A Model For Predicting Food Insecurity in Nigeria using Deep Learning Technique

Emmanuel A. Dan[1], Bolanle F. Oladejo[2] and Victor E. Ekong[1]

[1]Department of Computer Science, Faculty of Science, University of Uyo, Uyo, 520001 Nigeria

[2]Department of Computer Science, Faculty of Science, University of Ibadan, Ibadan, 200001 Nigeria

E-mail: emmanueldan@uniuyo.edu.ng, Oladejobola2002@gmail.com, victoreekong@uniuyo.edu.ng

Abstract

This paper presents a Deep Neural Network (DNN) model for food insecurity prediction in Nigeria among households at the subnational level peculiar to the socioeconomic characteristics of the country. We developed a Multi-Layer Perceptron DNN (MLP-DNN) prediction model. Data on Nigeria general households survey (GHS) on households' standard of living concerning food insecurity were obtained from the World Bank and National Bureau of Statistics (NBS) repository covering a period of four years. The developed model predicted the state of the household in the context of Nigeria as a food secured or food insecure country. The MLP-DNN model, using ReLU and sigmoid activation functions achieved a remarkable accuracy even where the original dataset were limited. Seventy percent (70%) of the dataset was first used to train the model, while thirty percent (30%) was used to adapt and fine tune the model. During the training and testing phases, network structures, and various parameters were adjusted using Python libraries and methods for preprocessing and model fitting to achieve the best accuracy results. The test results show a high accuracy rate in identifying food insecure and secured zones in the country. The model was able to achieve a 98% performance accuracy, which is a significant achievement when compared with a Logistic regression (LR) and an ANN model that both had 93% performance accuracy respectively. Thus, the study presents a useful tool that can predict food insecurity in any country using its socioeconomic characteristics.

Keywords: Food insecurity, Food Security, Socioeconomic Characteristics, Nigerian peculiarities, Predictive model

1. Introduction

The sphere of computing technology is interdisciplinary in nature. Even so, notwithstanding the massive applications to complement human efforts in problem-solving, some areas concerning our welfare have received little or no attention in some parts of the globe; and one such is the food insecurity crisis. Currently, food insecurity is the predominant factor behind acute hunger, starvation, malnutrition, and deteriorating health status among many households in Nigeria [1, 2].In compliance with the United Members States' agenda for Sustainable Development with 17 Sustainable Development Goals (SDGs) to mitigate poverty, hunger, and other deprivations, it is imperative to innovate possible ways to archive these goals in Nigeria [3, 4]. Food insecurity is an index of SDG-2, zero hunger; which seeks to uphold sustainable agriculture, achieve food and nutrition security, and end hunger. In [5, 6] the concept of food security implies that all people at all times must have physical, social, and economic access to food for a healthy and active life. Early prediction of food insecurity among Nigerian households would contribute significantly to mitigating food insecurity in Nigeria. Achieving these objectives requires multidimensional approaches; thus, deploying modern computational technologies will be a milestone. Computational technologies have been the backbone in problem-solving domains, especially in modern research, with the application of scientific theories, mathematical models, and computer algorithms. The domain of AI builds intelligent systems that adopt the functionalities of the human brain in solving real-life problems; computer systems are programmed and/or trained to learn on their own to process a sequence of datasets for knowledge discovery [7, 8, 9, 10]. In modern research, the paradigm shift is focusing on deep learning in problem-solving.

However, despite the efforts in applying AI in agriculture, the challenges of food insecurity have some undertone peculiarities to a region or country; thus existing models appear to be country-dependent; limited in countries with different socioeconomic factors, and conflict-driven areas. Countries like Nigeria that are faced with a high level of insecurities, which have displaced many farming communities, low levels of employment, and poor socioeconomic development would not be adequately represented by such models. Also, from Nigeria's perspective, exciting models are based on a statistical analysis of empirical observations; as such, research in Nigeria's context using the AI approach in predicting food insecurity is sparse. An improved food insecurity prediction should be based on indicators within each dimension of food security, and this depend on the fiscal measures, and social development needs of a country. This gap further limits the level of accuracy in predicting food insecurity in countries such as Nigeria, hence the purpose of this study; developing a data-driven model that integrates the peculiarities for food security in predicting the state of the food insecurity crisis among households in Nigeria would contribute immensely towards improving food security.

The remaining sections in this work are structured as follows; Section 2 presents the theoretical background. Section 3 is the review of related works. This study's methodology and implementation are presented in section 4. Section 5 and 6 discuss the results and performance evaluations, and the conclusion of this study is drawn in Section 7 with recommendations.

2. Theoretical Background

Deep learning is an AI paradigm developed from the concert of machine learning to utilize the hierarchical function that runs its inputs through a biologically inspired Artificial Neural Network (ANN) architecture to model and process nonlinear relationships, and adopt the operations of the human cognitive function in data processing in various domains such as computer vision, speech and face recognition, image and pattern classification, and phenomena predictions [11, 12]. DNN is a variant of machine learning techniques that are built with the concept of ANN, but defined based on the depth of the network; the number of hidden layers. Objectively, deep learning techniques complement the shortfalls of traditional machine learning algorithms in terms of accuracy and speed due to their efficiency in processing large volumes of datasets without external intervention [12]. Deep learning technology has become a booster to other domains of AI in their different fields of application as it drives through many areas of research such as health, education, automotive, telecommunication, entertainment, social intelligence, forensic and cyber security, and agricultural productivity among others [11, 13].

