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MODELING THE DETERMINANTS OF HOUSEHOLD'S FOOD SECURITY IN PAKISTAN USING CLASSICAL AND MACHINE LEARNING METHODS

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ABSTRACT

This study investigates the situation of households' food security in Pakistan. Food security is a comprehensive concept surrounding the nature, security of the food supply, quality, food access problems, and proper food utilization. The world has been facing the contradiction of widespread food insecurity and undernutrition. Present studies indicated that Pakistan country is a low-income developing country with an income per capita. Pakistan is one of the lowest in the world, but it, in general, has the economic capability to import the required food. However, in Pakistan, most areas are still food insecure, mostly belonging to Sindh and Baluchistan provinces. This study observes the main features of determining Pakistan food security, particularly household income, household economic evaluation, employment status, household expenditure, section, region, head age, head gender, agriculture status, livestock status, etc.

Are studied indicators to measure the household food security status, whether it has food secure or insecure? And want to look at what conclusions can practically be drawn out of analysis when conducted within a conceptual framework. In this study average daily kilocalories per capita consumed index is used to measure the household's food security level. Ordinal logistic regression and multiple linear regression models are used for analysis. For ordinal logistic regression model divided the Pakistan households into four categories based on the food security index that is daily kilocalories per capita. The research of this study shows that the primarily peoples living in Baluchistan, Sindh lies in food insecurity. Some households of KPK province lie in the food insecurity category.

For conducting this study (PSLM), 2018-2019 survey data is used for analysis. Classical ordinal logistic and multiple linear regression models and machine learning, which includes ordinal logistic regression and multiple linear regression models, are used to analyze household food security in Pakistan. The model is finalized for best prediction based on the minimum Standard Error of the coefficient.

KEYWORDS: ***Food Security, Ordinal Logistic, Machine Learning, Supervised Machine Learning***

INTRODUCTION

Background of the Study

Individuals are assessed for food insecurity the extent to which food has been separated from its source, among other things. Food safety, as defined by the United Nations.

The food Security Committee is the process of ensuring that all people have access to adequate, safe, and nutritional food that meets their food preferences, dietary requirements for work and living in the United Nations system, and other conditions.

There is a different way of eating that is unconcerned about one's social class, gender, or geographical location. For some time, food safety has been a source of concern, particularly in light of reports of central experts in ancient China and ancient Egypt delivering food to those on the verge of starvation.

When the 1974 World Food Conference convened, the article "food safety" was highlighted. Food security was defined as the availability of adequate and dependable supplies of essential food staples to ensure continuous food consumption growth while compensating for changes in progress and expenses and supplementing a varied, changed, and moderate international food supply framework. In subsequent definitions, broadened the definition to include issues related to requests and access. According to the 1996 World Food Summit, food safety is achieved when all people are reliably directed to consume adequate, safe, and nutritious food to meet their dietary needs and food trends for a working and healthy life. Food security exists. Poverty reduction, in all cases, has been double the success of development in different locations. On the other hand, food insecurity often leads to misery and damages the ability of a country to develop its economic, economic, agricultural, and industrial sectors.

Access to a high-quality, nutrient-dense diet is critical for human survival. Secure access to food can have a beneficial long-term effect.

- Increased global security and stability
- Improved wellness and medical services
- Economic development and job creation
- Poverty reduction
- Trade openings

Additionally, when everyone consistently and effectively approaches a sustainable livelihood, it is perceived that food safety exists in the family. People who are safe to eat do not fear hunger or longing in the same way. A limited or uncertain state of access to foods that are nutritionally adequate and safe, combined with a narrow or limited ability to obtain socially viable sources of food, is defined by the United States Department of Agriculture (USDA) as "food vulnerability." Drought, worsening weather, fuel shortages, financial instability, and war all pose threats to food security. A sense of solidarity is required to prevent or impede essential food supply due to these threats.

The United Nations, Food and Agriculture Organization has identified four pillars of food safety: accessibility, access, use, and stability. These pillars are accessibility, access, use, and strength (FAO). Specifically, the United Nations Human Rights Declaration of 1948 recognizes the right to food and states that must meet all other requests for this right to be realized.

At the 1996 World Food Safety Summit, participants agreed that "food should not be used as a policy and economic pressure tool." Many peaceful agreements and food security tools have been established throughout history, and many more are in the works. The Sustainable Development Goals (SDGs) are the world's most significant agreement on poverty and hunger. Under the Zero Hunger project, global hunger elimination, food security, and enhanced nutrition objectives will be met by 2030.

If a country has an adequate public food supply, this does not mean that every citizen has sufficient food to eat. The use and payment of HHs may well require that food access be included as an additional critical element of food security. Access to food means people have enough resources to provide a dynamic and healthy lifestyle with nutritious food. These measures are most likely to be quantified by numerous indicators, such as wages, food consumption per capita, work and the cost of food, and so forth.

The Board of Directors of the United Nations pointed out that the lack of food authorities in a country or country is the most common cause of hunger and desire. The issue of access is typically a matter of misery, which implies a lack of resources to buy nutritious food. These people have adequate assets in terms of wealth and food shortages, and they can maintain sufficient food to meet their needs. The spatial openness and reasonableness of food distributors, unlike food buyers, has explicitly determined factors such as shopping time, food quality, and accessibility, and food costs among customers. Module 3, which drew from the U.S. Atlas of Food Access, examined both sustenances. Some groups and sites face more significant barriers to access healthy and reasonable food retailers, especially those with low pay who can adversely affect diet and food safety. For example, whether farmers have entire or under-maintained livelihoods, their ability to produce and store food sufficient to supplement or consume food is affected by food access to farmers' food.

