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Deep Learning Jugaad and Structured Innovation: Constraint Ceativity with Systematic Approach

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***Abstract*—Jugaad is an indigenous, frugal, and improvisational approach to innovation that has historically enabled low-cost and resource-efficient solutions in developing economies. Despite its effectiveness, such innovations often remain limited in scale, dependent on individual users, and lack formal structure. The rapid development of artificial intelligence, particularly deep learning, presents an opportunity to enhance Jugaad-driven solutions, making them more scalable, predictive, and sustainable. This conceptual paper examines how deep learning can augment Jugaad by incorporating data-driven accuracy, personalization, automation, and systematic scalability. By synthesizing insights from research on frugal innovation, deep learning technologies, and grassroot innovation practices, the paper proposes a unified framework termed Deep Learning Jugaad. A concise but effective Literature review outlines the findings from scholars on Jugaad, frugal innovation, and AI-supported structured innovation. This integrated approach offers a promising pathway for addressing challenges in healthcare, agriculture, resource management, and other development sectors in underserved regions. The study contributes by presenting a model that bridges grassroots ingenuity with advanced computational intelligence, providing a foundation for sustainable, scalable, and contextually relevant innovations.**

***Index Terms*—Jugaad, Deep Learning, Frugal Innovation, Structured Innovation, AI for Development, Healthcare Innovation, Scalable Technology**

I. INTRODUCTION

Innovation in emerging economies frequently arises under conditions of scarcity, prompting individuals and communities to develop resource-efficient, low-cost, temporary solutions. This improvisational approach, widely recognized as Jugaad, emphasizes flexibility, frugality, and the creative repurposing of locally available materials (Radjou, Prabhu, & Ahuja, 2012; Birtchnell, 2011). Jugaad excels in addressing immediate challenges, yet it often lacks systematic structure and scalability, which limits its broader adoption and long-term impact (Prabhu & Jain, 2015). Simultaneously, advancements in deep learning, a subset of artificial intelligence capable of learning complex patterns from large datasets, have transformed sectors including healthcare, agriculture, finance, and manufacturing (LeCun, Bengio, & Hinton, 2015; Esteva et al., 2017). Deep learning provides predictive accuracy, automation, personalization, and data-driven decision-making capabilities, aspects typically absent in traditional Jugaad solutions. The integration of Jugaad with deep learning termed Deep Learning Jugaad offers a hybrid innovation paradigm that combines grassroot creativity with computational intelligence. Jugaad thrives in resource-constrained environments by prioritizing minimal input, reconfiguration of existing assets, and improvisational problem-solving. Conversely, deep learning usually requires high computational resources and data-intensive environments. However, the emergence of lightweight architectures, model compression, edge computing, and TinyML demonstrates that deep learning models can now operate on low-power, inexpensive devices, reducing technological barriers for grassroots innovators (Lin et al., 2020; Reddi et al., 2021; Zhang & Singh, 2021).This hybrid model enables the development of solutions that are simultaneously affordable, scalable, and technologically advanced. In agriculture, for example, recycled smartphones or low-cost IoT devices embedded with compressed convolutional neural networks can diagnose crop diseases and forecast yields, delivering precision agriculture to smallholder farmers at minimal cost (Kamilaris & Prenafeta-Boldú, 2018). Similarly, rural water purification or sanitation systems can integrate low-cost sensors and offline neural networks for real-time anomaly detection, offering robust, low-maintenance, and energy-efficient solutions. By embedding deep learning intelligence into frugal and locally sourced designs, the approach enhances accuracy, reliability, and automation without compromising affordability (Cai, Gan, Zhu, & Han, 2020; Sangameswaran, 2022). Beyond technical efficiency, the Jugaad deep learning paradigm promotes inclusive, hyper-local AI, empowering communities to co-create tools tailored to specific socio-economic and environmental contexts. Informal workers, for instance, can employ low-bandwidth AI-driven demand prediction systems to optimize inventory and reduce wastage, while continuous learning algorithms adapt to evolving local patterns (Chakravarty, 2020; Das & Subramanian, 2023). Additionally, embedding sustainable practices within AI deployment aligns with circular economy principles. The reuse, repair, and repurpose ethos of Jugaad complements energy-efficient edge AI, mitigating the environmental footprint commonly associated with large-scale machine learning deployments (Weyrauch & Herstatt, 2017; Banbury et al., 2020). Overall, the fusion of Jugaad, frugal innovation, and deep learning creates a contextually intelligent, socially inclusive, and environmentally responsible innovation framework. It enables emerging economies to leapfrog traditional development constraints by merging local ingenuity with advanced computational capabilities. This conceptual paper proposes that Deep Learning Jugaad provides a structured yet adaptable approach to sustainable innovation, particularly relevant for resource-constrained settings, including rural healthcare, precision agriculture, disaster management, and smart villages. By moving Jugaad from improvisation toward systematic, scalable, and evidence-based innovation, this model offers a blueprint for technological transformation that is affordable, robust, and inclusive.

