Transforming Community Engagement with Generative AI: Harnessing Machine Learning and Neural Networks for Hunger Alleviation and Global Food Security

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Abstract

This essay examines the intersection of generative artificial intelligence (AI) with community engagement practices, which are designed to address hunger and food security. It draws on a wide range of stakeholders and collaborators and is supported by a literature review. One of our objectives is to frame how initiatives in AI and machine learning that employ neural networks and other related approaches can realize a significant impact both intra- and inter-regionally, broadly speaking, in the Global South and in collaboration with the UN's Sustainable Development Goals. An additional purpose of this essay is to begin answering some of the challenges, opportunities, and activities our research, expert, practitioner, technical, and policy informants have seeded in our inquiry.

Harnessing the power of new technologies has the potential to ameliorate some of these global challenges and is by international norms and practices related to technology for good. This is made explicit by the Convention on Biological Diversity, which explicitly notes that the general orientation of science and technology, including biotechnology, should be toward the development of technologies and related activities and inputs that are safe, effective, and affordable. Moreover, there are several ethical and social benefits of this research. Our work is based on case studies, and real-world examples in Canada, India, and other places are highlighted in the essay. After identifying significant ethical considerations and developing an understanding of stakeholders and impacted communities, we discuss policy implications and future directions.

Keywords: Generative AI, Community Engagement, Hunger, Food Security, Neural Networks, Machine Learning, Global South, Sustainable Development Goals, UN Collaboration, Technology for Good, Convention on Biological Diversity, Biotechnology, Ethical Considerations, Social Benefits, Case Studies, Policy Implications, Stakeholders, Impacted Communities, International Norms, Technology Development, Real-World Examples.

1. Introduction

Artificial Intelligence (AI) in general, and Generative AI more specifically, have the potential to help alleviate hunger and enhance global food security. More than 800 million people globally face chronic hunger daily, and approximately 66 percent of children endure moderate to severe food insecurity. What is more, over 3 billion people cannot afford a healthy diet. Therefore, to address these wicked problems, innovation at scale and innovative multi-stakeholder approaches are needed. This essay revolves around one such innovation, which is Generative AI. It is well recognized that communities possess local knowledge, develop their context-specific solutions, determine their priorities, and deliberate on a wide range of inclusive tools and policy decisions that would work for them. However, routine socio-economic conditions, poor motivation, and negative shocks such as economic recession, climate hazards, and political instability, amongst many others, appear to exacerbate decision-making capacities and community engagement. Innovative tools and approaches are needed to motivate people through wealth creation, higher income, enhanced access to markets, development of inclusive value chains, and promotion of quality standards. These endeavors would enhance people's engagement in adaptive research, and community-driven development, and ensure sustainability for leaving no one behind. Generative AI is more likely to play a crucial role as a motivational intervention because it has already demonstrated potential, taken communities out of extreme poverty, and enhanced their well-being and income in many parts of the world. This essay elaborates on the role

of some of the key stakeholders operating at the local level of the food system in painstakingly implementing AI.
A critical need exists to ensure broader dialogue and discussions around how Generative AI could play a critical role in enhancing community engagement. The next section of this essay discusses some of the critical development issues related to hunger, the global food system, and the role of disruptive innovation, and elucidates the pivotal role that AI could play in enhancing creativity and problem-solving abilities at the local level of the food system, especially for smallholder farmers and community members who are experiencing hunger and deprivation. Later sections of this essay will systematically discuss the characteristics of Generative AI, community engagement, and its role in development. They will also offer some practical ways forward to reduce incumbent friction as indicated by the stakeholders, highlight some barriers, enablers, and pitfalls to maximize the use of Generative AI, and discuss how to harness them for better AI and inclusive development.