RESEARCH GAP / RESEARCH PROBLEM

There are many research papers published in a journal about machine learning methods as well as classical methods but no anyone research paper which determined the household food security data by using ordinal logistic machine learning model and linear regression machine learning model and then these models compared with classical ordinal logistic and linear regression models.

This research paper determined the household food security data by using machine learning ordinal logistic and linear regression models and by using classical ordinal logistic and linear regression models.

OBJECTIVES OF THE STUDY

The main objectives of this study are

- Determined the factors which are affecting household food security.
- Estimation of the model by using Classical and Machine Learning methods.
- Selection of the best models for food security and result interpretation.
- Suggest Policies for improving food security in Pakistan.

LITERATURE REVIEW

Marup Hossain et al. (2019) analyzed the calories-based household food security in a rural area of Bangladesh. For this purpose, the data was taken from Bangladesh Integrated Household Survey (BIHS). XGboost and Random Forest machine learning methods and non-machine learning methods include OLS regression and logistic regression, used to predict the calories-based food security data. These models are used to predict Bangladesh's household food secure data and then compare the results of which model is best for prediction and concluded that all estimated models Machine Learnng and Non-Machine Learning, have the same accuracy for forecasts. As a result, the study concluded that 63% of the household of Bangladesh rural are food insecure or inferior in a particular food.

Joris et al. (2021) analyzed the study to evaluate the transitions in food security status. For this purpose, they selected the area of study from Ethiopia. Using open-source data, data were collected at a spatial granularity of livelihood zones and for lead times of one to 12 months. From these datasets, 19 categories and 130 variables were derived used as predictors of the transition in the state of Ethiopia of food security. This paper used Extreme gradient boosting, Cat Boosting, and Random Forest machine learning methods to forecast monthly changes in food FS. The paper's primary purpose is to compare these three machine learning models' predictions for transitions of food security. It concluded that the XGBoost machine learning method is best fitted for predicting growth in food security.

Abdul Razzaq et al. (2021) conducted the study to evaluate the food security data of Pakistan. For this purpose, they are collected from Punjab province and selected areas/districts and 756 farm households from three agro-climatic zones. The data collection technique was used multistage stratified sampling. The first phase distributed five strata according to zones, and in the second phase using stratified purposive sampling techniques and 12 districts were selected from a total of 36 districts. As a result, food security status has been examined.

Furthermore, the mobile app has been developed and trained by applying machine learning techniques, including support vector machine, naïve Bayes, k-nearest neighbors, random forest, logistic regression, and neural network. To compare these machine learning algorithms concluded that the Random Forest techniques give more accurate results for prediction than another technique. Thus, the proposed FA App is beneficial for reducing malnutrition, healthy eating, and improving the overall country’s population’s health and nutritional status.

Moreover, machine learning techniques have been introduced in food security and survey analysis. It is an advanced technology with a large number of successful applications in various areas. The FA App will also help collect the data of food intakes which will improve the overall efficiency and accuracy of the system toward the goal.

METHODOLOGY

Model’s Specification

The explained variable and explanatory variables are decided based on the past studies in Pakistan, it is agreed from the literature of Pakistan, according to (Bashir et al. (2012)), The selected variables like income, education, employment, and livestock positively impact food security and head age, and family size hurts food security. Also, the variables mentioned earlier have a significant impact on food security (Niazi and Naeem (2010)). In the model, the explanatory variables capture the effects of food security data, and for this purpose, we chose these explanatory variables that significantly affect food security. For example, if a family has a high income, they expend more on food, and their food is secure. A family has a low income, so they don’t expand on food, so this family food is not safe, so it means that the payment has a positive effect on food security, and payment is the most important for food security because, in Pakistan, households spend most of the part of income on food. Education is also the most important for food security. It has a positive effect on food security because if a household has accurate information about food utilization. Hence, the family probably falls in the food-secure category if a home has livestock. Therefore, it is also probable to fall in the food security category because they can utilize their livestock to get the calories. It means that the livestock positively affects food security and those families that have their agricultural status. Hence, they are probable for a certain category because, as we know that the agriculture has a positive impact on food security. In the literature, we also include that the head age also positively affects food security because the head age increases. Hence, he or she has more knowledge about food security from their experience. The families whose family size is large are likely to fall in the insecure food category. As we know, when the family size is large, the dependency ratio is also high, which means that the family size harms food security.

So, the mathematical model for using this information can be written as

$$\mathbf{Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9 + \beta_{10} X_{10} + \beta_{11} X_{11} + \beta_{12} X_{12} + \beta_{13} X_{13} + \beta_{14} X_{14} + \beta_{15} X_{15} + \beta_{16} X_{16} + \beta_{17} X_{17} + \beta_{18} X_{18} + \beta_{19} X_{19} + U_i}$$

Where Y = Food security status 1 if the household food is insecure; 2 if the household food is moderate insecure; 3 if the household food is mild insecure; and 4, if the household food is secure, and in continuous form, Y is the per day Calories per capita of the household. Ui = random error term and description of the explanatory variables are given in Table 3.1

DATA AND CONSTRUCTION OF VARIABLES

Table 3.1 Description of explanatory variables

Variables	Variable label	Codes	Description
X_1	Household's size		No. of people in a household
X_2	KPK		1= KPK, 0=otherwise
X_3	Punjab		1=Punjab, 0=otherwise
X_4	Sindh		1=Sindh, 0=otherwise
X_5	Region		1=Urban, 0= Rural
X_6	Head age		Head age in the year
X_7	Head gender		1=male, 0=female
X_8	Marital status		1=married, 0=unmarried
X_9	Head education		Head education in the year
X_{10}	Spouse education		Spouse education in the year
X_{11}	Log-Income of household's head		Log of income per year
X_{12}	Live stock	0=No, 1=Yes	1=have livestock, 0=otherwise
X_{13}	Agriculture Status	0=No, 1=Yes	1=have agri.status, 0 =otherwise
X_{14}	Head employer		1=have employer, 0=otherwise
X_{15}	Head paid		1=head earning, 0=otherwise
X_{16}	Spouse paid		1=spouse earning, 0=otherwise
X_{17}	Couple employed		1=Both earning, 0=otherwise
X_{18}	House ownership		1=ownership, 0=otherwise
X_{19}	Square-Household's size		Square of household's size

