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Feature Selection Methods for Predicting Household Food Insecurity

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Abstract: Feature selection is a method of dimension reduction that is used to select a specific subset of appropriate features from the original features by removing unnecessary and redundant features that do not have a benefit in classification or prediction. In this paper, the feature selection approach was conducted using three feature selection methods namely: Filter based, Wrapper based and Embedded based to predict household food insecurity from the household income, consumption, and expenditure survey data (HICE). To implement the above feature selection methods, we proposed new hybrid method by integrating the filter based feature selection methods which is Feature importance, Univariate (chi-square) and Correlation coefficient. To validate the efficiency of the proposed feature selection methods, we used five classification algorithms namely: K-Nearest Neighbor (KNN), Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), and Naive Bayes (NB).

Keywords: Machine learning, Feature selection, Food insecurity, Classification, HICE

I. INTRODUCTION

We are living in the 21st century and have made tremendous development in manufacturing, infrastructure and finance. We've achieved great scientific advances, improving human health and extending the lifespan. Given this development, almost a sixth of the world's population currently suffers from chronic hunger and malnutrition due to a lack of food (FAO 2017). Households are said to be food insecure in the absence of economic access to the food they need, no access to cash for food production and whose consumption of dietary energy (kilo/calories) is below the acceptable standard.According to Kakwani et al. [1] 842 million people in the world suffered from chronic hunger, which is 12% in 2011-2013. Organization for Food and Agriculture (FAO) measures food insecurity based on the prevalence of undernourishment, comparing common food intake expressed in terms of dietary energy (kilo/ calories) to certain energy quality requirements. It also measures food insecurity based on the percentage of the population whose consumption of dietary energy is below the average for energy requirement.Prediction of food insecurity is instrumental in leading stakeholders towards early intervention relief. Consequently the effect of food insecurity can be monitored and/or eliminated in the process. In some parts of the world, the science of predicting food insecurity has produced positive results. Effective management of federal programs, food assistance and other government initiatives will reduce food insecurity, if accurate monitoring of food insecurity is carried out [2]. The study conducted by okori and obua [2] shows that prediction of food insecurity can play a vital role in resolving the household problem for the respective bodies whose duty is to take action on prevention and intervention activities. Government and other stakeholders or humanitarian organizations set up to support those who are victims of food insecurity and require additional assistance to save their lives. Food insecurity prediction is a demanding task in developing countries due to the lack of reliable and sufficient data to predict food insecurity status.Machine learning algorithms are used to select the best features from the original data that would reduce computational costs and improve the prediction with greater precision. Feature selection is the method of choosing the proper attributes to construct a learning model. The selection of the correct attributes increases the accuracy of the designed model while the incorrect selection of attributes significantly decreases model efficiency.Here are three types of notable feature selection methods, namely Filter, Wrapper and Embedded Method. The filter method uses a statistical test to determine the correct features. A subset of features is first selected in the wrapper process, then the model is trained and results are obtained. Selecting or rejecting particular features from the data set is determined based on the result. Embedded methods incorporate the aforementioned method of selecting features. Feature selection methods are used as a dimensionality reduction strategy with the goal of selecting a small subset of important features from the original features by eliminating obsolete, redundant or noisy features that may not have a classification or prediction advantage. For example, the feature selection has the following advantages: improved learning efficiency, lower computational costs and better interpretability of models [4]. It is also used to identify and remove unnecessary, insignificant and redundant features from data which do not contribute to a predictive model's accuracy.In the classification domain, feature selection is very crucial for improving classification performance particularly in the case of high-dimensional data. By removing unnecessary and redundant features, selection of features is conducive to improving learning speed, predictive accuracy and simplicity and understandability of the results learned [5].Machine learning is the process of creating a scientific model based on the knowledge discovered from the data set for sample training. Furthermore, identifying patterns automatically and making an intelligent decision based on the sample data is a complex computing operation. Features selection in machine learning is the method of selecting a subset of the most important features for use in model construction [6]. A critical issue

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in machine learning is the identification of a sample features from which to construct a classification model for a particular task. Good feature sets are highly correlated with the class but uncorrelated with each other [6]. Machine learning offers a method for automatically analyzing large amounts of data, and it is important to select features.The remaining part of the paper is structured as follows: Section II reviews related work reported in the related areas. Section III discusses Feature selection methods used in this paper, Section IV presents the classification algorithms, Section V explains the description of the data variables for HICE data set, the experimental results of each feature selection method are discussed in Section VI with the classification algorithms and finally the paper is finalized in Section VII with concluding remarks.