In agriculture, deep learning has been applied in crop and livestock production, soil management, disease and weed management, and some other areas [11, 14, 9, 15]. Agriculture is the main source of food security. In Nigeria, depletion in agricultural productivity, and inefficient policies concerning food and agricultural challenges by successive governments among other factors have resulted in a food insecurity crisis, reflecting in widespread impoverishment, hunger, and malnutrition among households [2, 6]. According to the world food programme of the food and agricultural organization (WFP-FAO) in 2020 [16], Nigeria is one of the 20 countries within the region with the likelihood of a spike in high acute food insecurity, exacerbated by several interleaved causative agents, and demands urgent attention. In this regard, identifying these factors in time and accurate prediction is essential for food security and humanitarian intervention.

3. Related Work

While delving into food insecurity challenges for solutions, it is imperative to understand that much research has been conducted in this domain. Addressing food insecurity involves interdisciplinary collaboration. Some researchers based their solutions on empirical observations and policy evaluation on agricultural land productivity and climate change, while some others presented statistical analysis on socioeconomic characteristics measures among households [17, 18]. While some projected computational technologies of AI on crop production yield, household demographic surveys, and price hikes. The literature review in this study considers the computational technological approaches and the conventional approaches in mitigating food insecurity or improving food security in these solution domains. In the conventional approach to mitigating food insecurity, [19] applied a Rasch modeling method to survey food security dynamics among 1,175 randomly selected households from two districts in Uganda, and made a comparative analysis of the households' food insecurity levels between the two districts. In [20] the probability of food insecurity amidst a cross-section of households in Nigeria based on socioeconomic characteristics analysis using the binary choice modeling technique was computed. The study identified household size, gender of household head, household income, and access to credits, educational qualification, and assets owned by households as the major socioeconomic characteristics that propel food insecurity among households. In their recommendation, more employment opportunities and more incomeearning activities by the Nigerian government were suggested for households' empowerment to alleviate food insecurity. Similarly, [21] applied the cost-of-calories (COC) method using a logistic regression (LR) model to identify and analyze food security measures in a given location in Nigeria. While about 60% of the sample households were identified as food insecure; household size, gender, educational level, farm size, and type of household farm enterprise were major determinants of food insecurity among households.

In the computational technological approach, many studies have been conducted on agriculture and food insecurity challenges. In [22] a systematic survey of 180 articles was performed on the application of AI in all dimensions of food security through open-access articles relating to AI applications in agriculture and food challenges. They identified major challenges in each of these dimensions and evaluated the applications of AI in achieving global food security based on these dimensions. The systematic survey provided an insight into previous research; the application of drones for smart agriculture, and neural network modeling in crop production among others. In [9] the application of machine learning, neural networks, and deep learning to agricultural challenges were analyzed. Crop analysis was identified as the commonest area in agriculture that has witnessed deep learning applications, while Convolutional Neural Network (CNN) was the most applied algorithm, and the most frequent input type for the neural networks was images. In another research, [14] surveyed deep learning algorithms deployed in solving problems in diverse areas of agriculture, such as; soil moisture content prediction, crop yield estimation, disease detection, identification and classification, and land cover classification among other fields. They affirmed that deep learning provides high accuracy than traditional algorithms. They recommended a future research to reduce the complexity and hardware demand in the existing deep learning algorithms. Similarly, [11] performed an empirical survey on 40 research that applied deep learning techniques to various challenges in agriculture and food production, with a comparative analysis between deep learning and other existing algorithms, concerning classification or regression performance. In their findings, deep learning also provided high accuracy and outperformed some regular image processing techniques. Also, they recommended further research in applying deep learning to some other agricultural challenges such as seeds identification, soil, and leaf nitrogen content, irrigation, plants' water stress detection, water erosion assessment, pest detection, herbicide use, identification of contaminants, diseases, or defects on food, and greenhouse monitoring.

According to [19], suitable and more realistic solutions for mitigating food insecurity depend on prior knowledge of the severity and magnitude of the problem. In furtherance of this, [21] determined food security status based on machine learning analysis of household survey data. The focus was on caloric and micronutrient intake. As such, variables were limited to the amount of food consumed. But predicting food security based on a single class of variables would not suffice in any country with multiple indicators. In [23], machine learning techniques were used to increase accuracy and reduce type II error in predicting the onset of food crises in East Africa based on a data-driven framework, by combining remote sensing data with household surveys and food price data. The approach would limit the prediction accuracy when applied in countries with different socioeconomic conditions like Nigeria. Similarly, [24] implemented a machine learning model to predict 2013 food security in Malawi based on market price, weather impact, and demographic data between 2010 and 2011. The model was deployed in food-insecure clusters of villages with 83% to 99% prediction accuracy. Notwithstanding the success, they further recognized that the model performed worse in areas with different agroecology and market policies, conflict-prone, and cut-off regions. Also, [25] developed a LR-based model for the analysis and prediction of food security status in developing countries. The model was empirically tested using household demographic data with 72.3% prediction accuracy. In [26], Andrew proposed a machine learning model that will integrate existing models with features of re-usability and improved performance for the prediction of food insecurity. The study aimed at addressing the challenges in the existing model; low prediction accuracy, high demand for computation resources, and high costs in collecting prediction data, such as household information. The scope was also limited to household information, price trends, and weather patterns within Uganda. In another study, [27] proposed the use of data mining technologies, and machine learning techniques on relevant datasets for knowledge discovery and understanding of how government policies, unresolved conflicts, climate crises, and human activities affect food security improvement and environmental sustainability in the Nigerian context. Intuitively, little or no computational technology has been deployed in predicting households' food insecurity status in Nigeria. This gap along with the SDGs objectives justifies the reason for this research paper.

