Scores of Hungers: Utilizing Global Datasets to Predict Regional Food Insecurity

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***Abstract*—This research project aims to devise a comprehensive score representing the food insecurity levels of diverse regions, underpinned by a series of predictor variables. These variables encompass unemployment rates, average income, local food prices, population density, drought conditions, and precipitation levels, among others. The crux of the study is to determine the intricate correlations between these predictor variables and the resultant food insecurity scores. Key research questions include discerning the most impactful predictor variables for a region's food security and exploring potential time-lagged effects. For instance, the study will investigate if unemployment rates from a preceding year bear a significant effect on the subsequent year's food insecurity. Additionally, geographical aspects such as proximity to water bodies and soil quality, which might be influential but often overlooked, will be evaluated for their bearing on food insecurity levels. Data sources to substantiate this research are diverse and robust. The Global Hunger Index offers a holistic view of hunger on global, regional, and national scales. National Statistical Offices provide region-specific data, ensuring granularity and precision in the research. International bodies like the OECD and FEWS NET impart valuable socio-economic and early famine warning data, respectively. Meteorological insights will be extracted from the World Meteorological Organization (WMO) and respective National Meteorological Services, pivotal for the drought and precipitation variables. Employment metrics, crucial for gauging the unemployment predictor variable, will be sourced from the International Labor Organization's ILOSTAT database. Furthermore, data from the United Nations' Food and Agriculture Organization (FAO) and World Bank Open Data will be instrumental in painting a comprehensive picture of global food security dynamics. This project aspires to provide a detailed, data-driven lens to scrutinize the multifaceted issue of food insecurity across regions, leveraging vast datasets and in-depth analysis.**

I. Introduction

It is impossible to overstate the seriousness of food insecurity as a worldwide problem. It is a multifaceted issue that is impacted by an intricate network of variables that differ greatly between geographical areas. With the goal of delving further into these complications, this research study, "Scores of Hungers: Utilizing Global Datasets to Predict Regional Food Insecurity," provides a nuanced and thorough data-driven viewpoint.

This study takes an interdisciplinary approach to tackle the problem. Through the integration of data from multiple domains, including meteorology, economics, agriculture, and sociology, our goal is to build a model that accurately captures the reality of food insecurity across various geographies. In addition to providing insight into the existing level of food insecurity, this model can be used as a forecasting tool to identify at-risk areas and the possible severity of their circumstances.

Many predictor variables are analyzed as the foundation of our study technique. These variables demonstrate the diverse character of food insecurity, ranging from natural factors like precipitation levels and drought to economic situations like average income and employment rates. Using this method enables us to distill the essence of food insecurity as a complex phenomenon shaped by a confluence of environmental and socioeconomic factors.

This study's emphasis on the changing nature of food insecurity is one of its key features. Understanding that a region's level of food security varies over time, the study looks at how shifts in the predictor factors affect the degree of food insecurity. This longitudinal research is essential to comprehending the long-term consequences of several elements in addition to their immediate effects.

Geographic variety is also emphasized heavily in the study. Food security is frequently impacted by region-specific characteristics such as soil quality, proximity to water sources, and urban-rural divides. The goal of the research is to provide insights that are relevant to the demands and features of various locations by examining these regional variations.

The study makes use of data from reliable and varied sources to guarantee the validity and trustworthiness of its conclusions. This includes specialist inputs from agencies like the International Labor Organization, the World Meteorological Organization, and the FEWS NET, as well as global indexes like the Global Hunger Index and comprehensive data from National Statistical Offices. A thorough approach to gathering data like this enhances the breadth and depth of our study while also bolstering the credibility of our research.

Furthermore, the study is intended to serve as more than a mere research project. Our goal is to offer policymakers, non-governmental organizations, and other stakeholders' useful insights by identifying the key factors influencing food insecurity and their interactions.

To sum up, "Scores of Hungers" seeks to meaningfully add to the ongoing global conversation about food security. This research aims to shed light on the strategies for addressing food insecurity and, in the end, make a positive impact on a society where everyone has access to enough food that is both sufficient and healthy through its in-depth and diverse analysis.

II. Research Framework

- Formulation of research questions
- Literature review
- Data collection and pre-processing
- Model building
- Model evaluation (testing)
- Results
- Discussion and conclusion

III. Literature Review

We build on the work of Nord, Coleman-Jensen, and Gregory, who employed regression analysis to establish a relationship between food insecurity in the United States and inflation, unemployment, and food prices. Between 2001 and 2012, they discovered a strong link between these economic variables and food insecurity. By using a larger range of predictors in sophisticated machine learning models, our research expands on this and has the potential to reveal more intricate linkages and offer predictive insights into the levels of food security. By considering other variables that interact with and affect economic situations, this could fill in information gaps and provide a comprehensive tool for strategic planning and policy making.

Building upon the panel data regression models utilized in the research "Climate Change and Chronic Food Insecurity," our study addresses the crucial need for adaptation strategies and an emission reduction as noted by Dasgupta & Robinson, adding a predictive component to the assessment of climate change impacts.