II. RELATED WORKS

Some articles related to food insecurity and feature selection strategies are reviewed, some of the papers reviewed are as followsEndalew et al. [7] describe factors affecting food security for households in various developing nations. The study result shows that features such as household head gender, educational level, household head age and income have a positive impact on food security while household size has a negative impact on household food security.Yildirim and Pinar [8] suggested several feature selection methods in the domain of machine learning. Such methods primarily aim to remove irrelevant or redundant features from the data set. For several purposes, feature selection strategies used, such as minimizing computational costs, being easy to interpret and reducing over fitting.Blessie and Karthikeyan [9] recommend methods for selecting features to decide how useful it is in determining an appropriate method for selecting features. Authors classify feature selection into the wrapper based, filter based and embedded method. To evaluate goodness, wrapper based method uses the predictive accuracy of a predetermined learning algorithm. Wrapper based approach is computationally expensive for large data set. The filter based approach selects important features independent of any learning algorithm and uses measurements such as distance, information and dependence.Srivastava et al. [10] proposed feature selection methods to achieve the common objective of optimizing classifier accuracy, minimizing related measurement costs by eliminating unnecessary and redundant features, reducing complexity and increasing the likelihood of a comprehensible and practical solution.Barbosa and Nelson [11] applied support vector machine algorithm to identify the food security status of agricultural households into food secure and insecure. Authors have been selected as the top 14 features from a total of 75 features and achieved 77% accuracy and 84% recall. Sanchez-Maro et al. [12] proposed selection methods for the filter and wrapper method. Wrapper method chooses the best features using the classifier, while filter methods choose features independent any classifier. This model is faster than the wrapper approach and results in a greater generalization.Endalew et al. [7] have researched the triggers, determinants and food security situation in Ethiopia. The result shows that greater household size, lower level of household head education achievement, and household head age increase are significantly associated with household food insecurity. Household food insecurity is associated with household size increases. There is an inverse relationship between the level of education attained by the head household and the likelihood of falling into food insecurity.Wrapper based feature selection methodology integrates supervised learning algorithms into the process of selection. It scores features that are based on the subset evaluation methodology. When selecting the features, correlations and relationships are considered between the features. Keeping in mind the prediction algorithm's bias helps to optimize algorithm performance. In support vector machine (SVM), each function is assigned weight during SVM learning. The key limitation of the wrapper strategy is the expense of computation related to the quest for the optimum set from a large dimensional space [13]

III. FEATURE SELECTION METHODOLOGY

Feature selection algorithms can be categorized as supervised, unsupervised and semi-supervised based on the label perspective and can be graded into Filter, wrapper and embedded based feature selection based on selection strategy. The most important features out of the original features are selected using wrapper, filter and embedded methods. Feature selection techniques were applied to the data set for the Ethiopian household income, consumption and expenditure survey that was collected at country level from 2011 to 2016. When using a feature selection a smaller number of features are selected, which means fewer model parameters. It strengthens the capabilities for generalization and reduces complexity and time for execution. The performance of the selected subset of features was evaluated using the KNN, LR, RF, NB and SVM classification algorithms.

A. Filter Based Feature selection

Filter method is a supervised learning process and selection is independent of any learning algorithm that uses data characteristics to choose and evaluate the features. Unwanted features are removed before classification begins in the filter method. In most cases, features are ranked on the basis of certain statistical parameters, choosing features with the highest ranking values. It is more general, faster, requires low computational complexity. Selecting features in this method depends on data characteristics such as consistency, distance, dependency and correlation. There see many filter based feature selection techniques , some of these are univariate(chi squared) feature selection, feature importance , correlation coefficient and hybrid methods are various filter based methods for ranking features. The last feature selection method is a hybrid method which is created by combining chi squared, feature importance and correlation coefficient.