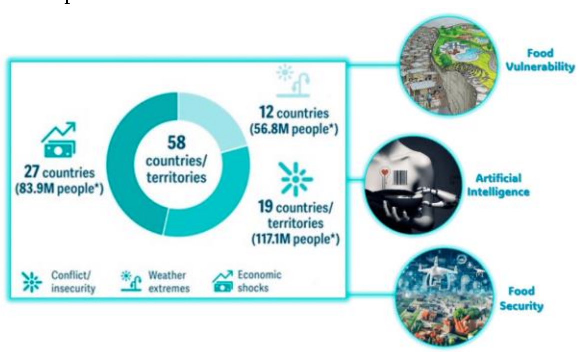

Fig 1 : Artificial Intelligence on Food Vulnerability

1.1. Background and Significance

Nearly 10% of the world suffers from moderate or severe food insecurity due to recurring natural and human-made disasters. Since 1992, the quantity of food distributed through international food assistance has increased fourfold. Hunger does not occur because of an insignificant food supply, but due to its distribution and access across distant localities. It ties communities together for aggregate solutions and requires multi-country engagements. The degradation of community functioning through famine or poverty circumscribes community-scale functioning. Recent innovations, enabled by technology, are reshaping community solutions to hunger. Both machine learning and neural networks can change the impact of these innovations and the required infrastructure. Machine learning, automation, and mobile networks have established barriers to community net insecurity. Mobile phones allow for direct answers from crowds of thousands to research queries asked hundreds of times. Generative AI and deep learning offer the potential for wider internet and famine policymakers to be equally engaged. Improving small efforts toward alleviating hunger is part of a larger trend of developing creative solutions that depend on consumers for organizational, legal, or technical effectiveness. Compensation is typically paid for reviewed work but is otherwise an individual or group expression of patterns of authority. The study examines whether one such approach works with communities in reducing hunger on small islands.

1.2. Research Aim and Objectives

To explore whether and how generative AI might transform community engagement methods. It identifies specific applications of generative AI that could have the potential to transform community engagement in hunger alleviation and global food security. Specifically, the work ultimately aims to identify whether any aspects of the four community engagement methods might be replaced by AI-generated representations. 1. To explore and identify specific AI applications that can provide additional methods of representing and sharing food systems and improve the exchange of knowledge. 2. To offer innovative and creative solutions to meet some of the most pressing challenges in hunger alleviation. 3. To identify potential barriers to the implementation of generative AI in community engagement and explore strategies communities might use to resist these. 4. To identify best practice guidelines for engagement with generative AI and a plan for necessary future research. Given the scale and nature of these objectives, and the broad nature of the geographical scope and related methods of community engagement in hunger alleviation and food security studies, this paper adopts an interdisciplinary perspective to achieve these objectives. Furthermore, it is motivated by the potential for genuinely transformative research. This paper...

Equation 1 : Predictive Model for Food Security Using Machine Learning:

$$F = f(D, C, P, T)$$

Where:

- F is the food security score.
- D is the data from local sources.
- C is the community engagement data.
- P is political factors influencing food access.
- T is technological interventions.

2. Understanding Generative AI and its Applications

Generative AI can synthesize or create novel data that are not present in the training sets, supporting a wide array of tasks and goals with generative and creative components.

Their outputs are original and may not always correspond to existing objects or attributes. Moreover, generative models can generate individual as well as collective outcomes. Their outputs range from textual and video-based content to combinational outputs such as recipes or chemical structures. Additionally, generative AI models can be trained based on conditioning information to generate personalized outcomes. Considering how generative AI operates, we can conceptualize a variety of applications. These include creating new data, images, or content; generating future simulations or strategies; and predicting potential outcomes by generating counterfactual scenarios.

Generative AI methods can be categorized based on their process of learning from the provided inputs. Discussions on such categorizations demonstrate that the field of generative AI models is diverse and crosses multiple dimensions of the machine and deep learning. An important classification is based on the network architecture of generative AI tools and the depth of learning by these networks. With a few additional layers, models learn the underlying data structure to construct novel data with lesser dimensionality. Alternatively, when the output structure is complex, like natural language or imagery, deep neural networks are required for end-to-end training of models using various tools and techniques in AI and machine learning. Generative AI models are now applied across a wide range of sectors, such as healthcare, pharmaceuticals, chemistry, retail, e-commerce, fashion, and art, to explore various tasks and challenges like recommendation systems, object generation, fraud detection, and adverse event prediction. Leaders also adopt generative AI methods in their creative tasks and services. These include generating human faces or art pieces, creating novels, producing face-aging images, or translating an image into poetry.

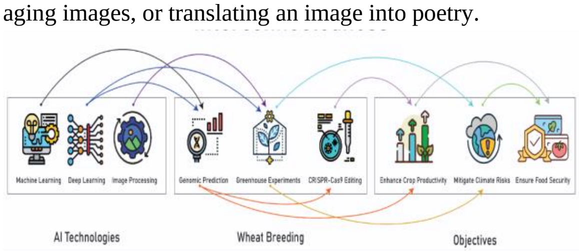

Fig 2 : Applications of Artificial Intelligence in Wheat Breeding for Sustainable Food Security

2.1. Overview of Generative AI

A generative model is a category of machine learning techniques in which the model generates new data from the distribution of a given training set. Generative models are used for synthesizing images, noise removal, artistic style transfer, new domain exploration, and adversarial searching among various other tasks. Generative models operate based on probability, where the likelihood of the model given an input is either calculated or based on maximized learning concerning the input. This formulates the parameters of a probability distribution that comes from a given data point, providing a likelihood that models the original data. These models can be based on several different learning techniques including random forests, recurrent neural networks, and convolutional networks. Generative adversarial networks and variational autoencoders are two well-known examples of generative models.