The data of all variables were collected from Pakistan Social and Living Standards Measurement (PSLM) 2018-19, which is also called Household Integrated Expenditure Survey (HIES) 2018-19. The household survey is collected from the website of "Pakistan Bureau of Statistics." Provide comprehensive data of familiar household variables by the Government of Pakistan. In the Household Integrated Expenditure Survey (HIES) 2018-19 there was 24809 household available out of which 19166 were selected absolutely for the analysis. HISE data consist of different socio-economic variables like household income, consumption pattern, and consumption expenditure; we decided on some appropriate households to measure food security in Pakistan with the help of the provided information.

After selecting the appropriate variable of the appropriate households from the Household Integrated Expenditure Survey (HIES) for the year 2018-19, we are interested in finding food security in Pakistan. The household's food security status can be determined on per day calories per capita consumed by each member of a family of Pakistan.

The number of quantities of different food items consumed by each household got us by (HISE). To analyze the food security, these food quantities that were consumed of each home we converted them into energy intake, measured in 1000gm calories unit using (UNICEF and GOP, 2001) food consumption table for Pakistan, consisting of nutrient contents data of different foods. We model the food energy intake empirically after converting food quantities into kilocalories equal to 1000gm calories.

The household's member consumed some items for a month and consumed some things for two weeks available in (HISE) data. To get per day calories for each household, for this purpose, calculated total calories consumed by each household's member for a month divided by 30 and calculated total calories consumed by each household's member for two weeks divided by 14. The daily energy consumption per capita is our indicator of evaluating food security in Pakistan. According to IFPRI (2007), this indicator is calculated by dividing the daily food energy of each household by the number of household members.

The average requirement for light activity at 2050 Kcal, belongs to the benchmark category for very low-level food security according to the IFPRI (2007) and for the developing countries, the daily consumed Kcal which exceeds 3400 Kcal follow the upper benchmark (Von Braun et al. 2005). In this study our food security framework is we find the average of a daily kilo or 1000gm calories per capita which are consumed by each household of Pakistan. If the Kilocalories of the household is less than 1500 then it will be considered in the food insecurity category if it is between 1500 and 1800, so it will be considered in moderate insecurity food, if it is between 1801 and 2100, it will consider in mild food insecure and if it greater than 2100 so it will consider in food-secure category (Akbar. M et al., (2020)).

It is very important to know that the requirements of food vary from gender, age group, physical activity as well as psychological needs so we have to calculate calories for these requirements includes gender and different groups of age, etc. categorize our dependent variable into four categories which are shown in given below Table 3.2.

Table 3.2 Food security status of households

Food Security indicator	The benchmark for APCD/Kcal	Values of F.S levels
Food insecure (FI)	<1500	1
Moderate insecure (MI)	1500 --- 1800	2
Mild insecure (M2I)	1801 --- 2100	3
Food secure (FS)	> 2100	4

To measure food security status there is a various index but some are very famous, some of these which are frequently used are the CCA approach which stands for cost calories approach, average per capita daily consumed kilocalories (APCDC/Kcal) approach, average household food security index which is also called AHFSI and food insecurity and vulnerability and map in the system which is denoted by FIVMS. These all are used to measure the status of food security and as we know, by any single indicator food insecurity and hunger cannot be captured. To determine the household food security status depends upon household level variety etc., for example, the food was adequate in quality or quantity consumed by the household? Are household members bring sufficient food at home for active and good health or not? If a household consumed any food in daily life so how much quantity or which quality of the food item was consumed? This means how much food is served or which types of food items are served in the household and after the serving, all food items, are the effect vary individual to individual within a household or the same effect. Such type of information is required to draw a proper and valid conclusion about the status of food security at the household level within a country.

For this purpose, there are different types of index available in studies but we need to choose the best one among these all which can produce better and sufficient results and based on these valid and sufficient results we able to make a valid prediction for the future. For this purpose, we chose the best one among them APCDC/Kcal index which is a better indicator to measure food security. In APCDC/Kcal approach we need to collect all the information from the household which item and what they have to consume. After collecting all information about a consumed item, we need to find kilocalories of the consumed items. We also find calories at gender and each age group as we know that the effect of consumed items is different in any individual in terms of age, gender, and health so for this purpose, APCDC/Kcal is one of the best methods to measure the status of food security at household level within the country. IFPRI (2007) also recommended this method to check or measure the status of food security at the household level within the country.

METHODS OF DATA ANALYSIS

Classical Multiple Linear Regression Model

The word regression was firstly introduced by Francis Galton and his famous articles about the relationship between the heights of parents and the height of children. He found that although tall parents had tall children and short parents had short children but the average height of children of tall parents as well as short parents tends to the average height of tall parents then according to Francis Galton average height of children regress the average height of the population. The modern definition of regression analysis is a comprehensive definition that follows.

"Regression analysis is used to investigate the dependence of one or more than one variable which is called dependent variable upon one or more than one variable called independent variables". When we have one dependent variable and one independent variable so it is called a simple linear regression model but if we have one dependent variable and one or more than one independent variable and we want to check the impact of the independent on the dependent variable so this is called multiple linear regression model. The dependent variable is also called explained variable, response variable, predicted variable, endogenous variable, controlled variable, outcome variable, and regressed variable, and independent variable is also called explanatory variable, stimulus, predictor, exogenous variable, control variable, and regressor variable.