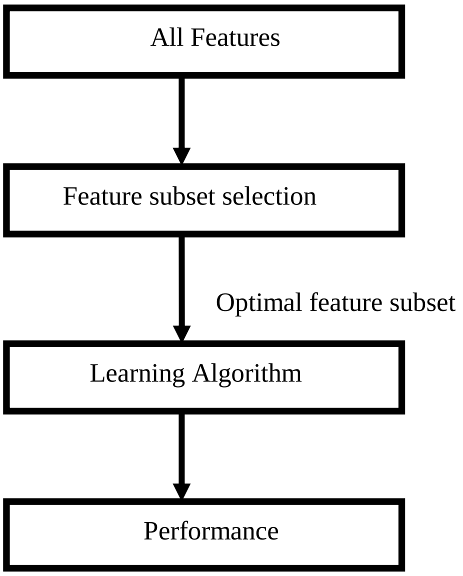

Figure 1: Filter based feature selection method [14]

1. Univariate (chi square) Feature selection

Univariate or chi square feature selection is a selection criteria in which the significance of a feature is evaluated by measuring the value of the x^2 statistic compared to the target class. Univariate feature selection examines each feature independently to assess the strength of the relationship between the feature and the target variable. Such methods are easy to run and to understand and good for a better understanding of the results. Univariate feature selection is implemented from the feature selection module of the scikit learn library using the Select KBest process. Select KBest selects the k highest scoring capabilities from the feature space. Table 1 demonstrates how univariate feature selection rank features.

Table 1: Ranking best 10 features using univariate method

RANK	FEATURE	SCORE
19	net calorie	9.802312e+06
17	Annual expend	5.146579e+06
16	WGT	1.057221e+05
13	age head	2.260284e+04
5	kebele	8.043564e+03
7	HH_size	4.518135e+03
10	REP	3.339410e+03
4	K_ketema	3.329778e+03
8	ADEQUIV	2.920728e+03
2	Region	4.990777e+02

2. Correlation coefficient

The predictive power of each single feature is assessed using this approach. Best features are the one with the highest correlation. One of the simplest methods for understanding the relationship of a feature to the target variable is the correlation coefficient which calculates the linear association between the two variables. The resulting value is [-1; 1], with -1 which is perfect negative correlation, + 1 which is perfect positive correlation, and 0 which is no linear correlation between the two variables.

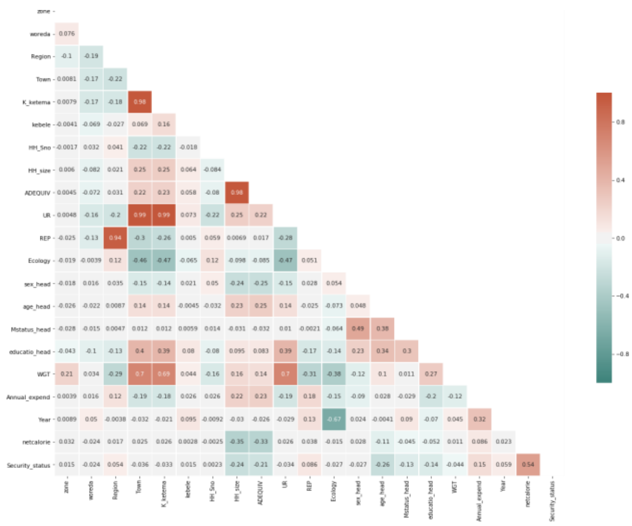

Figure 2: Correlation based Feature selection Method

3. Feature Importance feature selection

Feature importance is a selection criterion in which the significance of a feature is determined by the calculation of the obtaining information in relation to the target class. Feature importance is an integrated class that comes with Tree Based Classifiers. We are using Extra Tree Classifier for selecting the best features in this work. Figure 3 depicts the features selected based on the feature importance method.