II. LITERATURE REVIEW

2.1 Jugaad and Frugal Innovation

Jugaad is widely acknowledged for its defining characteristics, including affordability, simplicity, improvisation, and constraint-driven creativity. Existing research underscores that Jugaad flourishes in contexts where financial and infrastructural resources are scarce, producing solutions that are functional yet frequently rudimentary (Birtchnell, 2011; Weyrauch & Herstatt, 2017). While effective in addressing immediate problems, these solutions often remain informal and lack the structural and procedural mechanisms required for large-scale implementation. Fundamentally, Jugaad represents a mindset attuned to scarcity, characterized by the inventive reuse, repurposing, or adaptation of available resources to generate practical solutions under pressing conditions. Birtchnell (2011) emphasizes that Jugaad is deeply embedded in socio-cultural contexts, emerging organically from everyday problem-solving within environments constrained by both resource limitations and institutional voids. In parallel, the broader construct of frugal innovation, explored extensively by Weyrauch and Herstatt (2017), highlights cost efficiency, value maximization, and the prioritization of essential functionality without superfluous complexity. Unlike the spontaneous and localized nature of Jugaad, frugal innovation is more structured, market-oriented, and strategic, although it shares Jugaad's core focus on resource minimization and affordability. This conceptual overlap positions the two approaches as complementary frameworks for understanding grassroots creativity. Both Jugaad and frugal innovation originate from a philosophical commitment to generating solutions under conditions of scarcity, emphasizing affordability, essential functionality, and optimal utilization of resources to achieve maximum impact. Radjou et al. (2012) describe Jugaad as embodying a "do-more-with-less" ethos, aligning closely with the central tenets of frugal innovation. Similarly, Weyrauch and Herstatt (2017) identify cost reduction, prioritization of core functions, and performance optimization under constraints as defining features of frugal innovation, which correspond closely to practices observed in Jugaad. Collectively, these paradigms challenge conventional innovation models reliant on substantial capital investment and sophisticated infrastructure, emphasizing instead the ingenuity that emerges from constraints. Birtchnell (2011) further contends that Jugaad constitutes a culturally embedded form of frugality-driven creativity, conceptually aligned with the structured discourse surrounding frugal innovation. Both frameworks aspire to deliver inclusive, accessible, and contextually sensitive solutions tailored to underserved or low-income populations. Despite these philosophical synergies, Jugaad and frugal innovation diverge in terms of process orientation, formalization, and scalability. Jugaad is predominantly informal, improvisational, and situational, emerging from rapid, locally tailored adaptations without systematic documentation or rigorous validation (Birtchnell, 2011). Its emphasis is on immediacy and practicality rather than durability or standardization. In contrast, frugal innovation represents a structured, strategic, and market-driven approach designed to produce scalable products that comply with regulatory requirements and satisfy end-user expectations (Weyrauch & Herstatt, 2017). While Jugaad relies on individual ingenuity and spontaneous problem-solving, frugal innovation emphasizes disciplined engineering design, optimization, and commercial viability. Radjou et al. (2012) further note that frugal innovation aspires to develop long-term sustainable solutions, whereas Jugaad outputs may remain temporary or informal due to limited technical refinement. Consequently, Jugaad tends to generate highly localized, context-specific improvisations, whereas frugal innovation is oriented toward delivering repeatable, distributable, and economically viable offerings suitable for broader markets. Nonetheless, both approaches face challenges in achieving systematic scalability and formal adoption. Jugaad's dependence on localized craftsmanship and situational improvisation can impede standardization, quality control, and long-term durability. Similarly, frugal innovations, despite their structured development, may encounter obstacles in meeting rigorous regulatory standards or attaining high-volume industrial production due to cost constraints. As a result, while both Jugaad and frugal innovation exhibit exceptional contextual relevance, resilience, and resource efficiency, they frequently fall short of achieving robust, repeatable, and large-scale impact without supplementary technological, organizational, or institutional support.