4. Materials and Methods

Successful implementation of this study required a systematic process and a pragmatic approach to developing a predictive model. Figure 1 illustrates the proposed methodology for food insecurity prediction model development. The methodology for the model development started with data collection. The availability of the dataset activated the next phase, which is data assessment and preprocessing with a sequence of sub-activities. The sequential behavior of the model development process continued with model building/training and testing state using the preprocessed dataset. The process ended with a predictive model for food insecurity after satisfactory testing and performance evaluation.

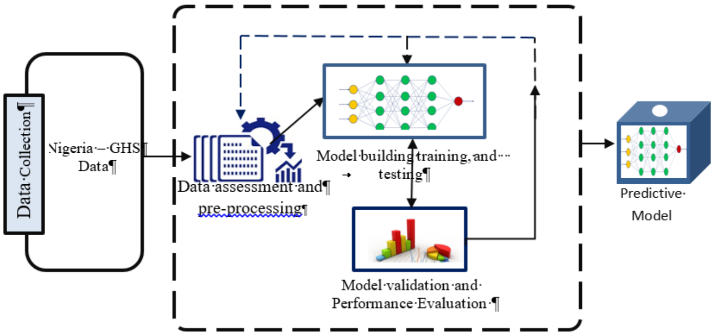

Figure.1: Proposed methodology for Food Insecurity Predictive Model

4.1 Data Collection.

Data collection is a systematic process of gathering and analyzing facts (data) to proffer solutions to a phenomenon. This study was furnished with secondary data from Nigeria – GHS on households' standard of living concerning food insecurity, downloaded from NBS; https://nigerianstat.gov.ng/elibrary and world bank database; https://microdata.worldbank.org. Table 1 shows the description of the dataset used for this study. The period for data collection includes wave 1 (2010/2011), wave 2 (2012/2013), wave 3 (2015/2016), and wave 4 (2018/2019).

Table 1: Feature Description in Household Survey Dataset Used for Model development

S/N	Features	Descriptions	Values
1.	**food_exp**	Amount spent on food for the last seven days before the survey	Amount
2.	**sex**	Gender of the household head	Male (1) or Female (0)
3.	**mrstat**	Marital status of the household	Married (1) or Not married (0)
4.	**education**	If the household head is educated or not	Yes (1) or No (0)
5.	**occupation**	If the household head has an occupation or not	Yes (1) or No (0)
6.	**Own bank account**	If the household head has a functional account or not	Yes (1) or No (0)
7.	**remit**	If a household receives remittance from any source	Yes (1) or No (0)
8.	**household-size**	Number of household size	Number
9.	**age**	Age of household head	Number
10.	**income_month**	Household head's income per month	Amount
11.	**phone**	If the household head services phone	Yes (1) or No (0)
12.	**Internet**	If the household head uses the Internet	Yes (1) or No (0)
13.	**sector**	If the household lives an in urban or rural with access to arable land	Urban (1) or Rural (0)
14.	**Pce**	Household per capita expenditure	Amount
15.	**Insecurity**	If insecurity affects household food access	Yes (1) or No (0)
16.	**FSL**	Food security line	Food Secure (1) or Not Food Secure (0)

4.2 Data Assessment and Preprocessing.

Data quality assessment was performed as a preamble to preprocessing activities to know which preprocessing techniques should be deployed in which order, and also at the end of each preprocessing activity. There were a lot of data anomalies, which include data inconsistency with other variables, mismatched values, outliers, and missing values. These observations called for data cleansing. Python libraries (NumPy and Pandas) were deployed on TensorFlow/Keras environment to invoke data.fillna() method to fill in the missing value with a null value for clarity, and data.dropna() method to drop any tuple with a null value in the household dataset. A total of 72,184 tuples of the household dataset were cleansed in wave 1; 55,440 tuples in wave 2; 89,460 tuples in wave 3; and 71,080 tuples in wave 4, with 22 variables (columns) in each wave. For more insight into the dataset, seaborn, and matplotlib libraries, along with some methods/ objects such as countplot(), subplot(), plot(), plot.pie(), and heatmap were deployed for data visualization. These tools proffer a high-level graphical interface for the statistical representation of information. Figure 2a and 2b presents the proportion of respective geopolitical zones in Nigeria in the dataset for different waves. This analysis ensured that the dataset was not skewed to one geopolitical zone.