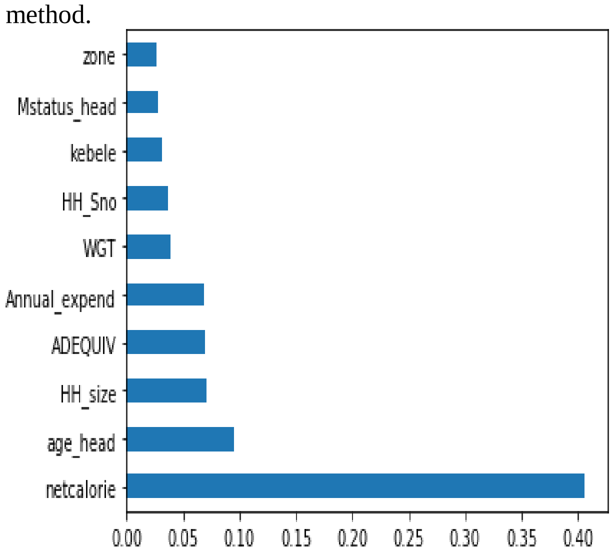

Figure 3: Best 10 selected features using Feature importance

4. Hybrid(Intersection) Feature selection

In our work, apart from the individual methods of selecting features, we find the hybrid approach for selecting common features from three methods of selection. Figure 4 and 5 demonstrate how hybrid method is computed from correlation coefficient, feature importance and univariate feature selection methods.

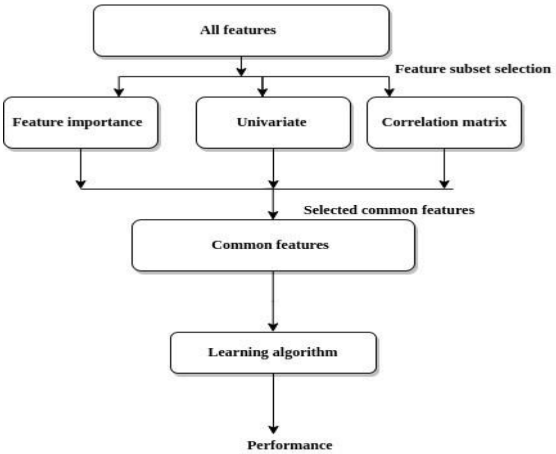

Figure 4: Hybrid feature selection model

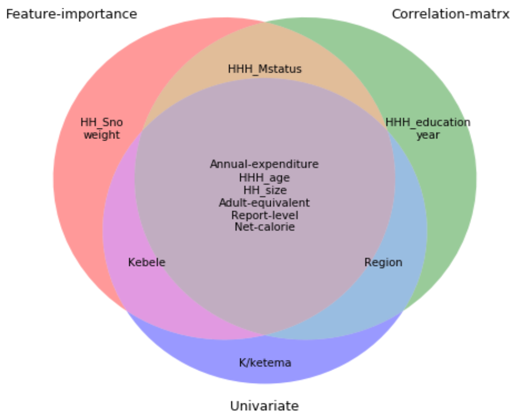

Figure 5: Selected features using hybrid features selection method

B. Wrapper Based Feature Selection

This method of feature selection uses variable combinations to determine predictive power. To evaluate the goodness of features, it uses the predictive accuracy of a predetermined learning algorithm and it is computationally expensive for high-dimensional data. Wrapper methods are based on greedy search algorithms as they analyze all possible combinations of features and find the combination that produces the best results for a particular machine learning algorithm and calculate the usefulness of features based on the performance of the classification. It is further divided into three, namely forward feature selection, backward feature selection and recursive feature elimination. Figure 6 depicts the graphical representation of the wrapper feature selection method.

1. Forward Feature Selection (FFS)

Ignoring unnecessary and insignificant features, construct an appropriate subset of features. Searches for the best feature in each iteration and adds an optimal set of features. If all features are already added or there is no change after adding any additional features, the search

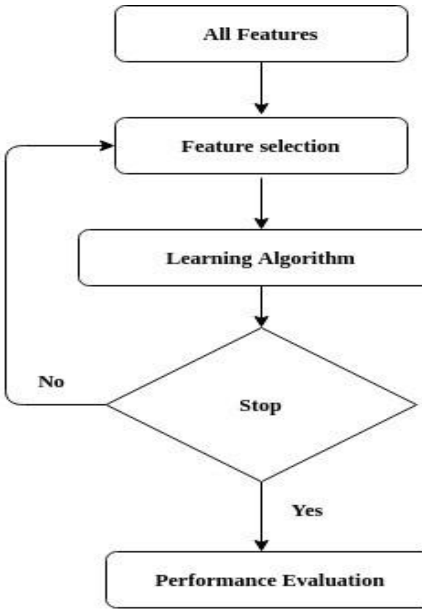

Figure 6: Wrapper Feature Selection Method [15]

stops and returns the current optimal set of important features. [13].