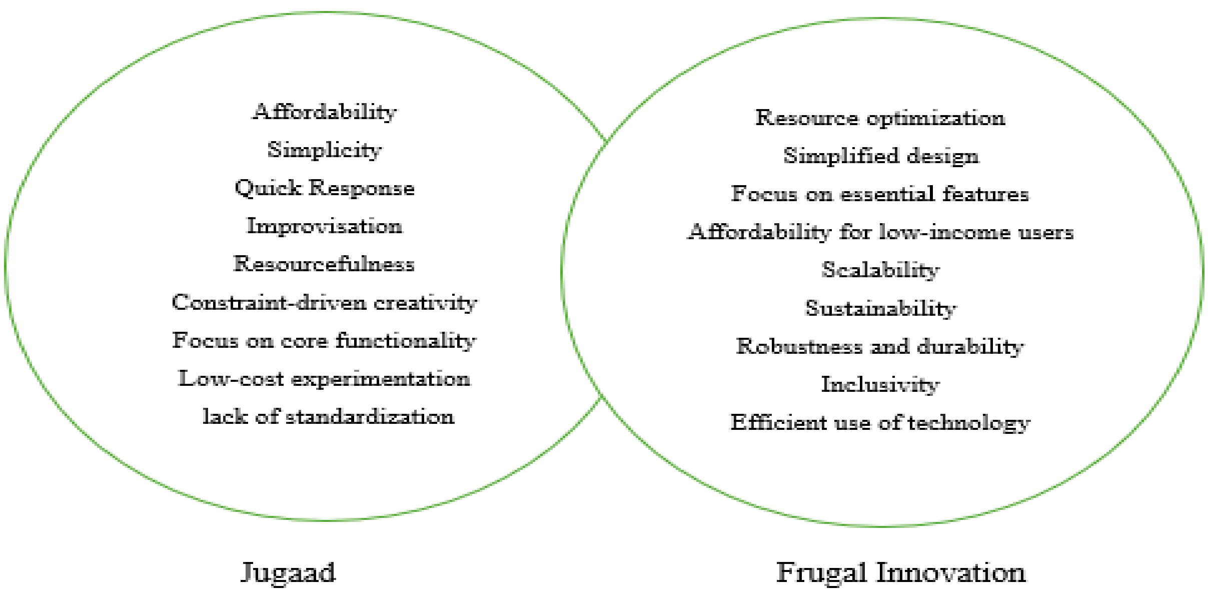

Figure 1. Characteristic of Jugaad and Frugal Innovation

2.2 Structured Innovation and Scalability

Structured innovation frameworks, such as Stage-Gate, TRIZ, Design Thinking, and Lean Innovation, provide disciplined and repeatable mechanisms for generating, refining, and scaling new ideas (Cooper, 2019). These methodologies differ significantly from Jugaad by emphasizing evidence-based evaluation, formal experimentation, and controlled iterative processes. The Stage-Gate model, developed by Cooper, organizes the innovation process into a sequence of stages interconnected by decision gates. These stages ranging from opportunity identification and preliminary assessment to full development, validation, and market introduction necessitate systematic data collection, cross-functional collaboration, and thorough documentation. Gates act as critical checkpoints where decision-makers evaluate commercial viability, technical feasibility, risk exposure, and resource requirements. By screening weaker concepts early and channeling resources toward promising initiatives, the Stage-Gate approach enhances predictability, reduces uncertainty, and facilitates effective resource allocation, making it particularly suitable for large-scale or high-stakes projects. TRIZ, which emerged from the systematic study of global patents, identifies recurring patterns in inventive solutions. Unlike intuition-driven approaches, TRIZ provides structured toolsincluding the Contradiction Matrix, the 40 Inventive Principles, and the Ideal Final Result concept—that assist innovators in resolving technical conflicts where improvements in one area may create trade-offs in another. This methodology is especially valuable in engineering-intensive contexts, where stringent constraints demand technically sound yet creative solutions. TRIZ's systematic problem-solving approach enhances reproducibility and fosters breakthrough innovations. Lean Innovation applies the principles of Lean Startup to the innovation process by emphasizing rapid experimentation and evidence-informed decisions. Rather than committing to fully developed products, teams start with Minimum Viable Products (MVPs) to test hypotheses with minimal cost. Feedback from users drives iterative refinements, pivots, or scaling decisions. This methodology is particularly effective in dynamic markets, early-stage ventures, and resource-constrained environments. Lean Innovation minimizes waste, accelerates the discovery of product-market fit, and mitigates financial risk by focusing exclusively on features that deliver customer value. Design Thinking is a human-centred approach that emphasizes a deep understanding of user experiences and needs. It generally unfolds in five phases: empathizing with users, defining core problems, generating a broad range of ideas, developing prototypes, and evaluating solutions through real-world testing. This approach encourages cross-disciplinary collaboration and prioritizes learning through rapid cycles of making and testing, reducing the likelihood of costly errors. By aligning solutions with social, emotional, and cultural realities, Design Thinking bridges desirability, feasibility, and viability, rendering it particularly influential in contexts where user acceptance and experiential value are critical. Collectively, these structured innovation frameworks enhance the reliability, sustainability, and scalability of innovation by integrating rigorous analysis with iterative refinement, offering a systematic alternative to improvisational approaches such as Jugaad. Unlike Jugaad, these formalized processes rely on empirical data, structured experimentation, and repeatable cycles of refinement. Scholars suggest that the adoption of formalized methodologies strengthens the reproducibility and long-term sustainability of innovations, ensuring broader impact and market applicability (Tiwari & Herstatt, 2014).