Generative models are appealing in artificial intelligence, as they operate between small sequences to larger sentences while showing flexibility, variation, and diversity in the sentence outputs. This breaks down the traditional line of command, where a robot is only capable of following a restricted set of instructions, to imbuing a robot with the potential to develop its creativity through understanding the data with which it is working. The generation of novel ideas provides opportunities for chefs, artists, and musicians, while laboratory researchers are utilizing these capabilities to discover new drug compounds from protein structures. The neural network structures supporting generative models can enhance both human creativity and problem-solving. In many respects, generative AI offers a shift from rule-based programming to machine learning techniques that seek a hidden directive, bringing what were once considered niche technologies into the public eye. Examples of AI-generated technologies successfully infiltrating modern industries include memes, the 'Teachable Machine' that allows convolutional network models to recognize users based on fun, and 'Quickdraw' which relies on CNNs for drawing doodles to identify and depict your drawings.

2.2. Types of Generative AI Models

Generative AI models can be segregated into various categories depending on their functionalities. Among these, Generative Adversarial Networks (GANs) are the most famous AI model, and their primary function is to create a synthetic data set from a given set of real data. Other AI models that fall into the category of GANs are:

1. Auxiliary Classifier GANs (AC-GANs)
2. Conditional GANs (cans)
3. Deep Convolutional Generative Adversarial Networks (DC-GANs)
4. Wasserstein GANs (WGANs)
5. Adversarially Learned Inference (ALI)
6. Bidirectional GANs (BiGANs)
7. Pretrained GANs (PGANs)

Variational Autoencoders (VAEs) are specialized in geometry preserving, 3D models, visio-linguistic models, super-resolution, and image-to-image translation. They offer natural audio generation and come with improved metrics. However, the method also has some limitations, such as a low success rate and increased computational complexity. Deep Convolutional Generative Adversarial Networks (DC-GANs) are famous for image generation, image editing, image-to-image translation, 3D object generation, and super-resolution. However, the DC-GANs come with increased computational complexity and the loss of colors in the generated image content. Bidirectional GANs (BiGANs) are used for output-conditional learning, output-to-input learning, and optimization, but they lag in terms of performance and accuracy. Introduced in 2017, PixelCNN and PixelRNN allow for pixel-based generation of images and come with promising results, but the method also has certain limitations, such as performing slower as the size of the input image increases. Moreover, they are non-autoregressive methods; thus, they can generate only nonsquare images. Intriguingly, GANs and VAEs provide a general framework for generative AI, but numerous AI models have been introduced based on GANs and VAEs. Similarly, other generative AI models have been introduced as an extension of existing models, and each type of model has its focus, significance, strengths, and challenges.

The selection of one particular model depends on the scenario, dataset size, related challenges, and research focus. However, food security and global hunger alleviation are great challenges, and numerous factors are involved in achieving these objectives. In this respect, the role of generative AI is not only to generate fake food images, recipes, or food-related videos, but it is further expected to provide humanitarian aid in recommending nutritious, diverse, or climate-smart meals by using local food recipes, classifying food ingredients, and recognizing a wide range of food to design an automatic system for monitoring dietary intake. Therefore, based on the desired research outcomes, this categorization system can be helpful for the selection of an AI model that is appropriate for the specific scenario. Besides this accepted categorization, some emerging architectures for generative AI models have also been developed in recent years, such as StyleGANs for photorealistic humans and generic objects; BigGAN for super-resolution; and RL(C)IR for hard exploration in Reinforcement Learning. Such advancements predict that various trends may emerge from these new models.

2.3. Applications in Various Fields

Various fields have increasingly been relying on generative AI for problem-solving and the development of new applications. Generally speaking, successful projects have been deployed across diverse realms, such as healthcare, education, bioscience, music and cultural heritage, and environmental management and planning. Uniting these past successes is an orientation toward enabling growth, discovery, and creativity in everyday human decision-making and communication through AI. When data is accessible, decision-makers have more options and make better choices. Work in data-driven generative methodologies has also been successful in ultra-niche domains, like the slow food and craft beer movement. This offers some indication of value for work in food systems more generally.

Successful applications of generative AI development also point to a potential role for AI in addressing pressing global issues. A food security decision-support tool has been developed to forecast upcoming famines, identifying food insecurity hazards up to four months in advance. At the educational level, gamified simulations informed by generative AI are being used in programs for more advanced educational and organizational partnerships. An internationally recognized nonprofit organization dedicated to innovation in Geographic Information Systems and spatial data management is working on enabling stakeholders in the ever-evolving craft beer and slow/local food markets and related communities. By using geographic information to generate new drug-related adverse event linkages, efforts are being made to improve adverse drug event reporting using both structured and unstructured data. These diverse fields of work point to the potential for interdisciplinary and community-based efforts in applied data science and machine learning using both quantitative and qualitative data.