2. Backward Feature selection (BFS)

In the beginning, it considers all features and then tries to remove the most unnecessary and redundant features, leaving a smaller optimal subset of features. It looks for the feature to be eliminated from the full set of data in each iteration. If the performance rate of the new subset of features is better than the previous subset then it replaces the current best subset of features. This process continues until every feature is eliminated from the data set and an empty set is reached [13].

3. Recursive Feature Elimination(RFE)

A feature selection method that suits the model and eliminates the weakest features until the defined feature number is reached. Features are graded recursively removing a small number of features per loop [13].

C. Embedded Feature Selection

Embedded methods complete the selection process of features in the construction of the machine learning algorithm itself and perform the selection of features during model training. There are many built-in feature selection methods that select the best features from the original data set, Lasso and Tree-based.

Lasso: is an embedded feature selection process that uses SelectFromModel for a meta-transformer and a coefficient estimator. Features shall be considered unimportant and shall be discarded if the corresponding coefficients or significance values are below the defined threshold parameter. The aim of lasso regression is to obtain the subset of predictors that minimize prediction error for a target variable. The lasso does this by placing a limit on the parameters of the model that allows regression coefficients to shrink to zero for some variables. Variables with a regression coefficient equal to zero are withdrawn from the model after the shrinkage process Variables with non-zero regression coefficient are most strongly associated with the target variable.

Therefore, when doing a regression model, it may be helpful to do a lasso regression to determine how many variables the model will include.

Tree-Based Feature selection

Tree-based Feature Selection is one of the most common machine learning algorithms and provides good predictive efficiency, low over-fitting and easy interpretability. This interpretability is based on the fact that it is simple to derive the value of each variable in the tree decision. In other words, it is easy to calculate how much each variable contributes to the decision.

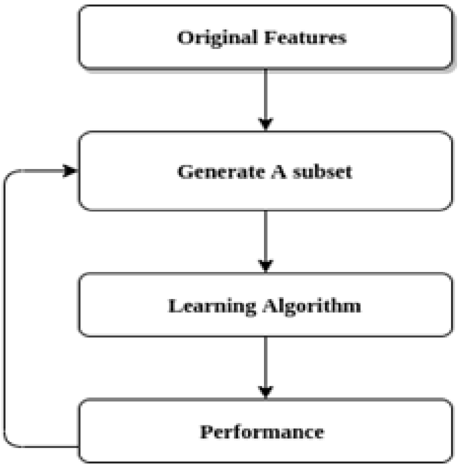

Figure 7: Embedded Feature Selection method

IV. CLASSIFICATION ALGORITHM:

In this study, five machine learning classifiers, namely KNN, LR, RF, SVM and NB, have been used to validate the usefulness of the proposed feature selection methods for household food insecurity. Below is the overview of the classifiers.

K-Nearest Neighbor (KNN): is a classification algorithm which resides with all available features and classifies new cases based on distance functions or measure of similarity. KNN is the basic classification algorithm that takes into account all the data set points to be categorized within their class belongingness. It considers k-nearest points from the data point selected and ranks them in ascending order.

Logistic Regression (LR): Logistic regression is the model of classification, where test data probabilities are estimated. It uses conditional probabilities for the classification of food secure and foo insecure problems with two possible outcomes 1 and 0.

Support Vector Machine (SVM): is a classification algorithm where we have several kernel choices, depending on the data distribution fashion. It can classify data in several linear ways but SVM gives us the best choice among all the options available. Kernel, linear, rbf, poly sigmoid forms.

Random Forest (RF): It is part of the ensemble learning and integrates several algorithms to obtain optimized efficiency. We combine decision tree classification algorithms multiple times in random forest classification.

Naive Bayes (NB) This is a Bayes Theorem-based mathematical classification methodology. It is one of the simplest supervised learning algorithms. Naive Bayes classifier is the algorithm that is fast, accurate and reliable and has high precision and speed on large data sets.