For example, if we want to check the effect of household income and family size on household consumption so there have two independent variables and one dependent variable so it is called multiple linear regression model because it has a linear relationship between dependent and independent variables so the regression model can be written as follows

$$\mathbf{Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \epsilon_i}$$

Where Y_i is household consumption which is called the dependent variable, X_{1i} is the household income, X_{2i} is the family size, and these both are called independent variables. β_0 is the intercept of the model and β_1, β_2 are the slope of the model which tells that how much change in dependent variable Y_i occurs due to independent variable X_{1i}, X_{2i}, ϵ_i is the random error term of the model.

The Multiple Linear Regression model is also called General Linear Regression Model which can be written in matrix form. Suppose there are k explanatory variables and one dependent variable so the multiple linear regression model can be written as follows

$$\mathbf{Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots\ldots\ldots\ldots + \beta_k X_{ki} + \epsilon_i}$$

So, we can write it in matrix form

$$\begin{bmatrix} Y_1 \\ Y_2 \\ . \\ . \\ Y_n \end{bmatrix} = \begin{bmatrix} 1 & X_{11} & X_{21} & . & . & X_{k,1} \\ 1 & X_{12} & X_{13} & . & . & X_{k,2} \\ & . & . & . & . & . \\ & . & . & . & . & . \\ 1 & X_{1,n} & X_{2,n} & . & . & X_{k,n} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ . \\ . \\ \beta_k \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ . \\ . \\ \epsilon_n \end{bmatrix}$$

Or

$$Y_i = X_i \beta + \epsilon_i$$

So, the above model is also called General Linear Regression Model. The dependent should be in quantitative form and the independent variables may be in quantitative or in the qualitative form in simple or in multiple linear regression model. In this study, there are 19 independent variables, some of these are in a quantitative form which

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are Household size, Age of head, Head Education, Spouse Education, Income of Head, and maximum variables are in a qualitative form which includes are Province, Region, Head Gender, Marital Status, Live Stock, Agriculture Growing, Head Employer, Head Paid, Spouse Paid, Couple Employed, House Ownership and the dependent variable in this study is in a quantitative form which is Calories Per Capita per day so in this situation, the Multiple Linear Regression Model is well for this type of data.

Classical Ordinal Logistic Model

In some cases, the response viable is in categorical form as well as in order form and the independent variable in qualitative as well as in quantitative form so in this situation, we can apply an ordinal regression model. Suppose the dependent variable is the teaching level (Teacher, Lecturer, Professor) and two independent variables are year of education as well as experience so in this situation we can use ordered logit or ordered probit model but bin literature ordinal logistic regression model is more perfect than ordinal probit model in statistical analysis because ordinal regression model coefficient is more interpretable than ordinal probit model (Zucknick and Richardson (2014)).

In a logistic regression model, there has one response variable and one or more than one independent variable, if the model has one response and one independent variable so it is called a simple ordinal logistic regression model but if the model has one dependent variable and more than one independent variable so it is called multiple ordinal logistic regression model. The logistic model is also the member of "generalized linear models" because in the logistic regression model we take logarithm to express response variable is the linear function of the explanatory variable.

The ordinal logistic regression model is the extension of the binomial logistic regression model which is also called the binary logistic regression model. The response variable has two categories 'Yes, No' or '1,0' etc and there has no order in the response variable but the explanatory variables may be one or more than one in binary logistic regression model but in ordinal logistic regression model the response variable is in the order form as well as categorical. The ordinal logistic regression model is used to forecast future value by using a single response variable with order and categorical form and a variety of explanatory variables which means that the different levels of the response variable are being measured by different explanatory variables. if a question asks from the respondent for collected information and the question lies between low and high so it didn't help us for getting a good or effect information later we added levels to our response like low, very low, medium and high, etc. suppose we want to collect information from the student about the satisfaction of the teaching method of the professor if our question lies between satisfied and dissatisfied so it is didn't help for getting information later we added another level like strongly satisfied, strongly dissatisfied, etc. so in this way we able to get good information about the teaching level of professor so it means the data is in ordered form and in this situation ordinal logistic regression will prefer for the predictive purpose of the response variable.

There are different kinds of ordinal logistic regression models to measure order form and categorical response variables like Continuation Ratio Models, Cumulative Logit Models, and Adjacent-Category Logit Models are famous, often Cumulative Logit Models are applied because the model interpretation is very easy or very easily interpretable. Cumulative models are further divided into three groups which are the Proportional Odds Logit Model, Non-Proportional Odds Logit Model, and Partial Proportional Odds Logit Model. Cumulative Logit Models give good results when the parallel lines assumption is fulfilled but sometimes this assumption does not hold so the Proportional Odds Logit Model gives incorrect results so in this situation we move to Non-Proportional Odds Model and Partial Proportional Odds Model.

In or study ordinal response variable has C number of categories so we want to introduce a latent variable which defines our categorical response variable, following (Long and Freese (2001)). Latent variable as ɭ range which between -∞ and ∞, and also the structural model is given by

$$ɭ = \beta X + \epsilon$$

Where X is the matrix of k explanatory variables and β is the vector of regression coefficient and ϵ is the random error term having logistic distribution. γ_c is the threshold parameter which we will change for each category. The response variable Y is defined is given below

$$Y = \begin{cases} 1 = if -\infty < \lfloor < \gamma 1 \\ 2 = if\ \gamma 1 < \lfloor < \gamma 2 \\ . \\ . \\ . \\ C = if\ Yc - 1 < \lfloor < \infty \end{cases}$$

It's mean that ⌊ categorized by thresholds in C intervals, corresponding to the C ordered categories. The first threshold γ_1 shows the upper bound of the interval corresponding to observed outcome 1, similarly, the last threshold γ_{c-1} takes the lower bound of the interval corresponding to observed outcome C, here γ_c is the boundary between the interval corresponding outcome C – 1 and c is equal to c = 1,2,3,………, C – 1. The threshold parameters are

$$\gamma^t = (\gamma_{min} < \gamma_1 \ldots\ldots\ldots < \gamma_{max})\ \text{min} = -\infty \text{ and max} = \infty$$

In this study we want to compare the Classical Regression Models with Machine Learning Regression Models, in the Machine Learning Regression Model there has no extension of the Ordinal Regression Model like Non-Proportional Odd Model and Partial Proportional Odd Models but there have available Proportional Odd Model so we will use Classical Proportional Odd Model and Machine Learning Proportional Odd Model.