I call for a marked increase in these sorts of projects at the intersection of AI and community practice, to existing networks and communities that can leverage industry and academic expertise to increase the real value and accessibility of data. It seems that current applications are limited mainly by the funding and expertise for their development. Use cases have spanned local and global approaches and explanatory and data-generating approaches. As such, this kind of AI has the potential to be applied to many more kinds of real-world data and problems. Generative AI development has offered possibilities for both low-resource and high-resource approaches and has been successful in fundraising at conference booths alongside qualitative researchers and ethnographers. The skills needed to work in these generative AI methods are increasingly well-understood and well-taught. If you are a community-based or interested services network, consider exploring this approach to problems within your community. If you have problem-solving skills and are already working in community or nonprofit sectors, please consider continually expanding your skill sets to include data analytics and machine learning to make the best use of nonprofit funding. As we move forward, it is important that community-based AI also looks to address racism based on mainstream data and the AI discipline more broadly.

3. Machine Learning and Neural Networks in Food Security

The opportunity to address problems in community engagement in food security using the latest AI technology of generative model design to create high-value and data-rich tools is appealing. This paper describes a generative adversarial network (GAN), a neural network algorithm that frames and functions fundamentally as a game, by creating two models whose adversarial competition motivates them to mutually improve. Applied to a novel area of domino-moving for other machine learning (ML) algorithms, we show that easily learned GANs can craft new data of high value, and we create a new dataset representing at least 200,000 individuals labeled by food security. The heart of our model uses the AI prompt of a particularly advanced language model to ensure that survey data has essential privacy-preserving and sensitive data protection criteria. These emerge due to the model's almost trivial characteristic of guessing ground truth labels accurately based on small, non-private group survey answers.

Machine Learning (ML) is an important branch of Artificial Intelligence (AI) that has gained significant popularity and applications in cybersecurity, smart cities, and several aspects of agriculture. By using various ML algorithms, you can create a mathematical model to understand data, learn a task, or even conduct some predictive analysis. However, ML can do more than traditional predictive and reactive applications. It can be leveraged in even larger data and prediction-driven systems. It can easily be combined with other methods and tools in a holistic community engagement approach. The opportunity to address problems in community engagement in food security using the latest AI technology of generative models, however, seems to be largely unrealized.

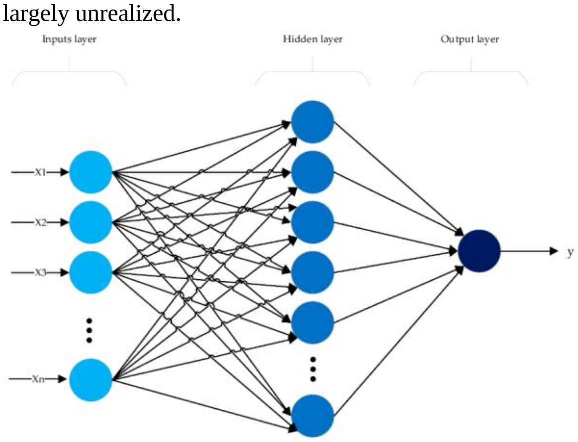

Fig 3 : Prediction of Food Production Using Machine Learning Algorithms of Multilayer Perceptron

3.1. Basic Concepts of Machine Learning and Neural Networks

Machine learning is a powerful and universal tool that can create models with almost countless applications across a range of different disciplines. It relies on the idea of allowing machines to learn and improve from experience, which is commonly achieved by providing the machine with massive sets of labeled data and a specific problem or task to solve. With machine learning, the learning can occur through supervised learning, unsupervised learning, reinforcement learning, or semi-supervised learning based on the learning approach, as well as through the utilization of one or more widely employed machine learning models such as neural networks, support vector machines, ensemble classifiers, or decision trees. By comparison, deep learning builds on machine learning through the use of specialized neural networks—typically artificial neural networks that are organized in successive layers, inspired by interconnected biological neural systems, and aim to process a large number of data points. In this way, deep learning models attempt to learn simple to complex features through automatic abstraction and hierarchical representation of complex data by the generation of non-linear mappings.

In general, neural networks refer to a class of powerful machine learning models that are often deployed with great success in big data analytics. Through a collection of interconnected computing units, these networks allow the machine to learn complex functions that map from a set of input variables to a set of output variables, with the interconnected units patterned after biological neural systems. Often referred to as neurons, these units are organized in layers as input units, hidden units, and output units, and tend to form powerful predictive models. Input neurons are fed with signal data while hidden neurons provide intermediate processing; output neurons generate the final output. Furthermore, the function that gets applied at each connection is modifiable over time, such that the system can be trained and retrained again with many examples using a particular optimization method. In this way, neural network models tend to become more specialized and domain-specific, giving rise to a powerful specialization called artificial neural networks that have become an indispensable part of artificial intelligence research.