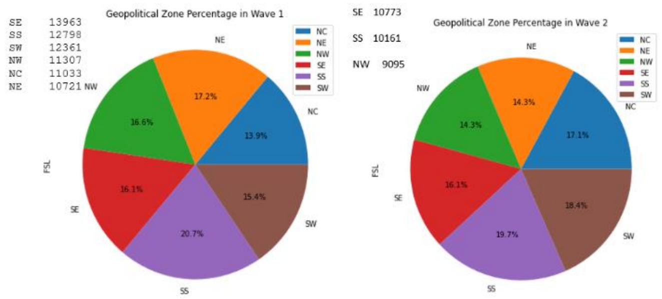

Figure 2a: Percentage of households from different geopolitical zones in the dataset (Wave 1 and 2)

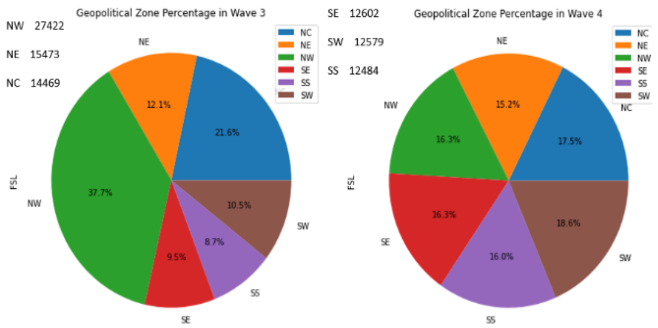

Figure 2b: Percentage of households from different geopolitical zones in the dataset (Wave 3 and 4)

Further analysis of the dataset was performed to establish the difference in classification on the food insecurity line (which is the target variable in this study) within respective waves. Figure 3 illustrates the household food insecurity classification in different geopolitical zones, which has shown the significant gap between food-secured households (represented by an orange bar, and encoded as 1), and food-insecure households (represented by the blue bar, and encoded as 0) within each wave, in all the zones. The divergence between the two classes in the target variable provided a significant trait for the model to leverage during training. Other variables in the dataset were also visualized to understand their influence or/and relationship with the target variable.

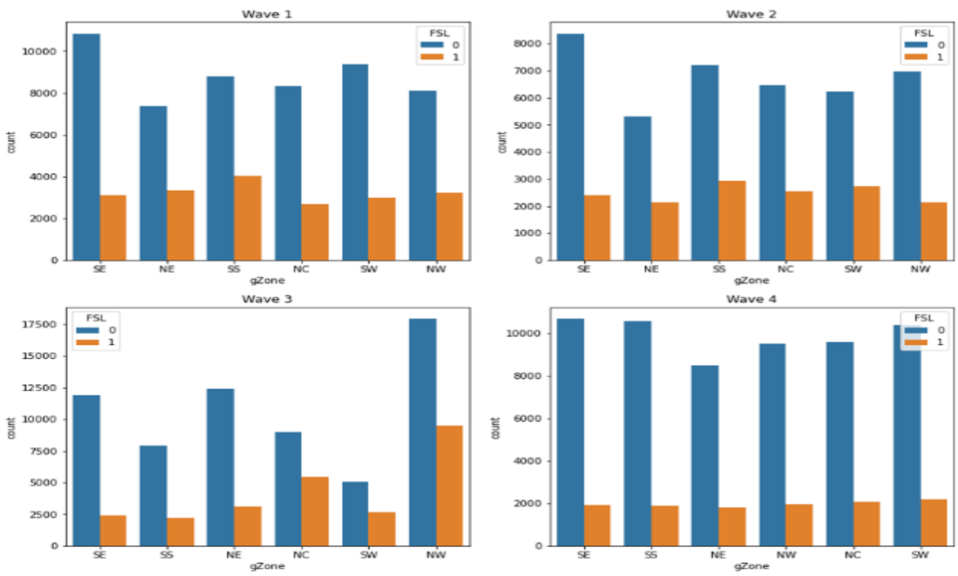

Figure 3: Household food insecurity and food security classification based on geopolitical zones

The preprocessing phase continued with data integration to merge the datasets from waves 1, 2, and 3 into a single data frame; and data reduction to analyze and reduce the dataset based on the most relevant features without compromising the integrity of the original dataset through attribute selection, numerous reductions, and dimensionality reduction. The dimension of the dataset was reduced to 216909 x 15. In data transformation, Python libraries and methods such as *sklearn.preprocessing*, *LabelEncoder*, and *OneHotEncoder* were deployed, to encode categorical values into binary values of zero (0) and one (1) for proper fit-in and model building, while *StandardScaler* was invoked for data normalization. Data preprocessing provided more useful, understandable, and efficient data, free of anomalies for the model building.

4.3 Model Building

We deployed a MLP-DNN on Keras/ TensorFlow framework using a Python environment to build an efficient binary classification model to improve prediction. Figure 4 presents the MLP-DNN architecture for model building and training.