2.3 Deep Learning and AI-Enabled Innovation

Deep learning has emerged as a transformative technology in multiple domains, including medical diagnostics (Esteva et al., 2017), predictive agriculture (Kamilaris & Prenafeta-Boldú, 2018), and personalized recommendation systems (Zhang et al., 2019). Its strength lies in recognizing complex patterns, delivering real-time insights, and automating intricate tasks. However, deep learning typically depends on structured, labelled datasets resources often lacking in environments dominated by Jugaad. The technology has become central across industries due to its capability to process large-scale data, identify subtle correlations, and produce highly reliable predictions. In healthcare, deep learning models have revolutionized diagnostic accuracy. For instance, research by Esteva et al. (2017) demonstrates that neural network-based systems can match, and occasionally surpass, expert clinicians in detecting conditions such as skin cancer, retinal disorders, tumours, and cardiovascular anomalies. Convolutional neural networks (CNNs), trained on millions of labelled images, detect subtle features that conventional analytical methods often miss, enabling earlier and more accurate disease detection. In agriculture, deep learning acts as an effective decision-support tool for farmers. Kamilaris and Prenafeta-Boldú (2018) report that models can accurately map crop types, forecast planting and harvesting cycles, detect nutrient deficiencies, and analyze satellite or drone imagery. These capabilities enable farmers to transition from reactive management to predictive strategies, a crucial advantage in regions facing limited resources or environmental variability. In digital platforms, deep learning supports personalized recommendations. Neural architectures including recurrent neural networks (RNNs), transformers, and deep collaborative filtering process user behavior, contextual factors, and historical data to provide individualized content. This dynamic adaptation improves user engagement by continuously updating recommendations as preferences evolve. The versatility of deep learning lies in its adaptability, real-time decision-making capacity, and ability to extract meaningful patterns from complex datasets, positioning it as a critical driver of modern innovation in healthcare, agriculture, retail, finance, and smart city applications. Jugaad, on the other hand, exemplifies bottom-up, resource-constrained innovation characterized by improvisation, context-specific adaptation, and low-cost problem-solving (Birtchnell, 2011). Frugal innovation builds on these principles by introducing structured mechanisms that emphasize affordability, essential functionality, and maximum value for underserved communities (Weyrauch & Herstatt, 2017; Zeschky, Widenmayer, & Gassmann, 2014). Recent advances in lightweight deep learning architectures, such as MCUNet and TinyTL, enable neural networks to function efficiently on microcontrollers and embedded systems, allowing AI integration in resource-constrained settings (Lin et al., 2020; Cai et al., 2020; Lin et al., 2022). In agriculture, these lightweight models can provide precise disease detection and yield forecasts on smallholder farms, demonstrating the potential for predictive AI even in low-resource contexts (Kamilaris & Prenafeta-Boldú, 2018). Similarly, in healthcare, deep learning-driven diagnostic tools—capable of dermatologist-level accuracy highlight the feasibility of high-precision applications outside conventional clinical infrastructures (LeCun, Bengio, & Hinton, 2015; Esteva et al., 2017). Frugal and reverse innovation approaches extend the reach of these solutions by enabling low-cost, scalable deployment beyond localized settings (Govindarajan & Trimble, 2012; Zeschky, Winterhalter, & Gassmann, 2014). Additionally, Edge-AI and TinyML solutions in rural healthcare and environmental monitoring illustrate how compact AI models can deliver affordability, usability, and local relevance (Chakraborty & Joshi, 2022; Das & Subramanian, 2023; Zhang & Singh, 2021; Banbury et al., 2020). Case studies such as GE Vscan demonstrate that frugal innovations can enhance healthcare access, and their integration with deep learning can further improve automation, prediction, and scalability (Ramdorai & Herstatt, 2015; Soni & Krishnan, 2014; Cunha, Rego, & Caldeira, 2014; Song-Myung et al., 2020; Brem & Wolfram, 2014). Collectively, these insights indicate that combining Jugaad, frugal innovation, and deep learning produces a hybrid model capable of delivering cost-effective, context-aware, and technologically robust solutions in resource-constrained environments.