Equation 2 : Generative AI Model for Simulating Food Distribution Needs:

$$D_{target} = G(A, L, N)$$

Where:

- D_{target} is the target distribution.
- G is the generative model.
- A is the historical agricultural data.
- L is local demand.
- N is neural network parameters.

3.2. Current Applications in Food Security

The growing use of ML and NN indicates increasing potential. Few current services of ML or NN within the food security domain exist; though hunger alleviation and global food security will undoubtedly see a rapid expansion of AI-enhanced capabilities. The nascent applications of use thus far remain mostly in the introduction of generative AI to crop management. Current uses of ML or NN for food security purposes understandably take considerable inflection from an agri-tech approach. It is being used in sowing practices, particularly in the optimization of time, best seed choice, and changing climate influence. As image recognition capabilities are becoming more sophisticated, the recognition of pests and diseases in crop plants is another area.

The AI process of drought monitoring and crop yield predictions is largely done through crop identification since how and when to water might be agri-tech's most important growing trend of all. Generative AI can also provide precision data in the monitoring of plant volatiles that can draw in pesticide access to test for harmful volatile organic compounds in surrounding plants. Weed and disease identification in weirs is a recent case of generative AI use. The company offers a weed image recognition service to farm machinery partners, having taken pictures of different plants and creating AI-trained models able to defeat humans at performing grass weed imaging.

4. Case Studies and Success Stories

CiPP seeks to provide real-world examples of the successful use of generative AI in community engagement and food security. This section includes short descriptions of various case studies and success stories about generative AI applications.

1. Using Machine Learning to Understand Engagement in the Fight Against Hunger In this case study, a project underway works with local partners to build and develop the capacity and improve citizens' well-being within the Great Lakes region. The goal is to create a shared understanding of the intersections between hunger, hopefulness, voice, and structures in this region. The project has two components. One is an HLPE-aligned scoping study using a food systems framework to understand more about vulnerable areas in the three countries. The second is in-depth action research in strategically chosen, specific locations that look specifically at value addition and trade.

AI in the Supply Chain Many of the potential benefits generated through the application of generative AI to the intersection of different scales have already been the subject of several research instruments in recent times and are discussed in more detail in the publications list in the references section. The rapid progress of AI technology goes towards showing how production and strategy-level changes would be both possible and achievable, but can also start the process of those changes today through tools. Given this, we focus our attention in this proposal on describing such AI transformation success stories, the lessons learned, the justification, and new insights for new research, and explore the prospects for wider adoption of knowledge shared by transformation success stories. In doing so, we turn to review a range of existing applications of AI technologies that feature generative AI in a variety of wider contexts.

4.1. Real-world Examples of Generative AI in Food Security

4.1. Increased Diversity and Consumption of Local Foods A concrete hunger issue that an AI system might help alleviate is increasing diversity and consumption of edible native plants. This initiative certainly does need AI, but this is our motivation. Indigenous people know the purpose, and they also know which plants help maintain a specific agroecosystem. Many of these digital initiatives are also developed with one eye on global food security and one eye on enabling financial and lifestyle opportunities for the population. How well specific projects might be able to contribute to kicking off a rapid diet-related sustainability change or become used or adapted in parts of the region, projects exacerbate between social groups where they operate. New initiatives are not developed with working with industry in mind as the main incentive. The case study is based in a small village with highly successful settler and nomad residents. We are building an application and are working slowly through field experiments, recipe testing, and food studies. There are two parts, namely "learn to love native" and the "artificial intelligence" part. Both parts provide opportunities for people to discuss and share perceptions and build trust. Both are co-designed between project staff and some residents.

Fig 4 : Harnessing AI for global food security

4.2. Peach Yield Forecasting A concrete hunger issue that an AI system might help alleviate is crop yield forecasting. This study concentrates on a concrete hunger issue that an AI system might help alleviate — crop yield forecasting. To that end, we examine a well-performing technique, machine learning with neural networks. We use peach data because peaches constitute a significant portion of worldwide fruit production, and canned peaches provide a staple food to aid organizations around the world. Our focus is not on deploying a pre-trained neural network to make predictions in another geographic region but rather to illustrate how such technology can be integrated into the local decision-making needs for optimal supply for local providers in their food distribution work. Neural network models are domain-agnostic, so the example provided can apply to any region and crop where such data is obtained.

5. Challenges and Ethical Considerations

Due to the ability of generative AI to generate real-looking unreality for both images and videos, it is important to ensure the privacy and data security of anyone contributing to an AI knowledge base. This includes the challenge of obtaining informed consent from all data sources, reflecting on what transparency is possible in AI-assisted community engagement, and assessing the legal rights and obligations of data created by AI. AI systems can misread object information; the risks of bias identified below may be exacerbated compared to humans by the sheer scale of data involved, and social impacts are unknown. Significantly, any data set, model, concept, or algorithm will have embedded within it the preferences, assumptions, and knowledge base of its designers. In developing countries, AI is applied in contexts where few policies, laws, or partnerships in place focus on data ethics or oversight. Community engagement work requires a detailed understanding of the particular social and cultural landscape of the country, applying principles of realism-based data collection and data storage protocols. These protocols should align with community expectations and be codified into project MOUs with trusted sourcing organizations. In considering additional AI systems complementing this community engagement work, we raise the following set of challenges—primarily questions without solutions—as waymarkers in a broader debate on AI creation and usage. We recommend that the process of development and the eventual AI deployment be governed by best practices and data governance and protection frameworks based on our work.