Although Jianchong Sun et al.'s paper "Data-driven models for groundwater level prediction" focuses on groundwater levels, our machine learning models provide a more comprehensive predictive analysis, filling in the gaps about the ways in which environmental elements like groundwater affect overall food security.

Our research uses a variety of machine learning techniques, as opposed to Olimar E. Maisonet-Guzman's work "Food Security and Population Growth in the 21st Century," which used OLS regression models to assess the relationship between population growth and agricultural productivity. Although Maisonet-Guzman discovered a positive association indicating that a growing population can result in higher agricultural output, our methodology seeks to comprehend how population growth influences food security in conjunction with other elements like policy changes and technical advancements. We hope to offer a more complete prediction model by incorporating these more variables, which can be a useful tool in tackling the complex issues surrounding food security in the twenty-first century.

We expand on the findings of Sue Booth and Christina M. Pollard, "Food Insecurity and Hunger in Rich Countries—It Is Time for Action against Inequality." Although their study of the literature carefully looks at the causes and prevalence of food insecurity in wealthy cultures, emphasizing structural inequality, our analysis of a larger range of socioeconomic determinants is made possible using logistic regression, random forest, and XGBoost models. This all-encompassing strategy aims to address the complex relationship between many types of inequality and food insecurity. By offering predicted insights that could guide more focused and successful interventions, we hope to close the research gap.

Incorporating USDA's foundational work on food security definitions and measurement, our project employs advanced algorithms to transition from defining to predicting food security levels, aiming to fill the gap between static categorization and dynamic forecasting.

Our methodology seeks to enhance the analysis presented by Diogo Miguel Salgado Baptista and Mai Farid in their study on the impact of climate change on food insecurity in Sub-Saharan Africa. While their research focuses on the economic consequences of climate shocks and the role of monetary policy in mitigating these impacts, our approach uses advanced machine learning models to predict food security. By incorporating a wide range of variables, including climate data, our model aims to provide a more comprehensive understanding of how numerous factors contribute to food security in the context of climate change.

Liana E. Pozza and Damien J. Field examine the critical relationship between soil health and food security in "The Science of Soil Security and Food Security," stressing the need of modifying techniques for meeting food demand and the need for sustainable land management. Their strategy is in line with our overarching goal of comprehending how environmental factors impact food security, even if our methodology mostly leverages machine learning to accomplish predictive modeling.

Alisha Coleman-Jensen, Matthew P. Rabbitt, Christian A. Gregory, and Anita Singh's paper "Household Food Security in the United States in 2020" offers a thorough statistical examination of food security in American households in 2020. Their research provides a descriptive picture of food insecurity, but our initiative integrates such empirical data for comprehensive forecasting by using predictive models to foresee future trends in food security.

According to Barclays study, there is a complicated interplay between natural disasters like floods and droughts and geopolitical events like the situation in Ukraine that contributes to global food insecurity. The paper emphasizes how these variables put pressure on food supply networks, resulting in shortages and exorbitant costs and highlighting the susceptibility of the global food system. It highlights the wider ramifications, such as social unrest and migration, underscoring the pressing need for effective measures to guarantee food security in the face of these difficult conditions. This broad viewpoint is consistent with the goal of our project, which is to forecast food security under different global challenges.

Our study builds on the findings of Setsoafia, Ma, and Renwick's research on sustainable agriculture methods in Ghana by employing sophisticated machine learning models. Although they use MESR models to examine the effects of agricultural practices, our approach may be able to capture a wider range of factors affecting food security.

Our methodology goes beyond Gomiero's examination of land shortage and soil degradation. Although Gomiero tackles the intricacies of land use change and its socio-economic impetuses, our predictive models combine these environmental elements with other global variables, providing a more comprehensive understanding of the dynamics of food security.

The strategy taken by Gholami, Knippenberg, Campbell, Andriantsimba, Kamle, Parthasarathy, Sankar, Birge, and Lavista Ferres in their study on food insecurity in Malawi is enhanced by our project's use of logistic regression, random forest, and XGBoost models. To forecast food insecurity, they use the Shapley additive explanations (SHAP) framework in conjunction with random forest and logistic regression models. Although both researches use sophisticated machine learning methods, our method may include more global factors, providing a more comprehensive view of food security forecasts.

IV. Data Collection and Preprocessing

Data Collection

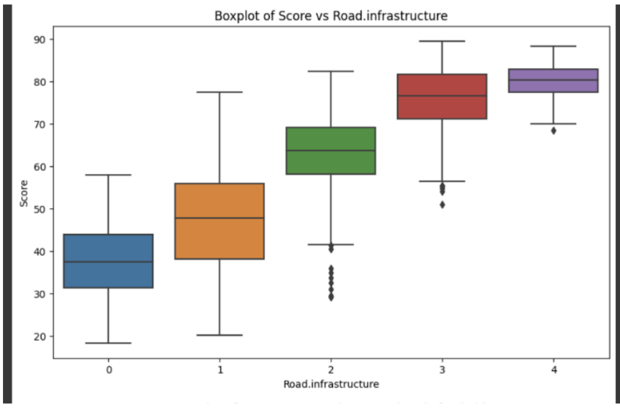
This study is based on a solid dataset that was assembled from three reliable sources: the Food and Agriculture Organization (FAO), the World Data Bank, and the Global Food Security Index (GFSI). An extensive assessment of the factors influencing food security in various geopolitical and economic contexts is made possible by this data triangulation.