Proportional Odd Model (POM)

When the parallel lines assumptions hold in ordinal response variable so Proportional Odds Model is often used (Brant, 1990; Bender and Grouven, 1998). The Proportional Odds Model proposed by McCullagh 1n 1980 for ordinal regression based on such kind of model is cumulative distribution function. The Proportional Odds Model can be estimated by using Cumulative Probabilities which is proposed by Kleinbaum and Ananth (1997) which is given in the below Equation.

$$P\ [Y \leq y_{j/x}] = \tau_j = [\frac{\exp(\alpha j - x'\beta)}{1+\exp(\alpha j - x'\beta)}]\ j = 1,2,3,\ldots\ldots\ldots, j - 1$$

Here estimator of the unknown parameters of threshold is α_j and index j = 1,2, 3**…………,** J – 1 for $\alpha_1 \leq \alpha_2 \leq \alpha_3 \ldots\ldots\alpha_{j-1}$ and β is the vector of parameters of independent variables and it can be written as $\beta = (\beta_1, \beta_2, \beta_3, \ldots\ldots, \beta_k)'$. The model can be transformed to linear form by taking natural logarithms of these Odds Ratios (Kleinbaum and Ananth, (1997)) which is given bellows:

$$(\alpha_j - x'\beta)\ j = 1,2,3$$

Machine Learning Multiple Linear Regression Model

Regression is the type of Machine Learning in which one is a Dependent variable which is also called the Outcome variable in Machine Learning language and one or more than one is an independent variable which is also called Feature variable in Machine Learning language. The Machine Learning Regression Model is also defined the same as the Classical Regression Model. The main difference between the Classical Regression Model and Machine Learning Regression Model is that there has no use for training and testing data in the Classical Regression Model (CRM), it means no need of splitting the data into two parts but there must be a need to split the data into train and test data sets in Machine Learning Regression model (MLR) for achieving the accurate results.

Linear Regression analysis is used to investigate the dependence of one or more than one variable which is called dependent variable upon one or more than one variable called independent variables and the relationship between this variable in the linear form". When we have one dependent variable and one independent variable so it is called a simple linear regression model but if we have one dependent variable and one or more than one independent variable and we want to check the impact of the independent on the dependent variable so this is called multiple linear regression model.

Linear regression is one of the most popular and easiest Machine Learning algorithms. LR is a statistical method or model which is used for predictive analysis means for future prediction. Linear regression makes predictions for continuous or numeric variables such as salary, expenditure, age, etc. it means the dependent variable should be continuous. The linear regression algorithm shows a linear relationship between one outcome variable (Y) and one or more than one feature variable (X) variables, hence it is called linear regression. So, the linear regression shows the linear relationship, which means that how the value of the outcome variable is changing due to the value of the feature variable. The machine learning linear regression model provides a sloped straight line representing the linear relationship between the variables.

Machine Learning Logistic Regression Model

Logistic Regression is the type of Supervised Machine Learning which is used for estimation and predicting the categorical response variable by using a given set of explanatory variables. Logistic regression predicts the output of a categorical response variable. That's why the outcome must be a categorical or discrete value. It may be either 0 or 1, true or False, etc. but instead of giving the exact value like 0 and 1, Logistic Regression gives the probabilistic values which lie between 0 and 1. The logistic regression model is much similar to the linear regression model but the linear regression model is used for regression problems and the logistic regression model is used for the problem of classification. Logistic Regression Models are a significant machine learning algorithm because they can provide probabilities and classify the new data using continuous and discrete input datasets.

The curve from the logistic function shows the likelihood of something like whether the household food is secure or not, students' presence in the class or not, etc. The logistic regression technique can be used to classify the observations by using different types of data and it can easily determine the most effective input variables used for the classification.

Logistic Function (Sigmoid Function):

The sigmoid function is a mathematical function that is used to map the predicted values to probabilities. LF maps any real value into another value within the range of 0 and 1. The value of the logistic regression must lie within 0 and 1, which cannot go beyond this limit, so it shows a curve like the "S" form. The S-form curve is called the sigmoid function and it is also called the logistic function. We use the concept of the threshold value in logistic regression, which defines the probability of either 0 or 1. Such as values above the threshold value so it follows to 1, and a value that below the threshold values so it follows to 0.

Machine Learning Ordinal Logistic Regression Model (POM):

The Ordinal logistic regression is the extension of the Binary Logistic Regression Model in which response variables in the form order are also categorical. The ordinal logistic regression model is used to forecast future value by using a single response variable with order and categorical form and a variety of explanatory variables which means that the different level of the response variable is being measured by different explanatory variables. if a question asks from the respondent for collected information and the question lies between low and high so it didn't help us for getting good or effective information later, we added levels to our response like low, very low, medium, and high, etc.