5.1. Data Privacy and Security Concerns

In community applications of generative AI, data privacy concerns emerge as an important consideration. Research and experience have shown that communities are hesitant to participate and share data with researchers, NGOs, and companies. In data-driven AI systems, the collection and use of personal data lie at the heart of generative AI. Protecting personal data and ensuring compliance with regulations are therefore paramount. A growing number of global regulations and frameworks at various levels of law and research seek to address data use. They include various initiatives and frameworks that do not mean an end to privacy, among others. In many low- and middle-income countries, data use is enabled by their publicly available data laws, freedom of information laws, or by making use of exemptions for research and public-interest activities. Data protection regulations in some countries and regions provide a legal basis to become compliant with international data-sharing rules, and they are sometimes used as a minimum standard in other legal frameworks. At the same time, ensuring compliance in contexts that are often under-resourced is difficult. Misuse of personal information can result in individuals and communities being the target of harmful interventions. In global machine learning-based AI systems, adversarial attacks can be used to intentionally generate incorrect data, training a generative AI model to produce food entitlements lower than what is socially acceptable, which could then be used to justify more widespread harm. Finally, data security measures must also take into account the communities in which they engage. Good data security measures not only protect and anonymize data but also adhere to ethical practices in handling data.
In summary, personal data protection and security are fundamental for communities to trust and participate in data-driven AI. Robust data security measures should be implemented not just to comply with regulations but also to support the accountable use of personal information. AI life

cycle data security measures are needed alongside institutional and local capacity building to support these and to ensure that both global and local ethical frameworks around data are adhered to. AI can have transformative potential in data-scarce contexts, but current global regimes for data sharing are deeply inequitable.

Equation 3 : Optimization Model for Hunger Alleviation Strategy Using Neural Networks:

$$O = \mathrm{NN}(H, I, S, R)$$

Where:

- O is the optimal allocation.
- H is hunger data.
- I is intervention strategies.
- S is the supply chain data.
- R is available resources.

5.2. Bias and Fairness in AI Algorithms

One of the most significant criticisms being leveled against the rapid growth in the utilization of AI is its potential for perpetuating or even enhancing bias if left unchecked. Bias in this instance refers to human prejudice that is inadvertently embedded within models making use of AI through pattern recognition and prediction, which can have extreme impacts on marginalized or vilified communities if not addressed. When using AI in community engagement, accurate data to represent marginalized communities is not always available. Some ways to prevent bias involve creating inclusive, multiply constructed datasets during the training stages, which requires a much more comprehensive engagement strategy than companies had in the past. Real-life case studies exist as examples in AI and machine learning of how the oversight of bias can have ripple effects on entire communities. Until recently, much of the work being carried out in adapting AI towards a more inclusive outcome has focused on locating undesirable biases in algorithms. Current practice on how to mitigate or potentially eliminate these biases often involves audits or 'preventative' testing, outside the development process with a subsequent cleanup of biases that have been found. Large and perhaps corrective reworking of the machine's decision-making is avoided. A major issue with this perspective is the lack of inclusivity in AI development processes, leading to an entrenchment of systemic inequity as a feature of modern AI. It effectively means a professional class of AI technologists and ethicists is tasked with correcting potentially harmful and undesirable decisions made by machines. The fact that the impetus for this work stems from an urgent need to address unnecessary human suffering makes the endeavor especially time-sensitive. Ethical and responsible business frameworks are more needed than ever.

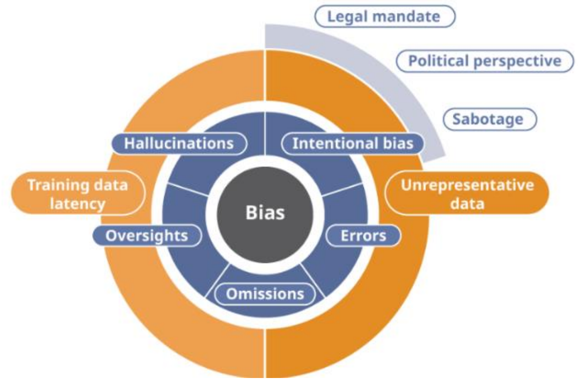

Fig 5 : The Accidental and Intentional Biases in GenAI Algorithms and Training data.