Data Integration and Cleaning

To ensure data integrity, the process of merging datasets from several sources needed to be done with extreme care. All the datasets, which came from the FAO, World Data Bank, and Global Food Security Index (GFSI), included variables and unique IDs relevant to food security evaluations. We combined these datasets using the rbind and merge functions, making use of the power of R programming to make sure that every record matched precisely between the various sources. Data reconciliation was done manually, cross-referencing each record to ensure accuracy where IDs did not line correctly.

We first used the read.csv function to import the datasets into a single CSV file. Then, we used the dplyr package to edit and connect the datasets using common keys, including the names of the countries and the years. To create a uniform framework, we also standardized the variable names and measurement units throughout this step. The ensuing data analysis and smooth integration made possible by this harmonization were crucial.

The crucial next stage after merging the datasets was cleaning. As a result, rows with NA values had to be found and eliminated because they can obscure actual relationships in the data. We removed these missing entries by using the na.omit function, which cleaned the dataset in

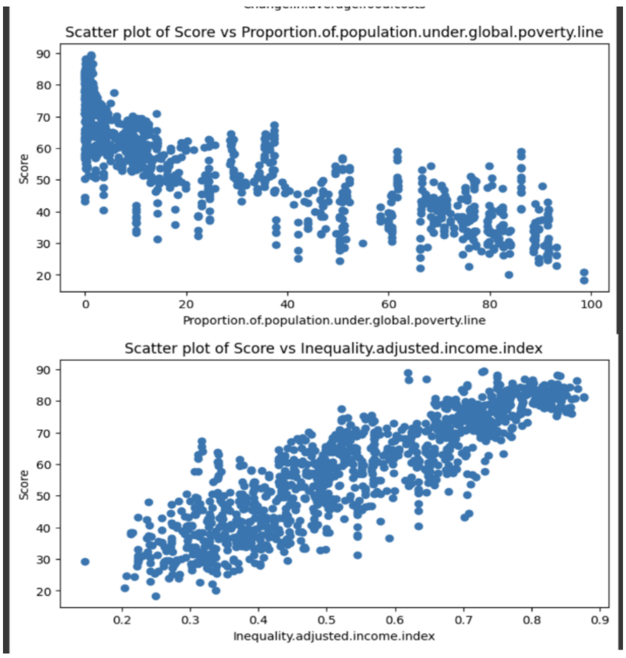


preparation for the next analytical procedures.

With no longer any missing values or inconsistencies, the resulting data set offered a uniform data frame that was prepared for the exploratory data analysis. The next stage would take a more in-depth look at outlier identification and normalization, laying the groundwork for a thorough statistical analysis of the variables influencing global food security.

Exploratory Data Analysis

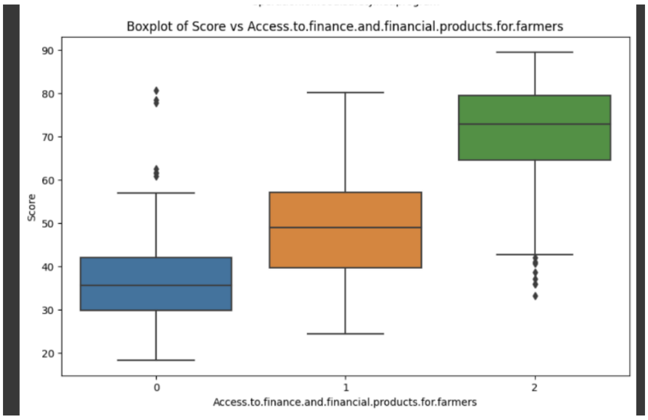
An investigation into the factors influencing food security scores was done to find those that were significant. Scatter plots were used to graphically illustrate continuous variables, highlighting possible linear relationships with food security ratings. Finding patterns and linkages that might not be immediately obvious through numerical analysis alone was made possible thanks in large part to this visual assessment.



Box plots provided an illustrated description of the data distributions for categorical variables, especially those with a small range of distinct values. The central tendency and variable dispersion that these plots revealed may be indicators of the variables' significance to food security scores.

Outlier Detection and Treatment

To further refine the dataset, we used a systematic strategy for identifying outliers. Understanding that outliers have the potential to significantly impact a study's findings, we determined the numerical variables' 2.5th and 97.5th percentiles to act as thresholds for outlier detection. Any data points outside of these boundaries were removed from the dataset as anomalies. To lessen the influence of statistical anomalies on the analysis, this trimming was essential.



