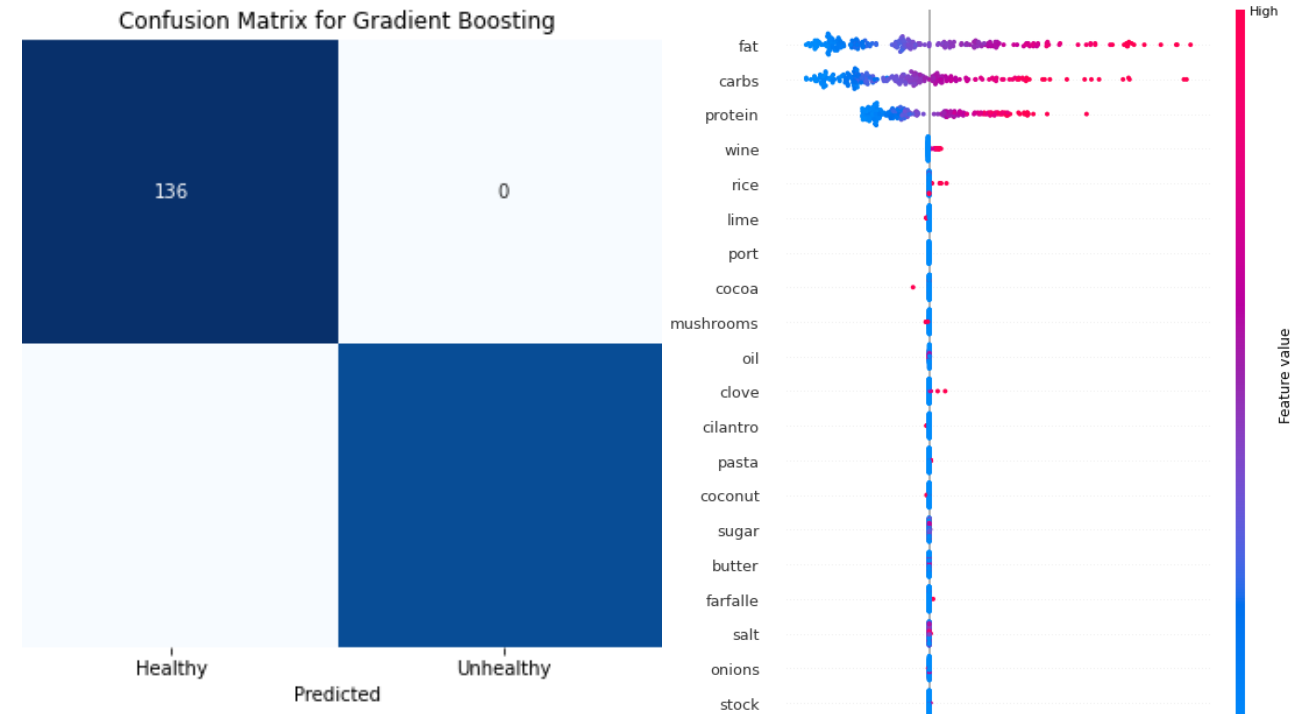
Accuracy on test set: 0.9182879377431906

Classification report:

	precision	recall	f1-score	support
Healthy	0.90	0.95	0.92	136
Unhealthy	0.94	0.88	0.91	121
accuracy			0.92	257
macro avg	0.92	0.92	0.92	257
weighted avg	0.92	0.92	0.92	257



GRADIENT BOOSTING



Evaluating classifier: Gradient Boosting

Cross-validation scores: [0.99514563 0.9804878 0.98536585 0.99512195 0.9902439]

Average cross-validation score: 0.9892730286526167

Accuracy on test set: 1.0

Classification report:

	precision	recall	f1-score	support
Healthy	1.00	1.00	1.00	136
Unhealthy	1.00	1.00	1.00	121
accuracy			1.00	257
macro avg	1.00	1.00	1.00	257
weighted avg	1.00	1.00	1.00	257