6. Future Directions and Recommendations

Several NGOs, international organizations, and the AI community are exploring generative AI to engage with communities in targeted, meaningful ways, addressing trust, equity, and respect in engagement, as reflected in AI principles around the world. These selected examples across different contexts, from Uganda to Australia, and with different audiences in mind, from Indigenous communities in Northern Australia to disaster preparedness in Vanuatu, have been initiated locally and had input from community members and elders in the ancestral rule of the land, and are generating new insights and successful partnerships between community and technologists. This is promising because knowledge and experience with generative AI will likely be shareable more broadly. Greater emphasis should be placed on ensuring that both technology developers and communities being targeted for generative AI engagement have the opportunity to learn from these and other pilot projects, should they be scalable in the future. As this is a new area, further research to accompany these pilot projects is recommended. Governance arrangements and proposals for broader policy are needed to promote the creation and execution of ethical, climate-smart AI in this generative domain. It is also vital to bear in mind that GAI models that are developed and adapted to diversity can change over time, under the right circumstances, continually producing analyses that are sensitive to community values. This ongoing learning means that the performance of these modern machine-learning systems will continue to improve, becoming more valuable in addressing and measuring food security and community engagement outcomes over time. GAI and other generative approaches should be incorporated into knowledge projects that improve data availability more directly and obtain data with known origins and relationships. Finally, regardless of approach or technological details, social science research should be at the heart of all work in this area, and efforts to engage communities should remain centered on maximizing benefits and reducing negatives. Monitoring food security outcomes over time, including looking at resilience, incidence, and reasons for newfound hunger, should be central to efforts that focus on equity.

6.1. Potential for Scaling Up and Replicability

Successful generative AI projects have the potential to scale up to larger settings. There are several reasons to expect the replicability of a successful generative AI intervention across different settings. First, generative AI technology is designed to be transferable. Because it utilizes neural networks trained on large, global datasets, successful initiatives are well positioned to be adapted in new settings that can provide the local data necessary for model retraining. Given appropriate validation, generative AI tools and solutions are designed to be owned and operated by home institutions working with their local communities. The wide distribution of projects is evidence of this: since 1997, resident scientists from various institutions in multiple countries have worked on these initiatives.

There are several key principles for the successful deployment of a new strategy developed in one environment into new contexts. First, the transfer of technology from one context to another must consider the unique needs of a new community and be responsive to the resources available. Second, new projects must engage stakeholders at scale, including broad networks of organizations and individuals, make key decisions consistently with their feedback, and raise local resources to support themselves.

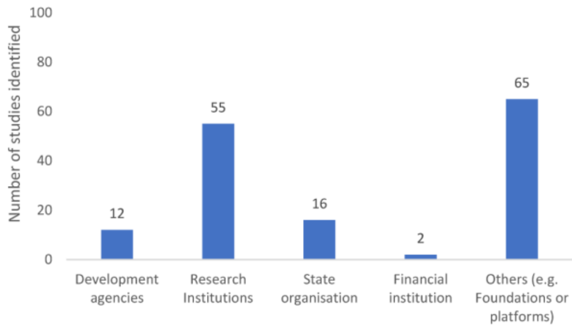

Fig 6 : The Application of Artificial Intelligence Models for Food Security

The Hunger Alleviation model successfully engaged small platforms of stakeholders and has sought feedback from a county stakeholder panel with the aim of better understanding the unique context of poverty and hunger as a basis for model validation. Finally, successful initiatives developed in one community can inform the priorities and focus of the new project and help to identify potential levers for success. A field-tested comprehensive evaluation framework follows generative AI tools or suggestions in the fields they implicate. There are also examples in related fields of action research or generative interventions to alleviate community needs that have been taken to operational scales through large institutions with wide geographic spread. Such an approach can also work to build commitment to societal benefits. Additionally, generative AI roadmaps could be based on opportunities for generative AI solutions to be shared more widely cross-regionally, where different models of operations and inputs result in generative AI approaches that are common or adjacent.

7. References

[1] Ravi Kumar Vankayalapati, Dilip Valiki, Venkata Krishna Azith Teja Ganti (2025) Zero-Trust Security Models for Cloud Data Analytics: Enhancing Privacy in Distributed Systems . Journal of Artificial Intelligence & Cloud Computing. SRC/JAICC-436. DOI: doi.org/10.47363/JAICC/2025(4)415

[2] Manikanth Sarisa , Gagan Kumar Patra , Chandrababu Kuraku , Siddharth Konkimalla , Venkata Nagesh Boddapati. (2024). Stock Market Prediction Through AI: Analyzing Market Trends With Big Data Integration . Migration Letters, 21(4), 1846–1859. Retrieved from https://migrationletters.com/index.php/ml/article/view/11245

[3] Tulasi Naga Subhash Polineni , Kiran Kumar Maguluri , Zakera Yasmeen , Andrew Edward. (2022). AI-Driven Insights Into End-Of-Life Decision-Making: Ethical, Legal, And Clinical Perspectives On Leveraging Machine Learning To Improve Patient Autonomy And Palliative Care Outcomes. Migration Letters, 19(6), 1159–1172. Retrieved from https://migrationletters.com/index.php/ml/article/view/11497

[4] Munjala, M. B. (2025). Harnessing the Power of Data Analytics and Business Intelligence to Drive Innovation in Biotechnology and Healthcare: Transforming

Patient Outcomes through Predictive Analytics, Genomic Research, and Personalized Medicine. Cuestiones de Fisioterapia, 54(3), 2222-2235.

