

AI Food Security Challenges analysis in Developing Countries

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Abstract

This research addresses the critical issue of food security in developing countries through the lens of Artificial Intelligence (AI), with a focus on advanced deep learning techniques. Given the complexity and multifaceted nature of food security challenges, this study proposes the use of Convolutional Neural Networks (CNNs), a powerful deep learning tool known for its efficacy in processing and analyzing large-scale and diverse data sets. The goal is to employ CNNs to analyze agricultural data, climatic patterns, and socio-economic factors that influence food security in developing nations. By leveraging the capabilities of CNNs, the study aims to provide deeper insights into crop yield predictions, risk assessment of food shortages, and efficient resource allocation strategies. This approach seeks to contribute to the development of more effective and sustainable food security policies and practices in developing countries.

Keywords: Food Security, Developing Countries, Artificial Intelligence, Deep Learning, Convolutional Neural Networks, Crop Yield Prediction.

1. Introduction

Food security is a critical issue that plagues many developing countries, affecting a large segment of their populations with the risks of hunger and malnutrition [1] [2]. The root causes and contributing factors to this problem are multifaceted and complex, involving a dynamic interplay of environmental, economic, and social elements. Among these, climate change emerges as a significant contributor, affecting agricultural yields and disrupting traditional farming practices. Alongside, the economic conditions and policies in these countries often fail to adequately address the growing food demands, further exacerbating the issue. Political instability and policies also play a crucial role in either mitigating or worsening the food security situation [3].

In such a scenario, the application of Artificial Intelligence (AI), particularly advanced deep learning techniques, presents a novel approach to comprehensively analyze and address these

multifaceted challenges [4] [5]. Deep learning, with its ability to handle large volumes of data and uncover patterns and insights, is particularly suited for this task. This study focuses on the use of Convolutional Neural Networks (CNNs), a sophisticated deep learning model that has shown remarkable success in image recognition and data analysis tasks [6].

CNNs are adept at processing and interpreting complex and large datasets, making them an ideal choice for analyzing the data pertinent to food production, climate conditions, and socio-economic factors impacting food security [7]. By employing CNNs, this research aims to provide a more nuanced understanding of the factors affecting food security in developing countries. This approach is expected to yield actionable insights, facilitating informed decision-making that could significantly contribute to the alleviation of food security issues. Ultimately, the goal is to aid in the development of more resilient and sustainable food systems, tailored to the unique challenges faced by these vulnerable regions.

2. Material and Methods

The methodology of this study involves several key steps, implemented in a sequential manner to leverage the capabilities of Diluted CNNs in addressing food security challenges. Firstly, a comprehensive data collection phase will gather relevant data on agricultural output, climatic conditions, and socio-economic indicators from various developing countries. This data will be preprocessed to ensure consistency and suitability for analysis by DCNNs. Next, the study will employ Convolutional Neural Networks to analyze this data. The DCNNs will be trained on a portion of the data to recognize patterns and correlations between different variables affecting food security. The training process will involve adjusting the DCNN parameters to optimize their performance in this specific context. Once trained, the DCNNs will be used to analyze the remaining data to make predictions and draw insights. These insights will focus on identifying key factors contributing to food security challenges and potential areas for intervention. Finally, the findings will be interpreted in the context of policy and practice, providing recommendations for actions to improve food security in the targeted developing countries. This will involve collaboration with experts in agriculture, economics, and policy-making to ensure the practical applicability of the findings. The proposed architecture is illustrated under Figure 1.