2.4 Integrating Jugaad with Deep Learning

Recent scholarship highlights the potential synergies between grassroots, frugal innovation and AI-enabled systems. Deep learning can enhance Jugaad by providing automation, efficiency, and predictive intelligence, while Jugaad contributes context specificity, affordability, and usability that are often missing in high-tech solutions (Chakravarty, 2020; Bound & Thornton, 2012). This integration can be conceptualized across five thematic streams. First, literature on Jugaad innovation underscores improvisation, adaptability, and low-cost problem-solving, particularly under severe constraints (Radjou et al., 2012; Birtchnell, 2011). These principles offer a frugal mindset essential for designing solutions tailored to underserved populations. Second, research on frugal innovation emphasizes cost efficiency, essential functionality, and optimal use of limited resources, which facilitates the scaling of grassroots ideas into viable products (Weyrauch & Herstatt, 2017; Tiwari & Herstatt, 2014). Third, structured innovation frameworks provide systematic evaluation, disciplined experimentation, and data-informed decision-making, demonstrating how formalized processes enhance repeatability and long-term sustainability (Cooper, 2019; Prabhu & Jain, 2015). Fourth, deep learning contributes advanced pattern recognition, predictive modeling, and automated decision-making, enriching frugal solutions with intelligence and reliability (LeCun et al., 2015; Esteva et al., 2017). Fifth, studies on AI applications in low-resource contexts illustrate how compact, cost-effective automation and real-time monitoring can elevate Jugaad innovations into scalable, smart systems (Bound & Thornton, 2012; Kamilaris & Prenafeta-Boldú, 2018). Collectively, these streams suggest that merging Jugaad and deep learning establishes a pathway for contextually intelligent, scalable, and sustainable innovation in resource-constrained settings.

III. CONCEPTUAL INTEGRATION: DEEP LEARNING JUGAAD

Deep Learning Jugaad represents the convergence of grassroots ingenuity with the computational power of deep learning, producing innovations that are both affordable and technologically sophisticated. Traditionally, Jugaad relies on improvisation, rapid problem-solving, and efficient use of scarce resources. While these solutions are clever and context-specific, they often lack repeatability, precision, and scalability. Introducing deep learning transforms these improvisations into intelligent, adaptive systems capable of processing data, recognizing patterns, and forecasting outcomes with high accuracy. Low-cost devices can thus become smart tools offering real-time insights, automated decision-making, and reduced human error, which is especially valuable in environments with limited technical expertise or professional support. Through this integration, Deep Learning Jugaad also enables innovations to expand beyond local contexts. Continuous data collection allows models to improve iteratively, making solutions robust and applicable to broader populations. Consequently, Deep Learning Jugaad fosters sustainable innovation by maintaining affordability while enhancing reliability, intelligence, and long-term utility in resource-limited settings.