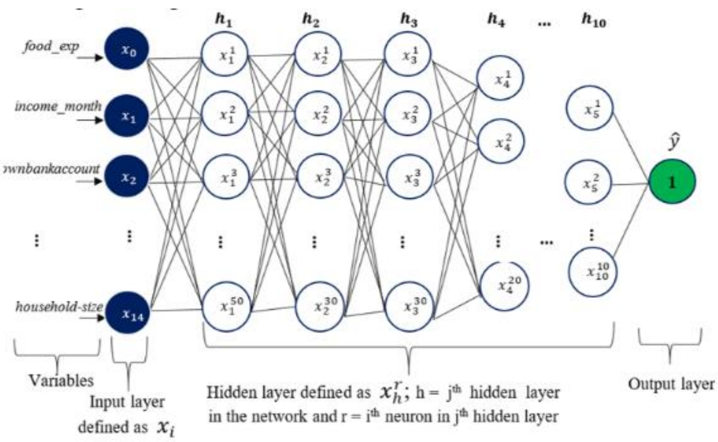

Figure 4: MLP-DNN Architecture

In the network model in Figure 4, each of the neurons in the first hidden layer is computed as Equation 1.

$$x_1^r = \sum_{i=0}^{I}(w_i * x_i) + b_r \quad (1)$$

Where

$x_i \in X$ is the i[th] input element in X
r =1, 2, …, 50 for the first hidden layer in the network.
i = 0, 1, 2, …, I, is the number of input units
b_r = the bias assigned to the neuron
w_i = weight assigned to the i[th] input element
Subsequent neurons in the network are computed as Equation 2.

$$x_h^r = f(\sum_{r=1}^{R}(w_r * x_{h-1}^r) + b_r) \quad (2)$$

where R is the number of neurons in a given layer, and f is the hidden layer activation function.
So the output value is computed in Equation 3.

$$\hat{y} = g\left(\sum_{r=1}^{R} w_r * f(\sum_{r=1}^{R}(w_r * x_{h-1}^r) + b_r)\right) \quad (3)$$

Where g is the output layer activation function.

The algorithm for the model computation is given as follows:

1. Initialization of the model parameters
2. For 1 = 1:P [where P is the number of epochs]
3. $\forall x_i \in X$, compute the hidden layer $\boldsymbol{x_h^r} = \sum \boldsymbol{w_i} * \boldsymbol{x_i} + \boldsymbol{b_i}$ throughout the network [where h is j[th] layer in the hidden layers, and r is the i[th] neuron in the j[th] layer]
4. Compute **y** = $\sum f(x_h^r)$ [$\boldsymbol{f}$ is the activation function at each hidden layer in network]
5. Compute the predicted value $\boldsymbol{\hat{y}}$ = **g(y)** [g is the activation function at the output layer]
6. Apply any appropriate method to adjust the model parameters

4.4 Network Model Training

In training the network model, the household dataset was first split into input (train_x) and output (train_y) variables. Each of the variables was further split into a training set (x_train, y_train) and testing set (x_test, y_test) using the Train_Test_Split approach for cross-validation with the ratio of 70:30; 70% of the dataset was used for model training, while 30% of the dataset was used for model testing. This standard approach was deployed to guide against bias. An MLP-DNN model of ten (10) hidden layers with 50:30:30:30:20:20:20:10:10:10 neurons respectively was built. The ReLU activation function was used for hidden layers, while the sigmoid activation function was used for the output layer. The binary cross-entropy loss function was used to calculate the loss between the actual values and the predicted values. Adam optimizer was used for gradient descent optimization, and the training performance evaluation was obtained using accuracy metrics.

5. RESULTS AND DISCUSSIONS

5.1 Results.

This section presents the result of this study and relevant discussion. The model training process was completed with 98% accuracy at 150 epochs and a batch size of 100 inputs with a loss of 2%. Figure 5 and 6 presents the model learning curves which demonstrates a good fit for the model training.

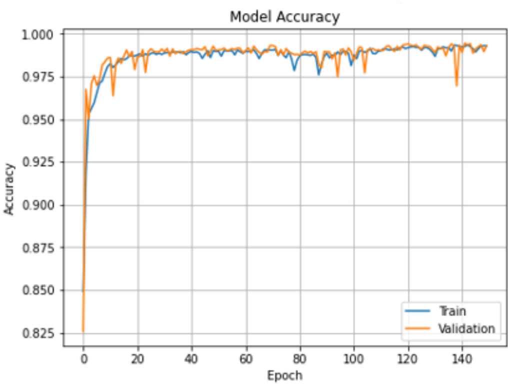

Figure 5: MLP-DNN model accuracy curve

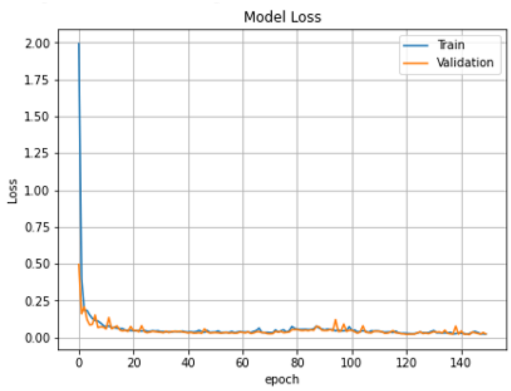

Figure 6: MLP-DNN model loss curve

5.2 Model Performance Evaluation.

The performance of the model was evaluated based on the confusion matrix analysis to measure the rate of recall (sensitivity), precision, accuracy, and the F_1-score. The performance evaluation was conducted on the test dataset. The result is shown in Figure 7 and 8.