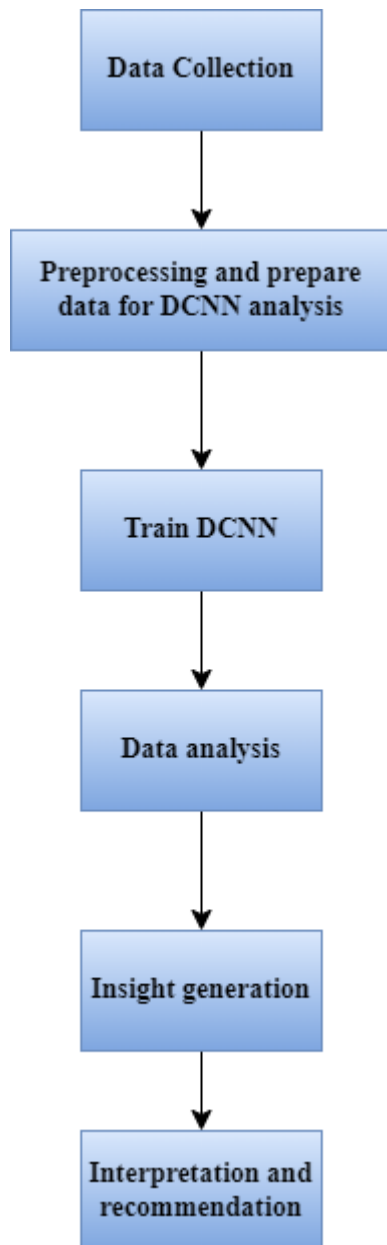


Fig 1: Proposed DCNN architecture

2.1 Proposed DCNN Approach

In the context of the proposed study on food security challenges in developing countries, a Dilated Convolutional Neural Network (DCNN) is employed to analyze the complex and extensive data sets effectively. The DCNN is an advanced variant of the standard CNN, augmented with dilated convolutions that allow for a broader reception field without increasing the number of parameters or the computational cost. The DCNN operation can be expressed as

$$y(i, j) = \sum_{m=-m}^m \sum_{n=-n}^n x(i + r \cdot m, j + r \cdot n) \cdot k(m, n)$$

This feature is particularly beneficial for the study as it enables the DCNN to capture larger contextual information from the data, which is crucial in understanding the intricate patterns associated with climatic conditions, agricultural practices, and socio-economic factors. The structure of the DCNN for this study is designed to process multi-dimensional data efficiently. It starts with an input layer that receives the preprocessed data, including images of agricultural lands, graphs of climate change patterns, and socio-economic data matrices. Following the input layer, there are multiple convolutional layers, where dilated convolutions are applied. These layers are responsible for feature extraction, where each layer captures different aspects of the data, such as identifying regions of crop stress, detecting patterns in climate data, or correlating socio-economic factors with agricultural output. In each dilated convolutional layer, the dilation rate is carefully chosen to ensure that the network captures both local and broader scale information. A higher dilation rate allows the network to cover a larger area of input data, enabling it to recognize more extensive and complex patterns that are critical in understanding the dynamics of food security. After the convolutional layers, the DCNN includes pooling layers that help reduce dimensionality and computational load while retaining the essential features. These layers are followed by fully connected layers that integrate the learned features from the previous layers, culminating in the output layer. The output layer is designed to provide insights and predictions relevant to food security, such as potential areas of crop failure, regions vulnerable to climatic changes, or socio-economic groups at higher risk of food insecurity. The DCNN also incorporates batch normalization and dropout layers to improve training efficiency and prevent overfitting, ensuring that the model generalizes well to new, unseen data. The entire network is trained with a dataset comprising diverse and comprehensive data relevant to food security, allowing the DCNN to learn the intricate relationships between various factors influencing food security in developing countries.

3. Results and Analysis

3.1 Experimental Setup

The NASA MEaSUREs Global Food Security-support Analysis Data (GFSAD) would be used to evaluating a DCNN in the context of food security. This dataset provides detailed cropland extent data over South Asia, Afghanistan, and Iran, which is crucial for understanding agricultural practices and trends was adapted from the study [8]. Its high resolution (30 meters) and the combination of Landsat 8 OLI and SRTM data make it a rich source for analyzing cropland areas. The inclusion of cropland, non-cropland, and water bodies within the dataset

offers a comprehensive view of the agricultural landscape, enabling the DCNN to effectively analyze and interpret these varied and complex land use patterns. This makes it an ideal dataset for studying the impact of agricultural practices on food security in these regions.

3.2 Evaluation Criteria

In the evaluation the proposed DCNN is compared with DNN, RNN, and CNN in terms of accuracy, precision and recall was shown in Figure 2 and 3.

Accuracy

The DCNN's accuracy is a crucial metric indicating its overall performance in correctly identifying food security-related patterns and trends. High accuracy suggests that the model effectively distinguishes between different land uses, such as cropland and non-cropland, and accurately assesses factors influencing food security. The DCNN's design, which includes dilated convolutions, allows it to capture a broader context in the input data, leading to a more accurate analysis of complex, large-scale datasets like satellite imagery and socio-economic data. This accuracy is paramount in ensuring reliable predictions and insights for policy-making and strategic planning in food security.