Performance metrics: Several assessment criteria are used with selected features to determine the efficiency of the algorithms. Classification accuracy, recall, precision, f1-score, confusion matrix and ROC are the most commonly used evaluation metrics.

Classification accuracy is the number of accurate predictions divided by the total number of predictions multiplied by hundred to turn it into a percentage.

$$CA = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Recall is determined based on True Positives (TP) number separated by True Positives (TP) number and False Negatives (FN) number. The number of positive results divided by the number of positive class values in the test data is another way of expressing this.

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

Precision is calculated based on the True Positives (TP) number separated by the True Positives (TP) and False Positives (FP) number. In another way the number of positive projections divided by the estimated total number of positive class values.

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

F1-measure: is calculated based on precision and recall

$$F1 = 2\frac{Precision * Recall}{Precision + Recall} \quad (4)$$

Confusion Matrix is a metric displaying result from a given test data correctly classified and misclassified, as shown in the following table.

Table 2: confusion matrix

<table>
<tr><td rowspan="4">Actual</td><td colspan="3">Predicted</td></tr>
<tr><td></td><td>Positive</td><td>Negative</td></tr>
<tr><td>Positive</td><td>True positive</td><td>False Positive</td></tr>
<tr><td>Negative</td><td>False Negative</td><td>True Negative</td></tr>
</table>

V. DATA SET DESCRIPTION

The data set used for this work was collected from the Central Statistics Agency (CSA) of the Federal Democratic Republic of Ethiopia. The data dealt with survey data on income consumption and expenditure from 2011 to 2016 at national level, and the survey covered both rural and urban areas of the country. The data set contains 21 features including the class label. The class label shows whether the household is food secure or insecure.

VI. EXPERIMENTAL RESULT

Features are selected from the original data set using filter, wrapper and embedded based feature selection methods.

For feature selection univariate, feature importance, correlation coefficient and hybrid methods are applied under filter based technique, backward, forward and recursive features selection methods are used under wrapper and lasso and tree based feature selection are used under embedded method. To validate the accuracy of selected features we trained and tested commonly used classifiers such as KNN, LR, SVM, RF and NB with same data set and compare their accuracy.

The experimental results shows under filter based feature selection method, feature importance approach with seven features score better result than others which is 99.98% accuracy using RF classifier.In the case of wrapper based feature selection method backward feature selection with ten features score better result than other with an accuracy of 99.97% under RF classifier followed by recursive feature elimination with five features using KNN which scores 96% accuracy.Finally under embedded method, by Tree based feature selection score better result than other under RF classifier with an accuracy of 96.7% followed lasso using RF classifier with 96.3%.

Table 3: Accuracy of filter based feature selection method

Classifier	Filter Type	No of features	Accuracy	Precision	Recall	F1 score	ROC
KNN	Correlation coefficient	10	92	88	93	91	92
		7	95	95	94	94	95
		5	96	96	95	96	97
	Chi-squared	10	91.5	90	90.4	90.3	91
		7	95.5	94.9	94.6	94.8	95
		5	95.3	95	94	94.7	95
	Feature Importance	10	87	86	84	85	87
		7	89	87	87	87	89
		5	89	87	88	87	89
	hybrid	5	96.7	96.3	96.2	96.3	97
RF	Correlation coefficient	10	99.96	99.94	99.98	99.96	1.00
		7	99.97	99.96	99.98	99.97	1.00
		5	99.95	99.96	99.96	99.96	1.00
	Chi-squared	10	99.95	99.92	99.98	99.95	1.00
		7	99.95	99.92	99.98	99.95	1.00
		5	99.97	99.94	1.00	99.97	1.00
	Feature Importance	10	99.98	99.96	1.00	99.98	1.00
		7	99.96	99.94	99.98	99.96	1.00
		5	99.96	99.94	99.98	99.96	1.00
	hybrid	5	99.95	99.94	99.96	99.95	1.00
SVM	Correlation coefficient	10	89	91	85	88	89
		7	90	88	88	88	90
		5	88	89	84	87.	89
	Chi-squared	10	88.7	90.2	83.8	86.9	89
		7	89.6	91	84.9	87.9	89
		5	88.7	89.7	84	86.9	89
	Feature Importance	10	96	96	96	95	96
		7	89	90	84	87	89
		5	89	90	84	87	90
	hybrid	5	89.4	90.8	84.8	87.7	89
LR	Correlation coefficient	10	89	87	88	87	89
		7	89	87	88	87	89
		5	89	87	88	87	89
	Chi-squared	10	81.8	80.5	77.5	79	81
		7	85	81	86.9	83.9	89
		5	89	87	88	87.6	89
	Feature Importance	10	87	86	84	85	87
		7	89	87	87	87	89
		5	89	87	88	87	89
	Hybrid	5	86.8	85.7	84.2	84.9	87