V. METHODOLOGY(MODEL BUILDING AND EVALUATION)

After completing the data preprocessing steps, we split the data into 80-20 train test splits and we used this split for all of our models.

Here are the models that we applied :

- Linear Regression
- Multivariate Adaptive Regression Spline (MARS) Model
- Lasso model
- Ridge model
- Random Forest model
- XGBoost model

Here is a brief description of all these models :

1. **Linear Regression:**
    - Linear regression is a fundamental statistical and machine learning technique where the model assumes a linear relationship between the independent variables (predictors) and the dependent variable (outcome). It is used to predict the value of the outcome variable based on one or more input predictor variables. The relationship is represented by a straight line in two-dimensional space (for one predictor) or a hyperplane in higher dimensions (for multiple predictors). This model is particularly useful when the data shows a clear trend and the variables are not too interrelated (multicollinearity). It's widely used in scenarios ranging from business forecasting to scientific research.
2. **Multivariate Adaptive Regression Splines (MARS):**
    - MARS is an advanced regression technique that extends linear models by incorporating non-linearity and interactions between variables. It does this through the use of piecewise linear regression models, or splines, that can adapt to different slopes in the data. The model identifies points in the data where the relationship between the variables changes and fits separate splines to these segments, allowing for more flexibility and accuracy in modeling complex data structures. MARS is particularly effective when dealing with large datasets with many predictor variables and when the relationship between the variables and the outcome is not linear.
3. **Lasso Model (Least Absolute Shrinkage and Selection Operator):**
    - The Lasso model is a type of linear regression that uses shrinkage and variable selection. Shrinkage means that the data values are shrunk towards a central point, like the mean. This is achieved by imposing a constraint on the model parameters that causes regression coefficients for some variables to shrink towards zero. Variables with a coefficient of zero after the shrinkage process are excluded from the model. This property makes the Lasso model particularly useful for models with a large number of predictor variables, as it performs variable selection and regularization, which helps to prevent overfitting and improve model interpretability.
4. **Ridge Model:**
    - Ridge regression is similar to linear regression but with a twist: it includes a penalty term that regularizes the coefficients of the model. This regularization term penalizes the magnitude of the coefficients, which helps to reduce model complexity and prevent overfitting. Unlike Lasso, Ridge regression does not force coefficients to be zero but rather shrinks them towards zero, which makes it suitable for cases

where many predictor variables are interrelated or when you do not want to exclude any variables entirely.

5. **Random Forest Model:**
    - Random Forest is an ensemble learning technique that combines the predictions from multiple machine learning algorithms to make more accurate predictions than any individual model. It builds a multitude of decision trees and merges them together to get a more accurate and stable prediction. Each tree in the forest is built from a sample drawn with replacement (i.e., a bootstrap sample) from the training set. Furthermore, when splitting each node during the construction of a tree, the best split is found either from all input features or a random subset of them. This randomness helps to make the model more robust than a single decision tree and less likely to overfit on the training data.
6. **XGBoost Model (Extreme Gradient Boosting):**
    - XGBoost is a highly efficient and scalable implementation of gradient boosted trees, designed for high performance and speed. Gradient boosting is an approach where new models are created that predict the residuals or errors of prior models and then added together to make the final prediction. XGBoost improves on this by introducing a more regularized model formalization to control overfitting, which gives it better performance. It is known for its efficiency in handling sparse data and its ability to carry out parallel processing, making it faster and more powerful. XGBoost is widely used in machine learning competitions and practical applications due to its flexibility, robustness, and ability to deal with a wide variety of predictive modeling tasks.

For the linear model, we used all the predictors we had selected during the data preprocessing phase as inputs and the Score as target variable. We trained the model on the train set and then made predictions on the test set. To evaluate the model, we used the R-squared metric and the actual vs predicted plots.

In the MARS model, we performed 10-fold cross-validation to select the optimum model parameters, and then trained the model using train set and made predictions on the test set. Here too, we calculated the R-squared value on the test set and plotted actual vs predicted values of the test set.

For the Lasso and Ridge models too, we performed cross validation to select parameters and then trained and tested the model and printed the R-squared value on test set and plotted actual vs predicted values.

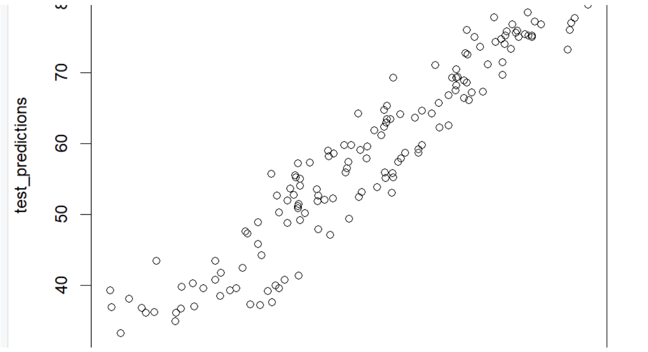
In the Random Forest model, we used 500 as the no. of trees and then created the model, trained it and the tested it and printed the actual vs predicted plot of the test set and R-squared value on the test set.
We also plotted the Variable Importance Plots and the Partial Dependence Plots from the random forest model to understand how our predictors were impacting the target variable and which of our predictors were the most significant in predicting Score.