3.1 From Improvisation to Intelligent Innovation

Jugaad traditionally delivers rapid solutions but relies heavily on user intuition and lacks precision. Embedding deep learning imparts the following capabilities:

1. Data-driven accuracy
2. Predictive functionality
3. Automated responses
4. Standardized performance

For example, a low-cost medical device equipped with basic sensors can become an intelligent diagnostic tool capable of predicting hypertension or arrhythmias using trained neural networks. Deep learning models trained on longitudinal data can personalize insights such as dietary adjustments, medication reminders, or lifestyle guidance. This transforms one-size-fits-all Jugaad tools into adaptive, user-specific systems. A key limitation of Jugaad is its dependence on users to interpret results; integrating deep learning allows automated alerts, remote physician notifications, and real-time anomaly detection, which are critical in underserved regions. Deep learning enhances telemedicine by providing accurate, data-driven analysis across diverse clinical contexts. It improves anomaly detection, identifying subtle irregularities in medical images, sensor readings, or signals. For instance, CNNs can detect arrhythmias from ECG data or early diabetic retinopathy signs with high sensitivity (Rajpurkar et al., 2017; Gulshan et al., 2016). RNNs and LSTM models enable the prediction of patient deterioration by analyzing longitudinal data, allowing proactive interventions in remote monitoring scenarios (Jiang et al., 2017). Deep learning also strengthens clinical decision support by generating diagnostic probabilities, triage suggestions, and treatment recommendations, sometimes matching or exceeding expert performance in dermatology and radiology (Esteva et al., 2017; Topol, 2019). Collectively, these capabilities make telemedicine more proactive, reliable, and scalable, extending the reach of grassroots innovations beyond local boundaries.

3.2. Scalability and Continuous Learning

Deep learning models improve as more users engage with the system, enabling solutions to scale beyond local limitations. While traditional Jugaad solutions are typically non-scalable and informal, AI-powered systems benefit from large datasets, transforming localized improvisations into national or global solutions. The integration of Jugaad and deep learning leverages both grassroots creativity and advanced computational intelligence. From the Jugaad perspective, the model incorporates affordability, contextual relevance, rapid prototyping, and local usability, features emphasized by Radjou et al. (2012) and Birtchnell (2011) as crucial for problem-solving in resource-constrained contexts. These characteristics ensure that innovations remain culturally aligned and accessible. Deep learning contributes high precision, automation, predictive analytics, and scalability, as demonstrated in healthcare (Esteva et al., 2017), agriculture (Kamilaris & Prenafeta-Boldú, 2018), and real-time decision systems (LeCun, Bengio, & Hinton, 2015). The synergy enables Jugaad solutions traditionally criticized for informality and temporariness to gain structure, reliability, and long-term viability, while deep learning becomes grounded, socially inclusive, and contextually relevant. This integrated paradigm is particularly transformative in sectors where affordability and real-time insights are essential, including telemedicine, precision agriculture, disaster response, and public health logistics. For instance, deep learning-enabled diagnostic devices can be embedded into low-cost rural healthcare tools, while AI-powered crop disease detection can be combined with frugal, locally adapted farming implements. The integration enhances performance, broadens access, and creates a sustainable, equitable innovation model tailored for the Global South.

IV. CONCLUSION AND FUTURE SCOPE

Jugaad exemplifies the capacity of resource-constrained communities to generate effective solutions through improvisation, repurposing, and contextual adaptation but it lacks sustainability and standardisation. Birtchnell (2011) conceptualizes this as “everyday innovation under scarcity,” emphasizing adaptive problem-solving in environments marked by limited capital and infrastructure. Frugal innovation, while sharing this foundational orientation toward scarcity, introduces a more structured methodology, emphasizing essential functionality, cost-effectiveness, and the creation of tangible value for underserved populations (Weyrauch & Herstatt, 2017; Tiwari & Herstatt, 2014). Deep learning, in contrast, represents the analytical and computational dimension of modern innovation, offering high-precision pattern recognition, predictive modeling, and scalable automation capabilities (LeCun, Bengio & Hinton, 2015; Esteva et al., 2017). The integration of these paradigms termed Deep Learning Jugaad constitutes a hybrid innovation model wherein the improvisational flexibility of grassroots problem-solving is complemented by the structured rigor of frugal design and the computational intelligence of deep learning. Conceptually, this framework enables the simultaneous achievement of affordability, reliability, scalability, and analytical rigor. It addresses inherent limitations in both domains: Jugaad gains methodological structure and predictive capability, while deep learning becomes contextually grounded, socially inclusive, and adaptable to environments with constrained resources. Operationalizing this framework entails the deployment of lightweight, energy-efficient neural networks, such as those enabled by TinyML, which can function on low-cost microcontrollers and embedded systems (Reddi et al., 2021). In agriculture, localized deep-learning applications demonstrate that predictive models can operate effectively within smallholder farming contexts, providing actionable insights while remaining sensitive to infrastructural and financial constraints (Kamilaris & Prenafeta-Boldú, 2018). Similarly, low-cost diagnostic tools incorporating embedded AI, exemplified by the MAIScope, illustrate the potential for community-level innovations to achieve enhanced accuracy, automation, and sustainability (Sangameswaran, 2022).