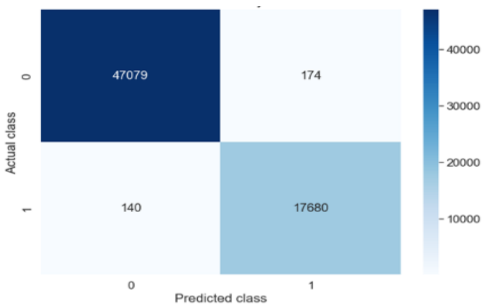

Figure 7: Confusion matrix for the MLP-DNN model.

	precision	recall	f1-score	support
0	1.00	0.97	0.98	47253
1	0.93	0.99	0.96	17820
accuracy			0.98	65073
macro avg	0.96	0.98	0.97	65073
weighted avg	0.98	0.98	0.98	65073

Accuracy: 0.98

Figure 8: The Precision, Recall, F1-score and Accuracy of the MLP-DNN model

A logistic regression (LR) and an ANN model is deployed and compared. Figure 9 and 10 shows the performance evaluation of the models. While in Figure 11 the performance evaluation comparison for the three models are presented.

```
***Logistic Regression Model***
[[45916  1337]
 [ 3042 14778]]

              precision    recall  f1-score   support

           0       0.94      0.97      0.95     47253
           1       0.92      0.83      0.87     17820

    accuracy                           0.93     65073
   macro avg       0.93      0.90      0.91     65073
weighted avg       0.93      0.93      0.93     65073

Accuracy: 0.93
```

Figure 9: Confusion matrix analysis and classification for the LR model

```
***ANN Model***
[[42937  4316]
 [  223 17597]]

              precision    recall  f1-score   support

           0       0.99      0.91      0.95     47253
           1       0.80      0.99      0.89     17820

    accuracy                           0.93     65073
   macro avg       0.90      0.95      0.92     65073
weighted avg       0.94      0.93      0.93     65073

Accuracy: 0.93
```

Figure 10: Confusion matrix analysis and classification for the ANN model

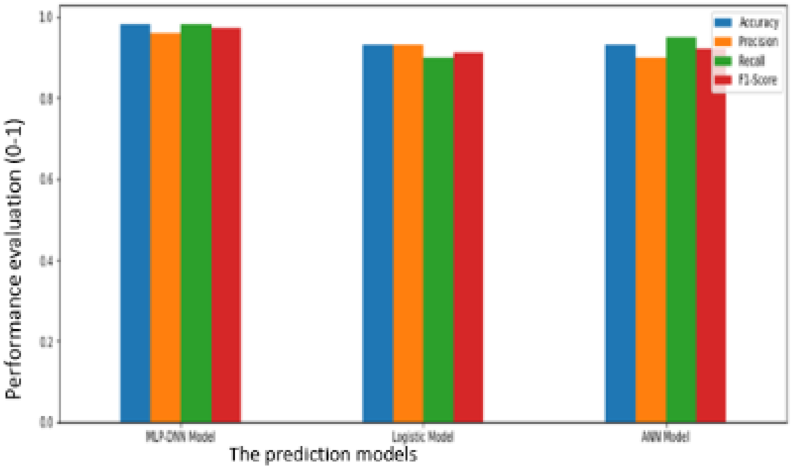

Figure 11: Performance evaluation for MLP-DNN, LR and ANN models

We obtained an accuracy of 93% with a 7% loss rate for the LR and an ANN model respectively. MLP-DNN outperformed the two models having an accuracy of 98 % with 2% loss ratio. This is a significant improvement in the accurate prediction of food insecurity status among households in Nigeria. Further evaluation was performed for validation purpose using household survey datasets from Nigeria - GHS wave 4 (2018/2019), Ghana Socioeconomic Panel Survey (2009/2010), and Ethiopia Socioeconomic Survey (2018/2019). The result is presented in Figures 12, 13 and 14.

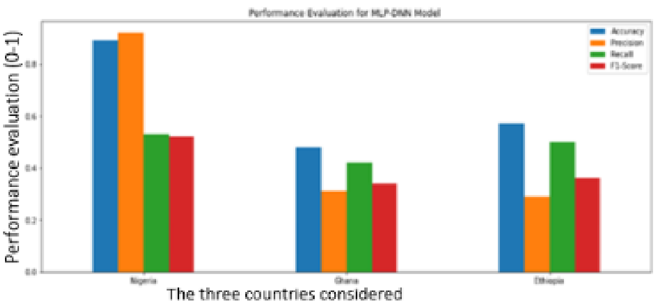

Figure 12: MLP-DNN model performance for Ghana, Ethiopia and Nigeria household survey dataset

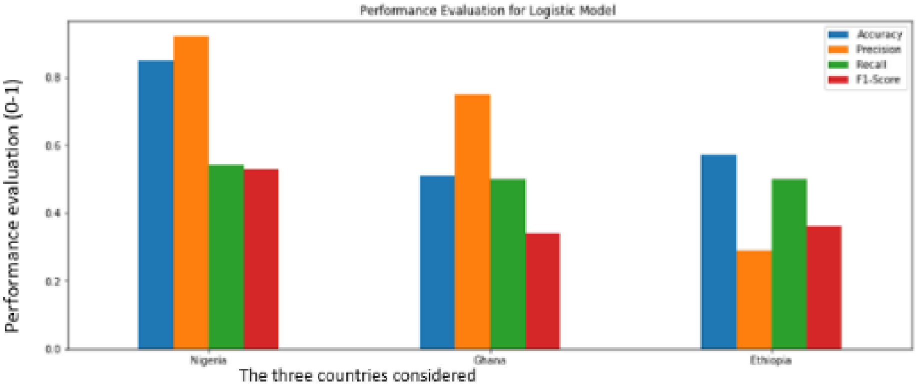

Figure 13: LR performance evaluation for Ghana, Ethiopia and Nigeria household survey dataset