We also used XGBoost model to see how it would perform on our data and using similar steps as in the previous models, we trained it, made predictions on the test data and printed the R-squared value and the actual vs predicted plot on the test set.

VI. RESULTS

LINEAR REGRESSION :

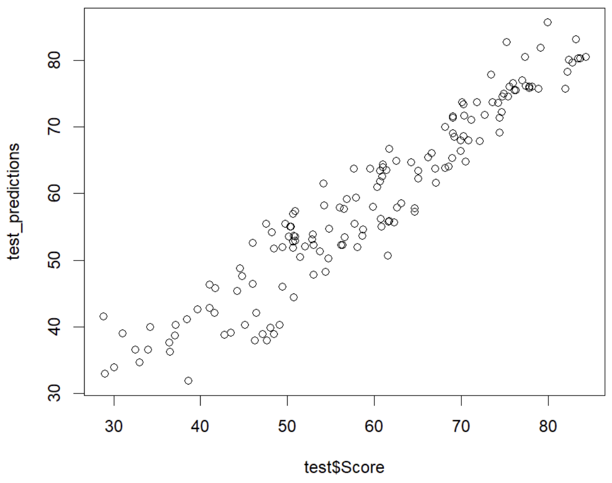
- RESULTS : R-SQUARED FOR TRAINING SET: 0.9194423
- R-SQUARED FOR TESTING SET: 0.908228
- ACTUAL VS PREDICTED PLOT :

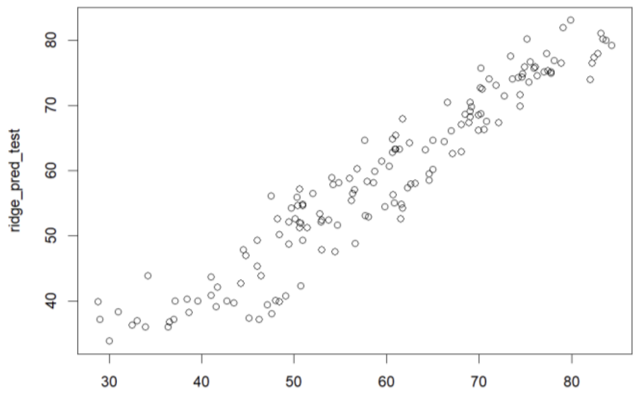


Some important predictors we got from summary of linear regression model :

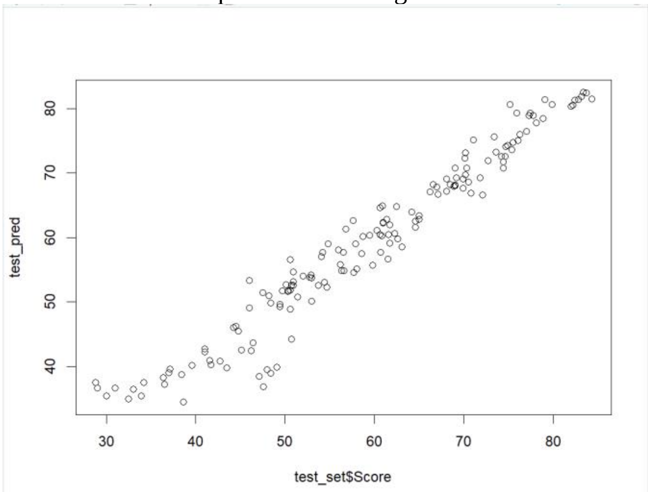
```
(Intercept)                                          ***
Proportion.of.population.under.global.poverty.line   *
Inequality.adjusted.income.index
Trade.freedom                                        **
Access.to.market.data.and.mobile.banking             ***
Planning.and.logistics                               ***
Road.infrastructure                                  ***
X.Air..port.and.rail.infrastructure
Food.supply.adequacy                                 ***
Political.stability.risk                             .
Corruption                                           ***
Gender.inequality                                    .
Share.of.non.starchy.foods                           *
Share.of.sugar.consumption
Protein.quality                                      **
```

MARS Model :
R-squared for Training Set: 0.9098528
R-squared for Testing Set: 0.9057779
Actual vs Predicted Plot :





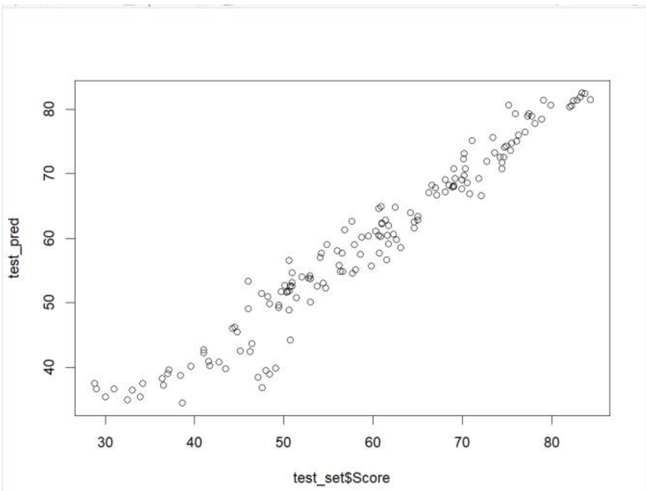
Random Forest model :
Results:
Random Forest R-squared for Training Set: 0.9897387
Random Forest R-squared for Testing Set: 0.9495487