4.1 Future Scope of Study

By positioning frugal, context-aware design alongside computational intelligence, the Deep Learning Jugaad paradigm offers a theoretically grounded approach for fostering sustainable, inclusive, and technologically robust innovations. Future research may empirically validate this framework through structured field trials, longitudinal studies, and pilot implementations across healthcare, agriculture, disaster management, and rural development, thereby advancing both scholarly understanding and practical applicability of hybrid innovation models. The convergence of Jugaad, frugal innovation, and deep learning presents a promising avenue for developing sustainable and contextually relevant solutions in resource-constrained environments. Jugaad, characterized by improvisation, affordability, and grassroots ingenuity, provides a foundation for localized problem-solving that addresses immediate societal needs (Birtchnell, 2011; Radjou, Prabhu, & Ahuja, 2012; Prabhu & Jain, 2015). Frugal innovation builds on this ethos by introducing structured mechanisms for cost-effectiveness, essential functionality, and scalability, enabling low-cost solutions to achieve broader adoption in emerging markets (Weyrauch & Herstatt, 2017; Tiwari & Herstatt, 2014; Zeschky, Widenmayer, & Gassmann, 2014). Integrating these principles with deep learning — including lightweight, energy-efficient architectures such as TinyML and MCUNet offers the potential to embed intelligence and predictive capabilities into grassroots innovations without significantly increasing cost or complexity (Lin et al., 2020, 2022; Reddi et al., 2021; Banbury et al., 2020). Future research can explore practical applications of this hybrid model across healthcare, agriculture, and environmental monitoring. For instance, deep learning can enhance diagnostic accuracy in low-resource medical settings, as evidenced by AI-powered malaria detection devices like MAIScope (Chakraborty & Joshi, 2022; Das & Subramanian, 2023; Esteva et al., 2017). Similarly, predictive models in agriculture can improve smallholder crop yield forecasts, while TinyML-enabled IoT devices can monitor environmental parameters in rural areas efficiently (Kamilaris & Prenafeta-Boldú, 2018; Zhang & Singh, 2021). Empirical investigations into user adoption, cost-benefit trade-offs, and scalability pathways will be essential to validate the viability of Deep Learning Jugaad. Policy and ecosystem support, coupled with open-source AI tools, can further empower grassroots innovators to harness computational intelligence while maintaining affordability and contextual relevance (Chakravarty, 2020; Angus & Bound, 2012; Bound & Thornton, 2012). By systematically integrating Jugaad, frugal innovation, and deep learning, future research can shape a paradigm where high-tech solutions are accessible, sustainable, and inclusive, driving socio-economic development in traditionally underserved communities (Govindarajan & Trimble, 2012; Song-Myung et al., 2020; Soni & Krishnan, 2014; Brem & Wolfram, 2014; Cunha et al., 2014).

REFERENCES

[1] Angus, A., & Bound, K. (2012). Innovation in low-resource contexts. NESTA.

[2] Banbury, C., Zhou, C., Fedorov, I., Navarro, R. M., Thakker, U., Gope, D., Janapa Reddi, V., Mattina, M., & Whatmough, P. (2020). MicroNets: Neural network architectures for deploying TinyML applications on commodity microcontrollers. arXiv. https://arxiv.org/abs/2010.1126

[3] Birtchnell, T. (2011). Jugaad as systemic risk and disruptive innovation in India. Contemporary South Asia, 19(4), 357–372. https://doi.org/10.1080/09584935.2011.569702

[4] Brem, A., & Wolfram, P. (2014). Research and development from the bottom up: Introduction of terminologies for new-product development in emerging markets. Journal of Innovation and Entrepreneurship, 3(9). https://doi.org/10.1186/2192-5372-3-9

[5] Bound, K., & Thornton, I. (2012). Our frugal future: Lessons from India's innovation system. NESTA.