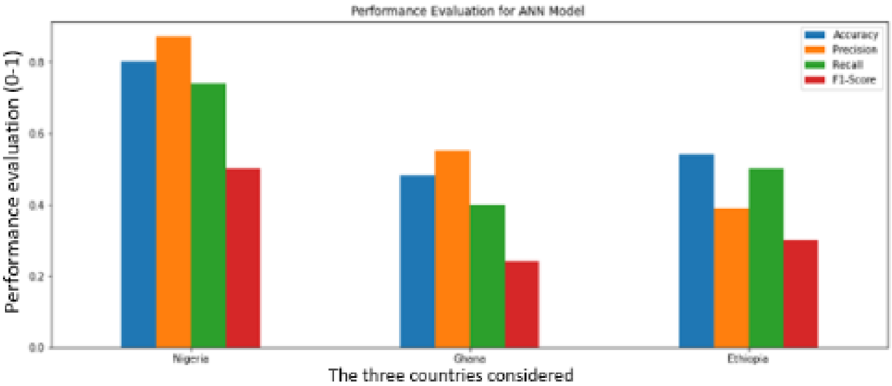

Figure 14: ANN performance evaluation for Ghana, Ethiopia and Nigeria household survey dataset

The performance evaluations showed a comparable result between the MLP-DNN, LR and ANN models. However, the models performed poorly with other countries' datasets. This significant difference can be attributed to socioeconomic differences and the format of measuring household characteristics between Nigeria and other countries.

6. CONCLUSION

The study presents the deployment of a data-driven technology to mitigate food insecurity. A 10 layer MLP-DNN using Keras/Tensor framework in Python was developed. This utilized ReLU and sigmoid activation functions at the hidden and output layers respectively. A binary cross entropy loss function computed the loss between actual values and the predicted values. Adam optimizer was used for the gradient optimization and the training performance evaluation accuracy was obtained as 98%. The same dataset were tested with a Logistic regression and an ANN prediction model and both had 93% performance accuracy. The MLP-DNN shows a high performance among the other prediction models and this result represents a better improvement over earlier studies. A further test of the models with dataset from two other countries showed a drop in performance accuracy signifying variation in socioeconomic measurement format of household characteristics with Nigeria. Future work would develop a predictive model that would be based on common socioeconomic factors for easy generalization. Another possible extension of this would be to develop a dynamic model based on reinforced learning prediction.

REFERENCES:

[1] E. E. Etim., O. O. Duke and O. J. Ogbinyi.. "The Implications of Food Insecurity, Poverty and Hunger on Nigeria's National Security". Asian Research Journal of Arts & Social Sciences, vol.4, no.2: pp. 1-10, 2017.

[2] E. Ajie. N.and C. Uche. "Food insecurity in Nigeria and the need for effectual mitigatingmeasures". American Journal of Basic and Applied Sciences", vol. 2, no. 9, 2019. Retrieved October 10, 2021 from: https://full.escipub.org/Articles/AJBAS/AJBAS-2019-02-2208.

[3] United Nation. "SDG Goal 2: End hunger, archive food security and improve nutrition, and sustain agriculture", 2021. Retrieved August 20, 2021 from https://sdgs.un.org/goals/goal2

[4] M. K. Anser, D. I. Godil, Aderounmu, B., and Onabote, A. “Social Inclusion, Innovation and Food Security in West Africa”. p.1–12, 2021. https:// doi.org/10.3390/su13052619.

[5] A. Nwozor, Olanrewaju, J. S., Ake, M. B. “National Insecurity and the Challenges of Food Security in Nigeria”. Academic Journal of Interdisciplinary Studies, vol. 8, no. 4,. 2019. DOI: 10.36941/ajis-2019-0032.

[6] Food and Agricultural Organization (FAO). “Committee on World Food Security: Coming to Terms with Terminology”. Thirty-ninth session, Rome, Italy, 15-20 October 2012. Retrieved August 16, 2021 from http://www.fao.org/3/MD776E/MD776E.pdf.

[7] A. K. Ojo, and Olanrewaju, A. B. “Knowledge Discovery in Medical Databases using Machine Learning Techniques”. International Journal of Computer Applications, vol. 178, no. 35, pp. 14–21, 2019.

[8] B. F. Oladejo. “Decision Support System for Prediction of Student Academic Performance”. Journal of Science and Logics in ICT Research, University of Ibadan, Ibadan, Nigeria, vol. 5, no. 1. pp. 98–111, 2020.. Retrieved February 17, 2022 from: http://journals.ui.edu.ng/index.php/uijslictr/article/view/92.

[9] K. Dokic, Blaskovic, L., Mandusic, D. “From Machine Learning to Deep Learning in Agriculture – the Quantitative Review of Trends”. IOP Conference Series: Earth and Environmental Science, 2020.. https://www.researchgate.net/publication/323357827_deep_ Learning_in_Agriculture_A_Survey.