[5] Sanjay Ramdas Bauskar, Chandrakanth Rao Madhavaram, Eswar Prasad Galla, Janardhana Rao Sunkara, Hemanth Kumar Gollangi (2024) AI-Driven Phishing Email Detection: Leveraging Big Data Analytics for Enhanced Cybersecurity. Library Progress International, 44(3), 7211-7224.

[6] Aravind, R. (2024). Integrating Controller Area Network (CAN) with Cloud-Based Data Storage Solutions for Improved Vehicle Diagnostics using AI. Educational Administration: Theory and Practice, 30(1), 992-1005.

[7] Pandugula, C., Kalisetty, S., & Polineni, T. N. S. (2024). Omni-channel Retail: Leveraging Machine Learning for Personalized Customer Experiences and Transaction Optimization. Utilitas Mathematica, 121, 389-401.

[8] Aravind, R., & Shah, C. V. (2024). Innovations in Electronic Control Units: Enhancing Performance and Reliability with AI. International Journal Of Engineering And Computer Science, 13(01).

9] Madhavaram, C. R., Sunkara, J. R., Kuraku, C., Galla, E. P., & Gollangi, H. K. (2024). The Future of Automotive Manufacturing: Integrating AI, ML, and Generative AI for Next-Gen Automatic Cars. In IMRJR (Vol. 1, Issue 1). Tejass Publishers. https://doi.org/10.17148/imrjr.2024.010103

[10] Korada, L. (2024). Use Confidential Computing to Secure Your Critical Services in Cloud. Machine Intelligence Research, 18(2), 290-307.

[11] Jana, A. K., & Saha, S. (2024, July). Comparative Performance analysis of Machine Learning Algorithms for stability forecasting in Decentralized Smart Grids with Renewable Energy Sources. In 2024 International Conference on Electrical, Computer and Energy Technologies (ICECET (pp. 1-7). IEEE.

[12] Eswar Prasad G, Hemanth Kumar G, Venkata Nagesh B, Manikanth S, Kiran P, et al. (2023) Enhancing Performance of Financial Fraud Detection Through Machine Learning Model. J Contemp Edu Theo Artific Intel: JCETAI-101.

[13] Jana, A. K., Saha, S., & Dey, A. DyGAISP: Generative AI-Powered Approach for Intelligent Software Lifecycle Planning.

[14] Korada, L. (2024). GitHub Copilot: The Disrupting AI Companion Transforming the Developer Role and Application Lifecycle Management. Journal of Artificial Intelligence & Cloud Computing. SRC/JAICC-365. DOI: doi. org/10.47363/JAICC/2024 (3), 348, 2-4.

[15] Paul, R., & Jana, A. K. Credit Risk Evaluation for Financial Inclusion Using Machine Learning Based Optimization. Available at SSRN 4690773.

[16] Korada, L. (2024). Data Poisoning-What Is It and How It Is Being Addressed by the Leading Gen AI Providers. European Journal of Advances in Engineering and Technology, 11(5), 105-109.

[17] Jana, A. K., & Paul, R. K. (2023, November). xCovNet: A wide deep learning model for CXR-based COVID-19 detection. In Journal of Physics: Conference Series (Vol. 2634, No. 1, p. 012056). IOP Publishing.

[18] Korada, L. Role of Generative AI in the Digital Twin Landscape and How It Accelerates Adoption. J Artif Intell Mach Learn & Data Sci 2024, 2(1), 902-906.

[19] Jana, A. K., & Paul, R. K. (2023, October). Performance Comparison of Advanced Machine Learning Techniques for Electricity Price Forecasting. In 2023 North American Power Symposium (NAPS) (pp. 1-6). IEEE.

[20] Mandala, V., & Mandala, M. S. (2022). ANATOMY OF BIG DATA LAKE HOUSES. NeuroQuantology, 20(9), 6413.

[21] Sunkara, J. R., Bauskar, S. R., Madhavaram, C. R., Galla, E. P., & Gollangi, H.

K. (2023). Optimizing Cloud Computing Performance with Advanced DBMS Techniques: A Comparative Study. In Journal for ReAttach Therapy and Developmental Diversities. Green Publication.