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NB	Correlation coefficient	10	77	70	81	75.9	78
		7	77	70	81	75.8	78
		5	78	72	84	77.8	79
	Chi-squared	10	77.9	71.9	82	76.6	78
		7	77.7	71.7	82	76.5	78
		5	81	73.5	89.3	80.6	81
	Feature Importance	10	77	70	84	76.7	78
		7	78	71	82	76.9	78
		5	78.7	72	84	77.8	79
	hybrid	5	78.7	72.4	84	77.8	79

Table 4: Accuracy of wrapper based feature selection method

Classifier	Feature selection Method	No of features	Accuracy	Precision	Recall	F1 score	ROC
KNN	Forward feature selection	10	0.90	0.87	0.92	0.89	0.91
		7	0.92	0.91	0.92	0.91	0.93
		5	0.95	0.95	0.95	0.95	0.96
	Backward feature selection	10	0.89	0.88	0.88	0.88	0.90
		7	0.93	0.91	0.92	0.91	0.93
		5	0.96	0.95	0.95	0.95	0.96
	Recursive feature elimination	5	0.96	0.96	0.95	0.95	0.96
SVM	Forward feature selection	10	0.88	0.90	0.82	0.85	0.88
		7	0.88	0.90	0.83	0.86	0.88
		5	0.91	0.92	0.87	0.89	0.91
	Backward feature selection	10	0.88	0.88	0.83	0.86	0.88
		7	0.88	0.90	0.83	0.86	0.88
		5	0.91	0.92	0.87	0.89	0.91
	Recursive feature elimination	5	0.89	0.90	0.84	0.87	0.89
RF	Forward feature selection	10	99.95	99.94	99.96	99.95	1.00
		7	99.97	99.96	99.98	99.97	1.00
		5	99.96	99.92	1.00	99.6	1.00
	Backward feature selection	10	99.97	99.96	1.00	99.97	1.00
		7	99.94	99.90	99.98	99.94	1.00
		5	99.96	99.92	1.00	99.96	1.00
	Recursive feature elimination	5	99.94	99.96	99.92	99.94	1.00
LR	Forward feature selection	10	0.87	0.86	0.84	0.85	0.87
		7	0.88	0.86	0.88	0.87	0.89
		5	0.88	0.86	0.87	0.87	0.89
	Backward feature selection	10	0.89	0.86	0.88	0.87	0.89
		7	0.83	0.82	0.77	0.80	0.83
		5	0.88	0.86	0.88	0.87	0.89
	Recursive feature elimination	5	0.86	0.85	0.83	0.84	0.86
NB	Forward feature selection	10	0.80	0.73	0.847	0.786	0.80
		7	0.797	0.73	0.847	0.786	0.80
		5	0.80	0.738	0.859	0.79	0.80
	Backward feature selection	10	0.79	0.73	0.859	0.79	0.80
		7	0.81	0.73	0.898	0.80	0.81
		5	0.81	0.74	0.87	0.80	8.81
	Recursive feature elimination	5	0.80	0.72	0.886	0.798	0.80

Table 5: Accuracy of embedded based feature selection method

Classifier	Feature selection Method	No of features	Accuracy	Precision	Recall	F1 score	ROC
KNN	Lasso	4	0.946	0.96	0.91	0.937	0.94
RF			0.963	0.979	0.93	0.957	0.96
SVM			0.93	0.95	0.88	0.918	0.93
LR			0.907	0.893	0.897	0.895	0.91
NB			0.786	0.71	0.86	0.78	0.79
KNN	Tree based feature selection	2	0.966	0.959	0.962	0.961	0.97
RF			0.967	0.96	0.965	0.963	0.97
SVM			0.90	0.92	0.867	0.89	0.90
LR			0.89	0.867	0.867	0.89	0.90
NB			0.85	0.767	0.954	0.85	0.85