DECISION TREES

Entropy and Gini Impurity

Criteria

Best performer: Entropy



Evaluating classifier: Decision Tree Entropy

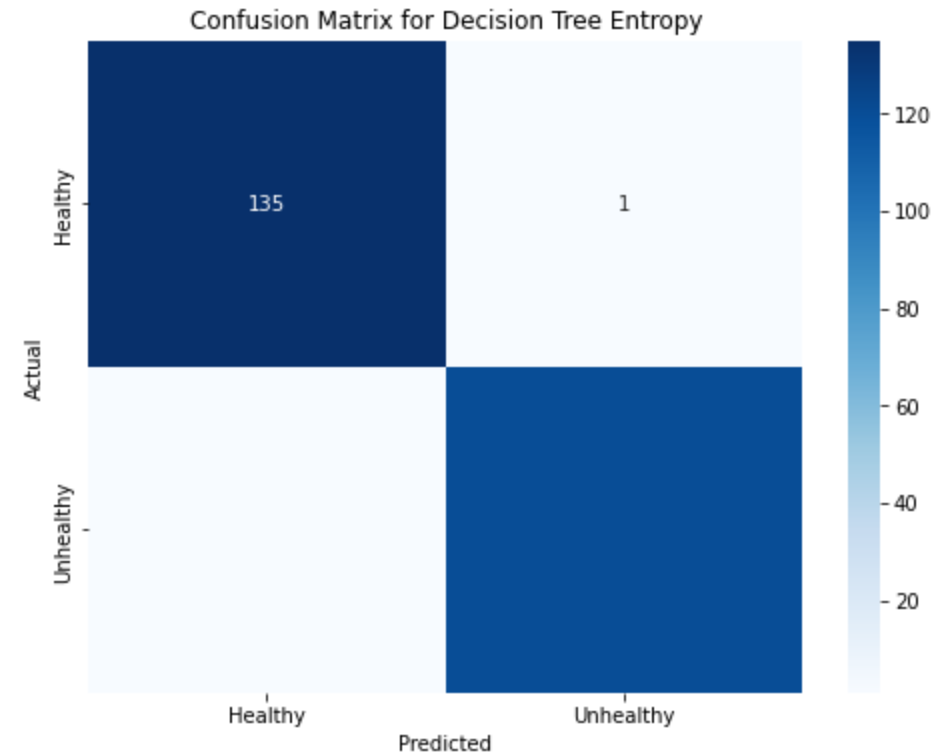
Cross-validation scores: [0.98543689 0.96585366 0.98536585 1.0 0.98536585]

Average cross-validation score: 0.9844044518115084

Accuracy on test set: 0.9922178988326849

Classification report:

	precision	recall	f1-score	support
Healthy	0.99	0.99	0.99	136
Unhealthy	0.99	0.99	0.99	121
accuracy			0.99	257
macro avg	0.99	0.99	0.99	257
weighted avg	0.99	0.99	0.99	257



LATENT DIRICHLET ALLOCATION



Evaluating classifier: LDA

Accuracy on test set: 0.5652173913043478

Classification report:

	precision	recall	f1-score	support
0	0.82	0.34	0.48	41
1	0.48	0.89	0.62	28
accuracy			0.57	69
macro avg	0.65	0.62	0.55	69
weighted avg	0.68	0.57	0.54	69

words representative of their class as identified by the lda
Topic #0:
sugar butter flour egg bake powder salt vanilla brown chocol
Topic #1:
pepper oil salt garlic onion chicken oliv sauc tomato chees
['latentdirichletallocation0' 'latentdirichletallocation1']

Methods and Models – Overall Results

Models and Accuracies:

- Logistic Regression (0.92)
- Multinomial Naive Bayes (0.70)
- Gaussian Naive Bayes (0.64)
- SVM (Linear Kernel) (0.95)
- SVM (Polynomial Kernel) (0.70)
- SVM (Radial Basis Function Kernel) (0.86)
- Random Forest (0.92)
- Gradient Boosting (1.0)
- Decision Trees (Entropy: 0.99, Gini: 0.98)
- Latent Dirichlet Allocation (0.57)

Top Three Models:

- **Gradient Boosting:**
 - Perfect accuracy: 1.0
 - Excellent precision, recall, and F1-score
 - Potential for overfitting, needs further validation
- **Decision Tree (Entropy):**
 - High accuracy: 0.99
 - Balanced performance
 - May need validation to ensure generalizability
- **Support Vector Machine (Linear Kernel):**
 - High accuracy: 0.95
 - Strong performance across classes
 - Recommended for further tuning

Results – Continued

Ingredient Patterns:

- Similar word clouds for healthy and unhealthy recipes
- Ingredient lists may not be the primary differentiator
- Other factors like ingredient quantities or serving sizes may be more significant

Quantitative Factors:

- Hypothesis: Quantity of ingredients (e.g., fats, sugars) differentiates healthy from unhealthy recipes
- Healthiness may be related to the amount consumed rather than ingredient presence

Caloric Content and Serving Size:

- Importance of serving size and caloric content in determining healthiness
- Recipes with similar ingredients may have different health implications based on portion sizes and calorie counts

Further Analysis Needed:

- Focus on ingredient quantities, calorie content, and serving sizes
- Refine model tuning and validate with new data to improve accuracy and robustness

What 100 Calories of Salad Fixings Looks Like



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Conclusion & Future Directions



- Complexity of modern eating habits and the influence of cultural traditions underscore the importance of effective tools and resources
- Recipes can guide individuals toward healthier choices, enhance cooking skills, and support a balanced lifestyle
- Foster positive lifestyle changes and improve overall quality of life
- Individuals can navigate dietary options more effectively and make meaningful strides toward achieving a healthier and more fulfilling life
- Can be useful for people with various health concerns (diabetes, hyperglycemia, etc.)
- Diet planning for kitchens at senior living facilities, schools, individual consumers
- Potential Use: app can be developed to use this data to help users track calories, fat, protein, etc.

★Note about healthy/unhealthy recipes