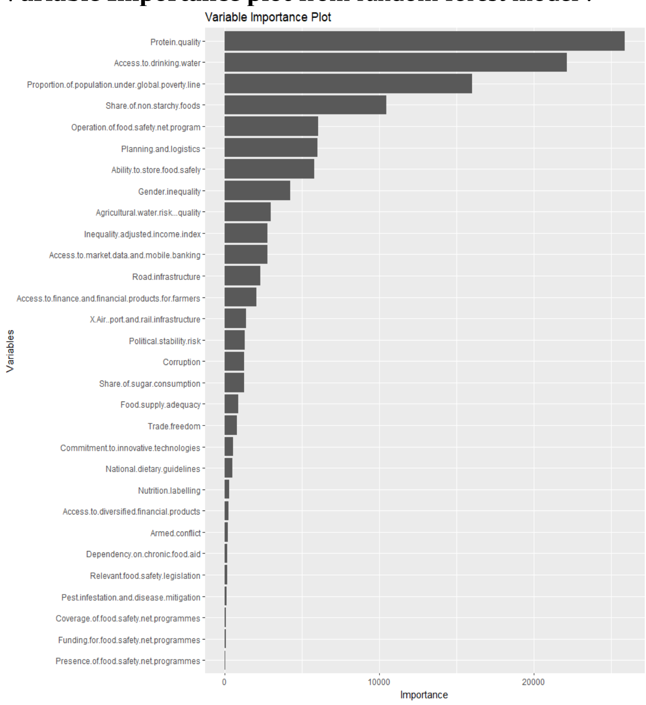
Lasso and Ridge models :
Lasso:
Results
Lasso R-squared for Training Set: 0.9188376
Lasso R-squared for Testing Set: 0.9088209

Ridge:
Results:
Ridge R-squared for Training Set: 0.9183641
Ridge R-squared for Testing Set: 0.9099601

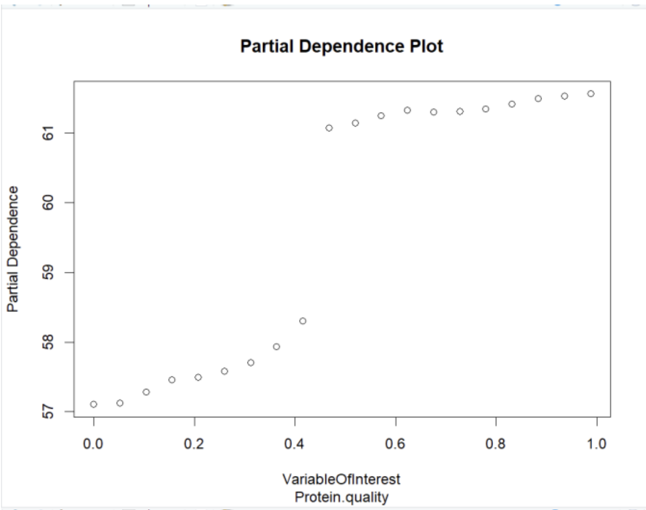
Actual vs Predicted Plots :