VII. CONCLUSION

Implementing selection of features in a large data set plays a critical role by simplifying the models and making them simpler to understand, shorter training times, avoiding the curse of dimensionality and increasing generalization by minimizing over fitting.Commonly used feature selection methods, such as filter, wrapper and embedded feature selection are implemented. In this paper,
the feature selection approach was conducted using three feature selection methods namely: Filter based, Wrapper based and Embedded based to predict household food insecurity from the household income, consumption, and expenditure survey data (HICE). To implement the above feature selection methods, we proposed new hybrid method by integrating the filter based feature selection methods which is Feature importance, Univariate (chi-square) and Correlation coefficient. We have been trained and tested with KNN, LR, SVM, RF and NB classifiers to validate the accuracy of all features and selected features. Based on the results of the experiment we conclude that selection of features is good for better classification and accuracy of predictions. With five classification algorithms, the entire data set, best ten, best seven and best five features are evaluated and results are compared. From the experiment result feature importance with seven features is the best feature and Random Forest is the best classification algorithm that scores better results than others with selected features which is 99.98% accuracy.

REFERENCE

1 N. Kakwani and H. H. Son, “Measuring food insecurity: Global estimates,” in Social welfare functions and development. Springer, 2016, pp. 253–294.

2 W. Okori and J. Obua, “Machine learning classification technique for famine prediction,” in Proceedings of the world congress on engineering, vol. 2, 2011, pp. 991–996.

3 C.-J. Alisha, M. P. Rabbitt, C. A. Gregory, and A. Singh, “Household food security in the united states in 2016,” United States Department of Agriculture, Economic Research Service, Tech. Rep., 2017.

4 J. Miao and L. Niu, “A survey on feature selection,” Procedia Computer Science, vol. 91, pp. 919–926, 2016.

5 M. Zhu and J. Song, “An embedded backward feature selection method for mclp classification algorithm,” Procedia Computer Science, vol. 17, pp. 1047–1054, 2013.

6 M. A. Hall, “Correlation-based feature selection for machine learning,” 1999.

7 B. Endalew, M. Muche, and S. Tadesse, “Assessment of food security situation in Ethiopia,” World Journal of Dairy and Food Sciences, vol. 10, no. 1, pp. 37–43, 2015.

8 P. Yildirim, “Filter based feature selection methods for prediction of risks in hepatitis disease,” International Journal of Machine Learning and Computing, vol. 5, no. 4, p. 258, 2015.

9 C. Blessie and E. Karthikeyan, “Sigmis: A feature selection algorithm using correlation based method,” Journal of Algorithms & Computational Technology, vol. 6, no. 3, pp. 385–394, 2012.

10 M. S. Srivastava, M. N. Joshi, and M. Gaur, “A review paper on feature selection methodologies and their applications,” IJCSNS, vol. 14, no. 5, p. 78, 2014.

11 R. M. Barbosa and D. R. Nelson, “The use of support vector machine to analyze food security in a region of Brazil,” Applied Artificial Intelligence, vol. 30, no. 4, pp. 318–330, 2016.

12 N. Sanchez-Maro, A. Alonso-Betanzos, and M. Tombilla-Sanrom´an, “Filter methods for feature selection a comparative study,” in International Conference on Intelligent Data Engineering and Automated Learning. Springer, 2007, pp. 178–187.

13 U. M. Khaire and R. Dhanalakshmi, “Stability of feature selection algorithm: A review, “Journal of King Saud University-Computer and Information Sciences, 2019.

14 B. Kumari and T. Swarnkar, “Filter versus wrapper feature subset selection in large dimensionality micro array: A review,” 2011.

15 B. Venkatesh and J. Anuradha, “A review of feature selection and its methods, “Cybernetics and Information Technologies, vol. 19, no. 1, pp.3–26, 2019

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