[6] Cai, H., Gan, C., Zhu, L., & Han, S. (2020). TinyTL: Reduce activations, not trainable parameters for efficient on-device learning. arXiv. https://arxiv.org/abs/2007.11622

[7] Chakraborty, S., & Joshi, A. (2022). AI for social good: Potential of machine learning in low-resource communities. IEEE Access, 10, 12345–12360. https://doi.org/10.1109/ACCESS.2022.3145234

[8] Chakravarty, A. (2020). AI and grassroots innovation: Opportunities for frugal ecosystems. Technology in Society, 63, 101–123. https://doi.org/10.1016/j.techsoc.2020.101123

[9] Cunha, J. V., Rego, A., & Caldeira, M. (2014). Good enough and frugal: On the quality and sustainability of low-cost products. Technological Forecasting & Social Change, 81, 90–100. https://doi.org/10.1016/j.techfore.2013.10.001

[10] Cooper, R. (2019). Winning at new products: Creating value through innovation. Basic Books.

[11] Das, P., & Subramanian, V. (2023). Edge-AI for rural healthcare diagnostics: A review. Frontiers in Digital Health, 5, 101234. https://doi.org/10.3389/fdgth.2023.101234

[12] Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. Nature, 542, 115–118. https://doi.org/10.1038/nature21056

[13] Govindarajan, V., & Trimble, C. (2012). Reverse innovation: Create far from home, then distribute globally. Harvard Business Review, 90(4), 120–127.

[14] Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. Computers and Electronics in Agriculture, 147, 70–90. https://doi.org/10.1016/j.compag.2018.02.016

[15] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521, 436–444. https://doi.org/10.1038/nature14539

[16] Lin, J., Chen, W.-M., Lin, Y., Cohn, J., Gan, C., & Han, S. (2020). MCUNet: Tiny deep learning on IoT devices. In Advances in Neural Information

Processing Systems, 33 (NeurIPS 2020). https://arxiv.org/abs/2007.10319
[17] Lin, J., Zhu, L., Chen, W.-M., Wang, W.-C., Gan, C., & Han, S. (2022). On-device training under 256 KB memory. arXiv. https://arxiv.org/abs/2206.15472
[18] Prabhu, J., & Jain, S. (2015). Innovation and entrepreneurship in India: Understanding jugaad. Asia Pacific Journal of Management, 32(4), 843–868. https://doi.org/10.1007/s10490-015-9421-7
[19] Ramdorai, A., & Herstatt, C. (2015). Frugal innovation and reverse innovation in healthcare sector: The case of GE Vscan. In Proceedings of XXX International Conference on Engineering, Technology and Innovation.
[20] Radjou, N., Prabhu, J., & Ahuja, S. (2012). Jugaad innovation. Jossey-Bass.
[21] Soni, P., & Krishnan, R. (2014). Frugal engineering and innovation: An overview. Journal of Management & Strategy, 5(2), 45–56.
[22] Song-Myung, L., Yuen, K. F., Kumar, A., & Yeong, W. L. (2020). Frugal innovation: Sustainable growth strategy for emerging markets. Journal of Cleaner Production, 253, 120015. https://doi.org/10.1016/j.jclepro.2020.120015
[23] Tiwari, R., & Herstatt, C. (2014). A framework for frugal innovation. Journal of Product Innovation Management, 31(1), 15–29. https://doi.org/10.1111/jpim.12105
[24] Weyrauch, T., & Herstatt, C. (2017). What is frugal innovation? Three defining criteria. Journal of Frugal Innovation, 2(1), 1–17. https://doi.org/10.1186/s40669-016-0005-y
[25] Zeschky, M., Widenmayer, B., & Gassmann, O. (2014). Frugal innovation in emerging markets: A conceptual framework. R&D Management, 44(3), 310–327. https://doi.org/10.1111/radm.12050
[26] Zeschky, M., Winterhalter, S., & Gassmann, O. (2014). From cost to frugal and reverse innovation: Mapping the field and future directions. Research-Technology Management, 57(4), 20–27. https://doi.org/10.5437/08956308X5704003
[27] Zhang, S., Yao, L., Sun, A., & Tay, Y. (2019). Deep learning-based recommender system: A survey. IEEE Transactions on Systems, Man, and Cybernetics, 49(1), 1–24. https://doi.org/10.1109/TSMC.2018.2876865
[28] Zhang, Y., & Singh, M. (2021). TinyML-based environmental monitoring for sustainable development in rural areas. Sensors, 21(9), 3056. https://doi.org/10.3390/s21093056