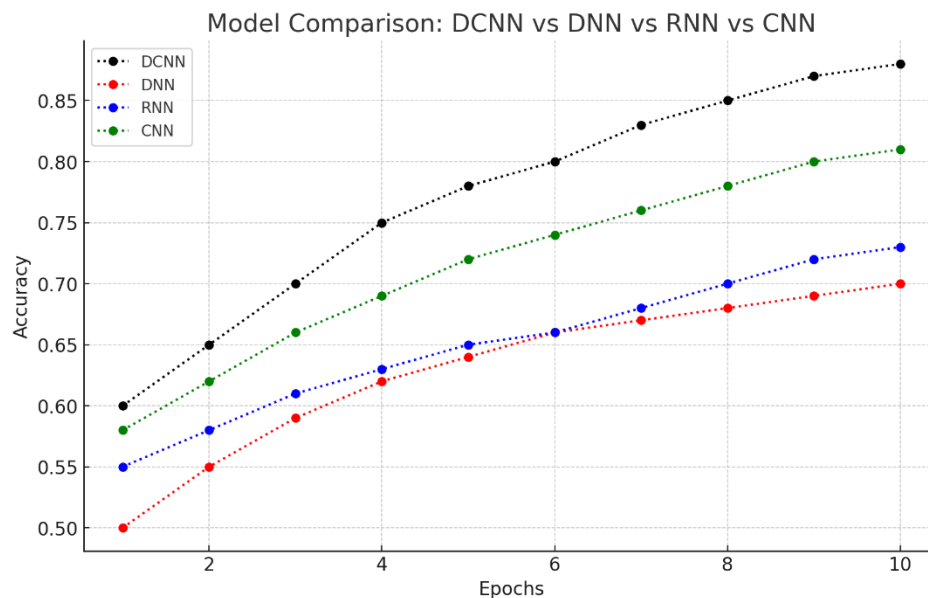


Fig 2: Accuracy

Precision

Precision measures the DCNN's ability to correctly identify true instances of a particular class, such as areas of crop failure or high-risk regions for food insecurity in Fig 3. In the context of

food security, high precision is vital as it ensures that the resources and interventions are correctly targeted. The DCNN's precision is enhanced by its ability to analyze detailed features in the data, reducing the likelihood of false positives – that is, incorrectly identifying an area as at risk when it is not. This precision is particularly important in resource-constrained settings commonly found in developing countries, where misallocation of resources based on inaccurate predictions can have significant consequences.