Suppose we want to collect information from the student about the satisfaction of the teaching method of the professor, if our question lies between satisfied and dissatisfied so it is didn't help for getting information later we added another level like strongly satisfied, strongly dissatisfied, etc. so in this way we able to get good information about the teaching level of professor so it means the data is in ordered form and in this situation ordinal logistic regression will prefer for the predictive purpose of the response variable. The Proportional Odd Logit Model is the simple form of Machine Learning Ordinal Logistic Regression Model which is used in our study.

RESULT AND DISCUSSION

Results of the Models

There have to apply two classical models on this food security data according to our problem. Firstly, we have to use the classical multiple linear regression model because the dependent is quantitative and independent.

Variables may be both quantitative and qualitative, some of these are quantitative, and some are quantitative, so in this situation, classical multiple linear regression model. After that, divide the dependent variable into four categories and give 1 for Food insecure, 2 for Moderate uncertain, 3 for Mild unsure, and 4 for Food Secure. Then, the dependent variable is converted into order and definite form. In this situation, we apply the classical ordinal logistic regression model, also called the Cumulative logit model. The cumulative logit model is further divided into three groups. Proportional odds logit model, non-proportional odds logit model, and Partial proportional odd model, but in the study, we have to estimate Proportional Odds Model because we want to compare it with Machine Learning Model.

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Table 4.1 shows the impact of different factors on household food security using a classical linear regression model. The Classical Linear Regression model is estimated by using the Ordinary Least Square (OLS) estimation technique.

Table 4.2 shows the household food security status using the classical proportional odds model, a classical ordinal logistic regression model. The above Classical Ordinal Logistic Regression model is estimated by using the Maximum Likelihood (ML) estimation technique.

We want to compare the Machine Learning Model with the Classical Model. Here we used two classical models, one is the multiple linear regression model and another is the proportional odds model which is the type of ordinal logistic regression model. Now we want to estimate these two models by machine learning techniques which are called machine learning multiple linear regression model and machine learning ordinal logistic regression model.

Table 4.3 shows the impact of different factors on household food security using a machine learning multiple linear regression model. The above Machine Learning Linear Regression model was estimated by using Gradient Descent (GD) estimation technique.

Table 4.4 shows the household food security status by using the machine learning proportional odds model which is the type of ordinal logistic regression model. The above Machine Learning Ordinal Logistic Regression model by using Stochastic Gradient Descent (SGD) estimation technique.

LIST OF TABLES

Table 4.1 Coefficients, Standard Errors and P-values of Linear Regression Model

Explanatory Variables	Categories	Coefficient	Standard Error	t value	P > |t|
Household Size	Continuous	-217.4587	6.4474	-33.728	0.0000
KPK	Otherwise	Ref			
	KPK	4.0074	30.9998	0.132	0.8954
Punjab	Otherwise	Ref			
	Punjab	675.1693	27.7915	24.294	0.0000
Sindh	Otherwise	Ref			
	Sindh	-198.3906	28.7470	-6.901	0.0000
Region	Rural	Ref			
	Urban	292.0114	19.2512	15.168	0.0000
Head Age	Continuous	2.1806	0.6999	3.115	0.0018
Head Gender	Female	Ref			
	Male	387.4449	238.4878	1.625	0.1043
Marital Status	Unmarried	Ref			
	Married	339.8245	753.7353	0.451	0.6521
Head Education	Continuous	13.2924	1.8206	7.301	0.0000
Spouse Education	Continuous	-0.7246	2.1844	-0.332	0.7401
Log Head Income	Continuous	297.7445	31.4241	9.475	0.0000
Live Stock	No	Ref			

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	Yes	382.8245	29.1117	13.155	0.0000
Agriculture Status	No	Ref			
	Yes	501.2623	30.8528	16.247	0.0000
Head Employer	No	Ref			
	Yes	83.4677	64.6614	1.291	0.1968
Head Paid	No	Ref			
	Yes	-118.7331	37.9898	-3.125	0.0018
Spouse Paid	No	Ref			
	Yes	68.7838	26.5885	2.587	0.0097
Couple Employment	No	Ref			
	Yes	24.5752	40.7599	0.603	0.5466
House Ownership	No	Ref			
	Yes	116.5013	22.3846	5.205	0.0000
H.Size^2	Continuous	6.2038	0.3052	20.327	0.0000
AIC	321617.5				
BIC	321782.6				
Log-Likelihood	-160787.8				

Table 4.2 Coefficients, Odds Ratio, Standard Errors and P-values of Proportional Odds Logistic Regression Model

Explanatory Variables	Categories	Coefficient	Odds Ratio	Standard Error	t value	P > |t|
Household Size	Continuous	-0.3903	0.6769	0.0162	-24.1437	0.0000
KPK	Otherwise	Ref				
	KPK	-0.1441	0.8658	0.0557	-2.5857	0.0097
Punjab	Otherwise	Ref				
	Punjab	0.8679	2.3819	0.0515	16.8663	0.0000
Sindh	Otherwise	Ref				
	Sindh	-0.4731	0.6231	0.0516	-9.1631	0.0000
Region	Rural	Ref				
	Urban	0.4616	1.5866	0.0357	12.9212	0.0000
Head Age	Continuous	0.0019	1.0019	0.0014	1.4251	0.1541
Head Gender	Female	Ref				