[10] S. Garg, Sinha, S., Kar, A. k. and Mani, M. A “Review of Machine Learning Applications in Human Resource Management”. International Journal of Productivity and Performance Management, 2021. https://doi.org/10.1108/IJPPM-08-2020-0427.

[11] A. Kamilaris, and Prenafeta-Boldú, F. X. “Deep Learning in Agriculture: a Survey”. Computers and Electronics in Agriculture, vol. 147. Pp 70-90, 2018. Retrieved September 22, 2021 from https://www.sciencedirect.com/science/article/pii/S0168169917308803

[12] S. Chibani, and Couder, F. “Machine Learning Approaches for the Prediction of Materials Properties”. APL Materials, AIP Publishing, vol. 8, no. 8, pp.80701, 2020. Doi:10.1063/5.0018384.

[13] S. Pouyanfar, Sadiq, S., Yan, Y. “A Survey on Deep Learning: Algorithm, Techniques, and Applications”, ACM Computing Surveys, vol. 51, no. 5, p1-36, 2019. https://doi.org/10.1145/3234150.

[14] L. Santos, Santos, F. N., Oliveira, P. M., Shinde, P. “Deep Learning Applications in Agriculture: A Short Review”, 2020. Retrieved September 13, 2021 from https://www.researchgate.net/publication/323357827_deep_Learning_in_Agriculture_A_short_review.

[15] A. Kavitha. “Deep Learning for Smart Agriculture”. International Journal of Engineering Research & Technology (IJERT), ICRADL – 2021 Conference Proceedings, vol. 9, no. 5, 2021. Retrieved from https://www.ijert.org/deep-learning-for-smart-agriculture

[16] World Food Programme (WFP) & Food and Agriculture Organization (FAO). Early Warning Analysis of Acute Food Insecurity Hotspots. Rome, 2020. Retrieved September 13, 2021 from *https://www.wfp.org/publications/wfp-fao-early-warning-analysis-acute-food-insecurity*-hotspots-October-2020

[17] H. S. Jatav, Jaipur, J., Kumar, S., and Jayant, H. “Mitigation Strategies for Food Security Under Climate Change” International Journal of Computer Applications, vol. 178, no. 35, pp.14–21, 2018.

[18] .M. O. Kehinde, A. M. Shittu, S. A. Adewuyi, I. O. O., Osunsina, and A. G Adeyonu. “Land Tenure and Property Rights, and Household Food Security Among Rice Farmers in Northern Nigeria”, 2021. Heliyon, https://doi.org/10.1016/j.heliyon.2021.e06110.

[19] A. Owino, R. Wesonga and F. Nabugoomu. “Determining Food Insecurity: An Application of the Rasch Model with Household Survey Data in Uganda”, Hindawi Publishing Corporation International Journal of Food Science, vol. 2014, Article ID 121269, 2014. http://dx.doi.org/10.1155/2014/121269.

[20] M. Muktar.Determinants of food insecurity in Nigeria: Application of Binary Choice Modelling Technique, In: Modelling Social Phenomenon in the 21st century, Bandara, HM and Gunasekara, K. R. H. (Eds.), Godage International Pub. Sri Lanka, 2011.

[21] A. Razzaq, U. Ahmed, S. Hashim, A. Hussain. N., Imran, A. and A. Asghar. “An Automatic Determining Food Security Status: Machine Learning Based Analysis of Household Survey Data”. International Journal of Food Properties, 2021, vol. 24, no. 1, pp. 726-736, DOI:10.1080/10942912.2021.1919703.

[22] R. M. S. R. Chamara,, Senevirathne, S.M.P., Samarasinghe, S.A.I.L.N., Premasiri, M.W.R.C., Sandaruwani, K.H.C., Dissanayake, D.M.N.N., De Silva, S.H.N.P., Ariyaratne, W.M.T.P. and Marambe, B. “Role of Artificial Intelligence in Achieving Global Food Security: A Promising Technology for Future”. Sri Lanka Journal of Food and Agriculture, 2020. vol. 6, no. 2, pp 43–70.

[23] L. Zhou and K. Baylis. “Predict Food Security with Machine Learning: Application in Eastern Africa”. Agricultural & Appled Economics Association Annual Meeting, Atlanta, GA, 2019

[24] E. C. Lentz, H. Michelson, K. Baylis, and Y. Zhou. “A Data-Driven Approach Improves Food Insecurity Crisis Prediction”. World Development, vol. 122, pp. 399–409, 2019. https://doi.org/10.1016/j.worlddev.2019.06.008

[25] J. Mbukwa. “A Model for Predicting Food Security Status Among Households in Developing Countries”. International Journal of Development and Sustainability, vol. 2, no. 2, pp. 544-555, 2013. Retrieved September 12, 2021 from https://isdsnet.com/ijds-v2n2-8.pdf.

[26] L. Andrew. “A dynamic model for prediction of food insecurity”. (Unpublished doctoral dissertation proposal). Uganda Technology and Management University (UTAMU), Uganda, 2015.

[27] O. Apampa. “Food Security and the Climate Crisis Data-Driven Analysis of the Nigerian Situation from 2011 To 2020”, 2021. Retrieved October 10, 2021 from: https://www.researchgate.net/publication/348974845