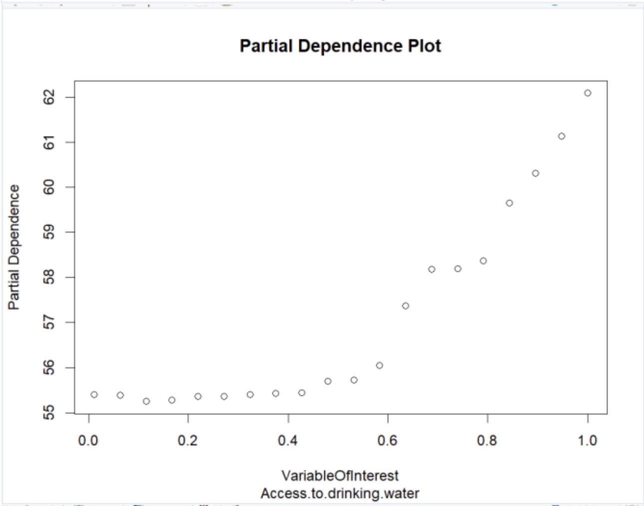


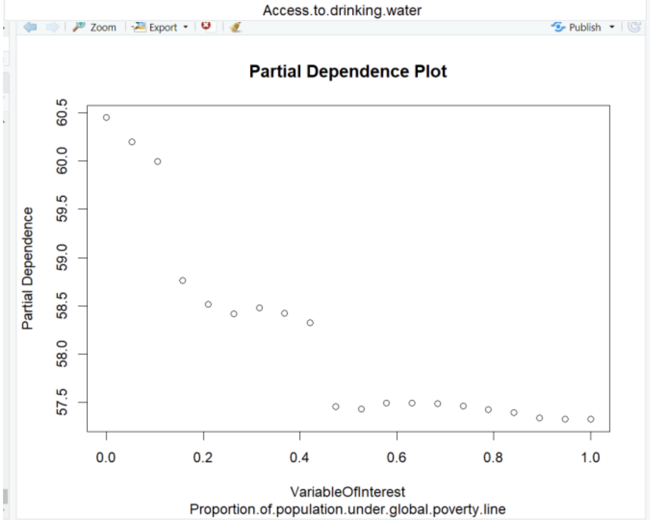
Variable Importance plot from random forest model :

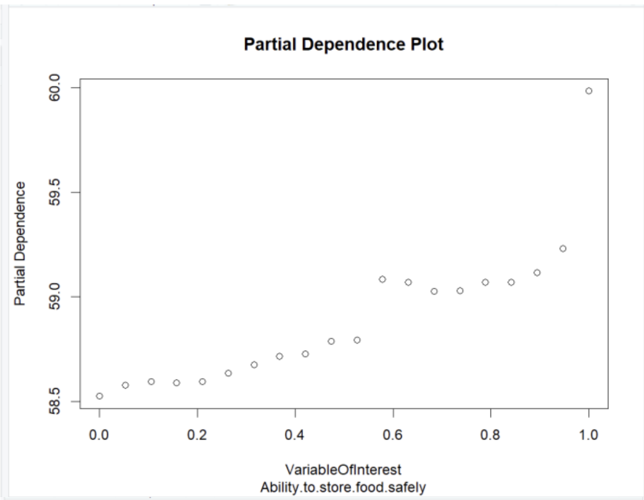


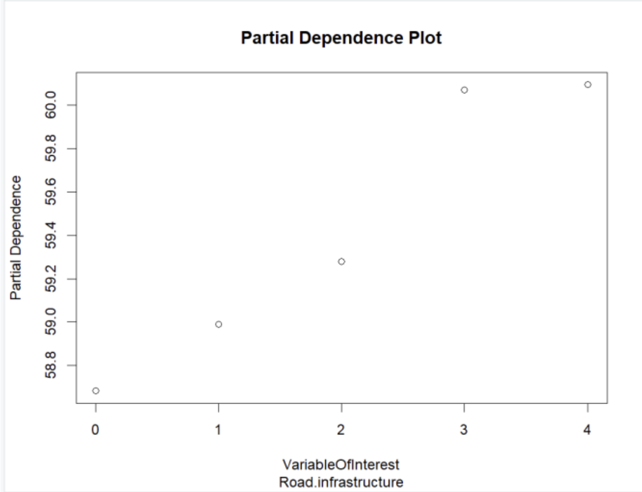
Partial Dependence plots of some important predictors :

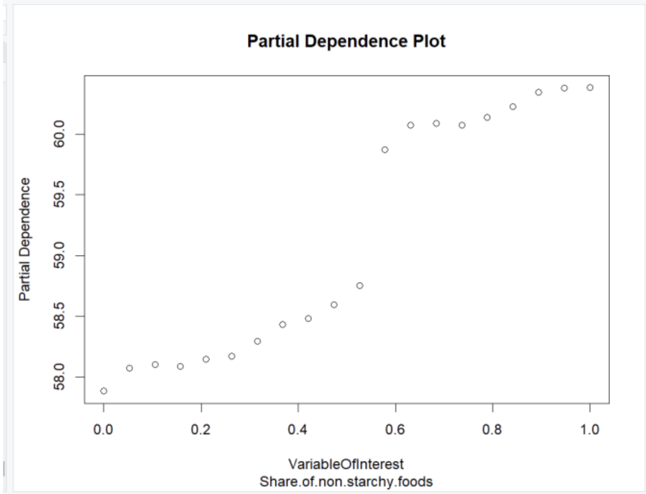

Partial Dependence Plot
Partial Dependence
57 58 59 60 61
0.0 0.2 0.4 0.6 0.8 1.0
VariableOfInterest
Protein.quality

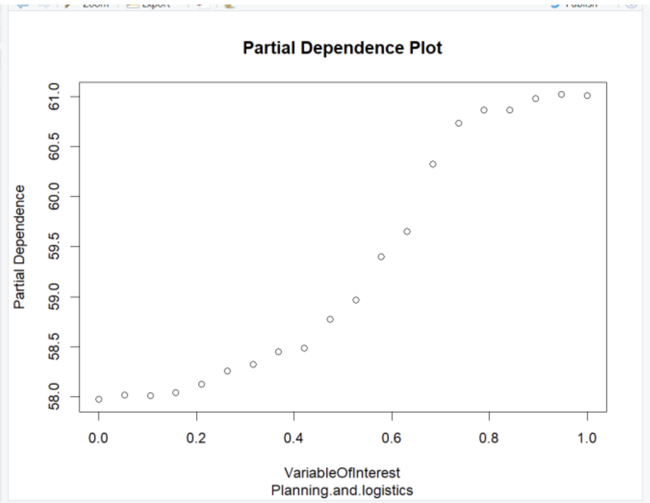

Partial Dependence Plot
Partial Dependence
55 56 57 58 59 60 61 62
0.0 0.2 0.4 0.6 0.8 1.0
VariableOfInterest
Access.to.drinking.water