	Male	1.7653	5.8433	0.4979	3.5451	0.0003
Marital Status	Unmarried	Ref				
	Married	0.3610	1.4348	0.3326	1.0857	0.2776
Head Education	Continuous	0.0247	1.0250	0.0035	7.1119	0.0000
Spouse Education	Continuous	-0.0021	0.9979	0.0041	-0.5154	0.6063
Log Head Income	Continuous	0.7281	2.0711	0.0616	11.8146	0.0000
Live Stock	No	Ref				
	Yes	0.6651	1.9447	0.0573	11.6008	0.0000
Agriculture Status	No	Ref				
	Yes	1.0037	2.7284	0.0633	15.8551	0.0000
Head Employer	No	Ref				
	Yes	0.1869	1.2055	0.1185	1.5772	0.1147
Head Paid	No	Ref				
	Yes	-0.2731	0.7610	0.0715	-3.8202	0.0001
Spouse Paid	No	Ref				
	Yes	0.1578	1.1709	0.0484	3.2599	0.0011
Couple Employment	No	Ref				
	Yes	0.1117	1.1182	0.0777	1.4374	0.1506
House Ownership	No	Ref				
	Yes	0.2544	1.2897	0.0409	6.2168	0.0000
$H.Size^2$	Continuous	0.0119	1.0119	0.0008	14.4978	0.0000
AIC	39882.36					
BIC	40055.3					
Log-Likelihood	-19919.18					

Table 4.3 Coefficients, Standard Errors and P-values of Machine Learning Linear Regression Model

Explanatory Variables	Categories	Coefficient	Standard Error	t value	P > |t|
Household Size	Continuous	-207.1902	7.0479	-29.398	0.0000
KPK	Otherwise	Ref			
	KPK	-1.3898	35.0448	-0.040	0.9684
Punjab	Otherwise	Ref			
	Punjab	659.8004	31.4148	21.003	0.0000

Sindh	Otherwise	Ref			
	Sindh	-221.3567	32.4273	-6.826	0.0000
Region	Rural	Ref			
	Urban	298.6254	21.7901	13.705	0.0000
Head Age	Continuous	2.0356	0.7900	2.577	0.0009
Head Gender	Female	Ref			
	Male	330.7489	254.2191	1.301	0.1933
Marital Status	Unmarried	Ref			
	Married	342.4371	762.2126	0.449	0.6533
Head Education	Continuous	13.6729	2.0585	6.642	0.0000
Spouse Education	Continuous	0.3516	2.4827	0.142	0.8874
Log Head Income	Continuous	283.2565	35.3646	8.010	0.0000
Live Stock	No	Ref			
	Yes	383.0133	33.3903	11.471	0.0000
Agriculture Status	No	Ref			
	Yes	494.6521	35.2594	14.029	0.0000
Head Employer	No	Ref			
	Yes	116.8727	73.5814	1.588	0.1122
Head Paid	No	Ref			
	Yes	-117.3955	42.5868	-2.757	0.0058
Spouse Paid	No	Ref			
	Yes	49.9761	29.9581	1.668	0.0953
Couple Employment	No	Ref			
	Yes	37.9822	45.7870	0.830	0.4068
House Ownership	No	Ref			
	Yes	107.2092	25.2446	4.247	0.0000
$H.Size^2$	Continuous	5.6791	0.3257	17.435	0.0000
AIC	257437				
BIC	257597.4				
Log-Likelihood	-128697.5				

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Table 4.4 Coefficients, Odds Ratio, Standard Errors and P-values of Machine Learning Proportional Odds Logit Regression Model

Explanatory Variables	Categories	Coefficient	Odds Ratio	Standard Error	t value	P > |t|
Household Size	Continuous	-0.3827	0.6820	0.17773	-21.5822	0.0000
KPK	Otherwise	Ref				
	KPK	-0.1818	0.8338	0.0625	-2.8922	0.0038
Punjab	Otherwise	Ref				
	Punjab	0.8191	2.2685	0.0577	14.1981	0.0000
Sindh	Otherwise	Ref				
	Sindh	-0.5424	0.5814	0.0578	-9.3798	0.0000
Region	Rural	Ref				
	Urban	0.4566	1.5787	0.0399	11.4167	0.0000
Head Age	Continuous	0.0025	1.0025	0.0015	1.6542	0.0981
Head Gender	Female	Ref				
	Male	1.6685	5.3042	0.5096	3.2740	0.0011
Marital Status	Unmarried	Ref				
	Married	0.3958	1.4856	0.3510	1.1272	0.2597
Head Education	Continuous	0.0265	1.0269	0.0039	6.8440	0.0000
Spouse Education	Continuous	-0.0026	0.9974	0.0046	-0.5607	0.5701
Log Head Income	Continuous	0.6746	1.9632	0.0683	9.8804	0.0000
Live Stock	No	Ref				
	Yes	0.6527	1.9207	0.0648	10.0740	0.0000
Agriculture Status	No	Ref				
	Yes	1.0280	2.7955	0.0713	14.4208	0.0000
Head Employer	No	Ref				
	Yes	0.2473	1.2806	0.1331	1.8581	0.0632
Head Paid	No	Ref				
	Yes	-0.2758	0.7589	0.0790	-3.4887	0.0004
Spouse Paid	No	Ref				
	Yes	0.0944	1.0989	0.0539	1.7513	0.0799
Couple Employment	No	Ref				
	Yes	0.1775	1.1942	0.0862	2.0597	0.0394
House Ownership	No	Ref				
	Yes	0.2714	1.3118	0.0457	5.9439	0.0000
$H.Size^2$	Continuous	0.0115	1.0116	0.0009	12.8582	0.0000
AIC	31923.48					
BIC	32091.5					
Log Likelihood	-15939.74					

CONCLUSION

Comparison

We have estimated four models consisting of two classical and two machine learning models. The first model is the classical multiple linear regression model, the second is the classical ordinal logistic regression model, the third is the machine learning multiple linear regression model and the last one is the machine learning ordinal logistic regression model. Results are clearly shown in Table (4.1), (4.2), (4.3) and (4.4) and see which model has a small standard error. First, compare classical multiple linear models with machine learning linear regression model and we conclude that the classical multiple linear models are well fitted for prediction as compared to machine learning multiple linear models because it has a minimum standard error. The second is want to compare the classical ordinal logistic model with the machine learning ordinal logistic regression model and also conclude that the classical ordinal logistic model is well fitted for prediction due to having a minimum standard error. In these four models, we want to check that which model is well fitted or which model is efficient for prediction so we conclude that the classical ordinal logistic model is efficient as compared to another three models because it has small standard errors. The result of this model is given in Table (4.2) clearly.