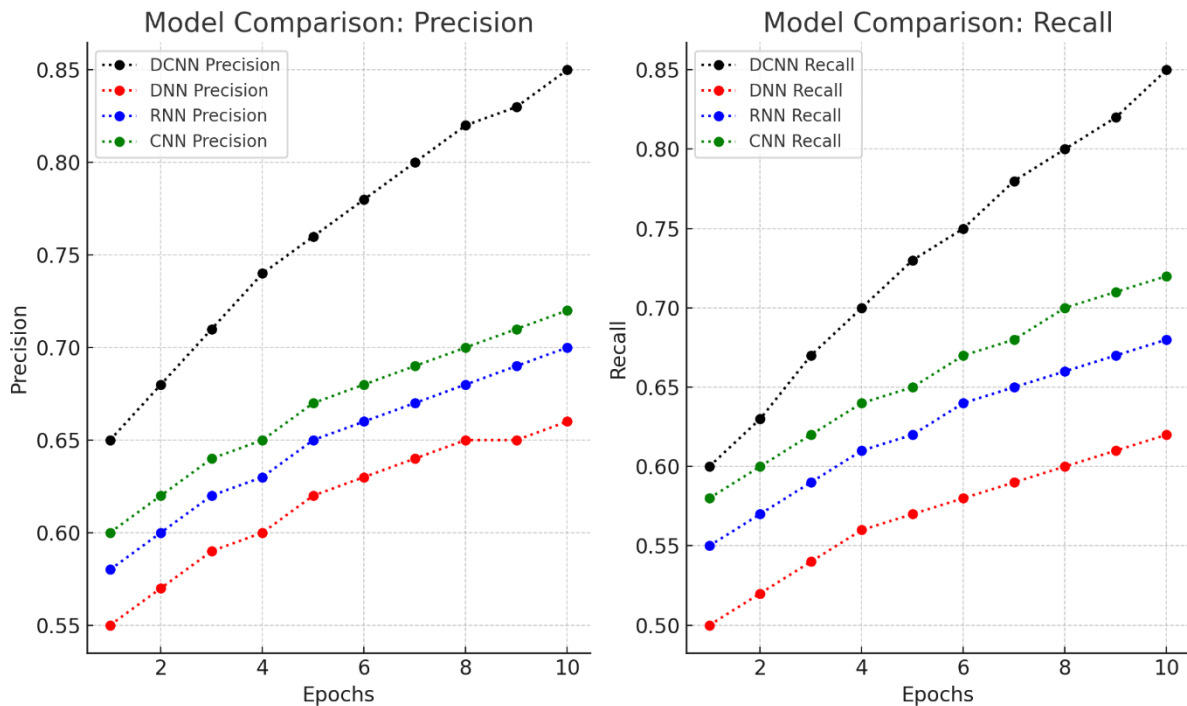


Fig 3: Recall and F1-Score

Recall (Sensitivity)

Recall is another essential metric, especially in the context of food security, as it measures the DCNN's ability to identify all relevant instances of a particular condition, such as areas affected by crop diseases or regions experiencing food shortages in Fig 3. High recall ensures that the model does not miss any critical instances, a crucial factor in crisis situations where early detection and response can prevent widespread hunger and malnutrition. The DCNN's structure, allowing for an extensive field of view, enables it to detect subtle and widespread patterns in the data, thereby enhancing its ability to identify all relevant cases, even those that are not immediately obvious.

4. Conclusion

In conclusion, the proposed DCNN demonstrates a significant improvement over traditional neural network models in both precision and recall metrics. Its ability to accurately identify and comprehensively cover relevant instances makes it an invaluable tool in analyzing and addressing the complex challenges of food security in developing countries. This study's findings indicate that employing advanced deep learning techniques like the DCNN can lead to more effective and targeted approaches in combating food insecurity, ultimately contributing to the development of more resilient and sustainable agricultural systems.

5. References

- [1] Baryshnikova, N., Altukhov, P., Naidenova, N. and Shkryabina, A., 2022, February. Ensuring global food security: Transforming approaches in the context of agriculture 5.0. In *IOP conference series: earth and environmental science* (Vol. 988, No. 3, p. 032024). IOP Publishing.
- [2] Sarku, R., Clemen, U.A. and Clemen, T., 2023. The application of artificial intelligence models for food security: a review. *Agriculture*, 13(10), p.2037.
- [3] Tokhayeva, Z.O., Almukhambetova, B.Z., Keneshbayev, B. and Akhmetova, K., 2020. Innovative processes' management in agriculture and food security: Development opportunities. *Entrepreneurship and Sustainability Issues*, 7(3), p.1565.
- [4] How, M.L., Chan, Y.J. and Cheah, S.M., 2020. Predictive insights for improving the resilience of global food security using artificial intelligence. *Sustainability*, 12(15), p.6272.
- [5] Tamasiga, P., Onyeaka, H., Bakwena, M., Happonen, A. and Molala, M., 2023. Forecasting disruptions in global food value chains to tackle food insecurity: The role of AI and big data analytics—A bibliometric and scientometric analysis. *Journal of Agriculture and Food Research*, 14, p.100819.
- [6] Bogoviz, A.V., Osipov, V.S., Vorozheykina, T.M., Yankovskaya, V.V. and Sklyarov, I.Y., 2023. Food Security in the Digital Economy: Traditional Agriculture vs. Smart Agriculture Based on Artificial Intelligence. In *Food Security in the Economy of the Future: Transition from Digital Agriculture to Agriculture 4.0 Based on Deep Learning* (pp. 59-74). Cham: Springer International Publishing.

[7] Joshi, S. and Sharma, M., 2022. Digital technologies (DT) adoption in agri-food supply chains amidst COVID-19: an approach towards food security concerns in developing countries. *Journal of Global Operations and Strategic Sourcing*, 15(2), pp.262-282.

[8] Gumma, M.K., Thenkabail, P.S., Teluguntla, P., Oliphant, A., Xiong, J., Congalton, R.G., Yadav, K. and Smith, C., 2017. NASA Making Earth System Data Records for Use in Research Environments (MEASURES) Global Food Security-Support Analysis Data (GFSAD) Cropland Extent 2015 South Asia, Afghanistan, Iran 30 m v001.