Partial Dependence Plot
Partial Dependence
57.5 58.0 58.5 59.0 59.5 60.0 60.5
0.0 0.2 0.4 0.6 0.8 1.0
VariableOfInterest
Proportion.of.population.under.global.poverty.line


Partial Dependence Plot
Partial Dependence
58.5 59.0 59.5 60.0
0.0 0.2 0.4 0.6 0.8 1.0
VariableOfInterest
Ability.to.store.food.safely


Partial Dependence Plot
Partial Dependence
58.8 59.0 59.2 59.4 59.6 59.8 60.0
0 1 2 3 4
VariableOfInterest
Road.infrastructure


Partial Dependence Plot
Partial Dependence
58.0 58.5 59.0 59.5 60.0
0.0 0.2 0.4 0.6 0.8 1.0
VariableOfInterest
Share.of.non.starchy.foods



<u>Comparison of models</u> :

Model	Training_R2	Testing_R2
Linear Model	0.9194423	0.9082280
Mars Model	0.9098528	0.9057779
Lasso	0.9188376	0.9088209
Ridge	0.9183641	0.9099601
Random Forest	0.9897387	0.9495487
XG Boost	0.9999228	0.9476693

We also took 5 countries from our dataset who had very high Scores and analyzed the values of their important predictors and we took 3 countries who had very low Scores and again analyzed the values of their important predictors.

Country.Name	Protein.quality	Access.to.drinking.water	Proportion.of.population.under.global.poverty.line	Share.of.non.starchy.foods	Operation.of.food.safety.net.program	Actual Score	Predicted Score
Ireland	0.9756691	0.950819672	0.007900677	0.826086957	1	84	81.65945333
Australia	0.927007299	0.998178506	0.007900677	0.97826087	1	83.8	82.74067
France	0.98783455	1	0.001128668	0.891304348	1	83.8	82.61902667
Germany	0.878345499	1	0	0.934782609	1	83.7	82.73618333
Austria	0.939172749	1	0.006772009	0.97826087	1	83.4	82.19272667
Burkina Faso	0.113138686	0.147540984	0.923250564	0.130434783	0	29.9	30.55110667
Tanzania	0.087591241	0.010928962	0.897291196	0.326086957	0	29.9	31.37056
Togo	0	0.27140255	0.856659142	0	0	28.4	31.93322667

VII. Discussion and conclusion

From the results of our models, we can see that our data is pretty linear in nature as the predictors have a pretty linear relationship with our target variable. This makes sense as the important predictors we got from our summary and variable importance plots should have a very direct impact on the food security score of a country.
Some of these variables were Access to Drinking Water, Protein Quality, Planning and Logistics, Ability to store food safely and Road Infrastructure. From the variable importance plot, we were able to see which predictors were the most significant in determining the food security score of a country.

Partial Dependence plots show the relationship between the target variable and individual predictor keeping all other predictors constant at their average values. In simple words, it tracks how the target varies with respect to changes in the values of individual predictors.
From the partial dependence plot of access to drinking water, we can see that it has a significant impact on Score. As the value of access to Drinking water increases, value of score increases and vice versa.
The plot of Protein Quality is similar and also has a direct relationship with our Score.
And we can see from the remaining PDPs how the important predictors we got from Variable Importance plots are impacting our target variable.

In our models, it was the Random Forest model which performed the best on our test data.

Now, we will compare the countries that have high Scores and the countries with low scores and analyze the values of their significant predictors such as protein quality, access to drinking water, etc to see how these values are affecting the Score.
We can see that the top 5 countries which have high Scores (Ireland, Australia, France..) have high values of protein quality and access to drinking water and a very low proportion of population under global poverty line whereas countries like Burkina Faso and Tanzania which have very low food security have very low values in protein quality indicator and access to drinking water and a high proportion of population under global poverty line. This tells us that our analysis was accurate and these predictors such as protein quality and access to drinking water which we got from variable importance plots indeed determine how high or low a country's food security score is.

Thus, governments or organizations that aim to improve a country's or even a region's food security should focus on these areas as improvement in these areas will improve the food security condition of that region as is shown by our analysis.

VIII. Future research

Future researchers could focus on a more specific analysis such as including smaller regions instead of countries and analyzing which predictors impact the food security conditions in those regions.
They should use this research as a base and try to explore different predictors from the ones we have used here to see their impacts and suggest methods to improve the significant indicators that affect food security thereby improving food security as well.

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