Interpretation of classical ordinal logistic model according to Table (4.2) are explain bellows. There are four categories of dependent variables these are food secure, mild insecure, moderate insecure, and insecure. The coefficient of household size effect is negative on food security so it tends to follow food insecure, -39% means that the household size may fall in food moderate insecure. The coefficient of KPK shows that the household living in KPK are food insecure as compared to Punjab. The estimated value of KPK is -14% show that the household's living in KPK tends to follow the mild food insecure category. The coefficient of Sindh shows that people living in Sindh are food insecure as compared to Punjab. The estimated value of Sindh is -47% show that the household's living in Sindh tends to follow the moderate food insecure category. The coefficient of Punjab shows that the household living in Punjab are food secure as compared to KPK and Sindh. It means that the people living in Punjab are food secure because in every model it gives a positive coefficient. The coefficient of Urban shows that the household's living in urban are food secure.

The estimated value of Urban is 46% which show that the households of urban area in Pakistan tend to follow food security as compared to the people who live in rural area. The head age estimated value of 0.19% shows that the household's head age is older is food secure but age has very less effect on household's food security. The estimated value of head gender is 176% which shows that the households their head is male are food secure as compared to these households their head is female. Head gender highly affects on household's food security. In table (4.2) the coefficient of marital status shows that those household heads are married their family status lies in the food-secure category. The estimated value of marital status is 46% which shows that those households their heads are married follow food security as compared to those households their heads are not married.

The estimated value of head education is positive it means that those households' heads are educated their family status lies within food security. The estimated value of 2% shows that the household's head is educated follows the food secure category but the coefficient shows that the household head is less effect on food security. The estimated value of spouse education is negative, it means that those households' spouses are educated their family status lies within food insecurity. The estimated value of -0.2% show that the household's spouse is educated follows the food insecure category but the coefficient shows that the education of the household's spouse is less effect on food security. The coefficient of log of head income shows that there has a positive effect of income of household's head on food security. The estimated value of 73% shows that those households' head income is high lies within the food secure category.

The coefficient of head income shows that the income of household heads is highly affected by food security. The households have their livestock that follows the food secure category. The coefficient of the household's livestock variable is 66% which means the household's livestock is food secure as compared to those households which have no livestock and it highly affected food security data. Also, the coefficient of agriculture growing variable show that the households follow food secure which have their agriculture. The coefficient of agriculture status is 100% which means that the households are following the food secure category which has their agriculture as compared to those households that have no agriculture. The agriculture status has highly effect on a household's food security.

The coefficient of head employer shows that head employer has a positive effect on household food security. 18% indicate that the household's heads are employer family status follows food secure category as compare to those household's heads are not the employer. The estimated value of head paid shows that the household's heads are employed has a negative effect on food security data of household. The coefficient -27% show that the households follow the food mild insecure category as compared to those households their heads are not employed. The estimated value of spouse paid shows that the households their spouses are employed in have a positive effect on the food security data of the household. The coefficient of 15% shows that the households follow the food secure category as compared to those households their spouses are not employed. The couple employed coefficient shows that those households' couples are employed have a positive effect on household food security.

The estimated value of couple employed variable 11% show that those household's couples are employed follow food secure category as compare to those household's couples are not employed and it has less effect on food security data. The variable house ownership coefficient is positive, which means that there has a positive effect of house ownership on household food security data. The coefficient of house ownership is 25% which means that those households which have their own house are food secure as compared to those households which have no own household. The coefficient of house ownership shows that there has a low effect of house ownership on household food security.

Future Policies

The last chapter presents the summary of the study. It concludes the research and offers policy implications and recommendations. In this study, try to evaluate the food security level in Pakistan to understand the reason behind the food insecurity in the country.

Some main factors affected the household's food security level in Pakistan in this study. Based on our analysis the food insecurity is usually high among household's their low level of head income, no agriculture status, no possession of livestock, the high sample size of household, female head, low level of education of charge, high level of spouse education, public authority, the typical age of a lead, living in the rural region, living in KPK and Sindh, head unemployed and head employed, spouse unemployed, couple unemployed, and non-house ownership.

It reveals the question of how to attain feasible food security at the household level. The study of the behavior of food security is essential because it does indicate not only past behavior of food insecurity level but also able to the guidelines for different policies. Some of the most critical factors are being identified by this study, which may help improve and aggravate household food security.

The main objective of this study is to analyze the food security level at the household level in Pakistan. By using appropriate methodology is developed to carry out an empirical analysis. The numerical data is collected carefully and analyzed. The average per capita daily kilocalories consumed index (per day calories per capita) is used to measure household food security level in this study. The multiple linear regression and ordinal logistic regression techniques are used in the Classical framework. In addition, multiple linear regression and ordinal logistic regression techniques in Machine Learning are also used to measure the significant effect of the factors.

The study concludes that Pakistan is not considered a secure food country because Low income of head, low level of education, insufficient food, large household size, lack of proper nutrition to access the market, and everyday people. The empirical findings indicate that Pakistan is considered a food-insecure country, and it faces too many problems about food security. Based on this study, some suggestions about food security are given bellows.

Expenditure and income are the most effective and more powerful factors to determine household food security in Pakistan. These two variables are highly significant in measuring the household's food security level in Pakistan. Education level is also the most crucial factor, and it directly or indirectly affects the household's food security level. Therefore, it is required attention about these most important factors to improve them and make Pakistan a food security country in the world.

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