International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 13 Issue: 08 | Aug 2026 www.irjet.net p-ISSN: 2395-0072

Advancements in Agricultural Residue Pelletization Technology, Autonomous Solar-Powered Farm Mechanization, and IoT-Driven Precision Resource Optimization: A Comprehensive Engineering Review

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Abstract-*Global agriculture is confronted with the dual imperatives of fulfilling escalating food security demands for an anticipated population of 10 billion by 2050 while drastically mitigating anthropogenic environmental impacts, greenhouse gas (GHG) emissions, and extreme fossil fuel dependency. In emerging agricultural economies, over 70% of the rural populace depends on agronomic livelihoods, yet conventional farm practices remain burdened by severe inefficiencies. These include high physical drudgery, inconsistent manual broadcasting and dibbling resulting in low seed emergence (<70%), excessive operational expenditure, extensive water wastage via unmonitored flood irrigation (which consumes up to80%offreshwaterresources),and massive post-harvest biomass burning of agricultural residues. This comprehensive engineering review synthesizes the paradigm shift toward sustainable agro-industrial ecosystems by critically investigating three interdependent technological domains: (1) Thermo-mechanical densification and pelletization technologies for agricultural residues (paddy straw, wheat straw, cotton stalks, and Stover) into standardized solid bio fuels with bulk densities exceeding 650–700 kg/m^3 and calorific values of 17.5–18.5 MJ/kg; (2) Autonomous and semi-automated solar-photovoltaic multi-crop seeding mechanisms engineered with high-torque DC drives, rotary shear cutters, calibrated frustum metering discs, and finite element method (FEM)-optimized structural chassis; and (3) Closed-loop Internet of Things (IoT) architectures integrated with supervised machine learning algorithms (Random Forest achieving 99.8% classification accuracy with 0.16 MSE, Naïve Bayes, SVM, and Logistic Regression) and cloud predictive analytics (ThingSpeak/Blynk) for variable-rate micro-irrigation and remote agronomic control. We rigorously analyze mathematical kinematic models of power transmission, shear stress distributions during furrow opening, machine learning predictive pipelines, and life-cycle techno-economic feasibility. Finally, the review identifies critical research gaps in thermal control, edge-AI deployment, multi-residue binder rheology ,and real-time field navigation, proposing a multi-objective engineering roadmap for scalable, zero-emission smart agriculture.*

Keywords-Agricultural Residue Pelletization; Solid Biofuels; Solar Photovoltaic Farm Machinery; Precision Seed Metering; Finite Element Analysis (FEA); Internet of Things (IoT); Supervised Machine Learning; Closed-Loop Smart Irrigation

1. INTRODUCTION

Agriculture represents the fundamental cornerstone of socio-economic stability and food security across the globe, especially in developing economies where more than 70% to 75% of the rural population directly derives subsistence and employment from agrarian activities [1, 2]. With global demographics projected to surpass 10 billion individuals by the mid-21st century, agricultural output must expand by an estimated 70%to double current production levels to stave off severe food shortages and malnutrition [8, 10]. However, conventional farming methodologies are fundamentally ill-equipped to sustain such escalating demand without causing severe environmental degradation and rapid resource depletion [9].

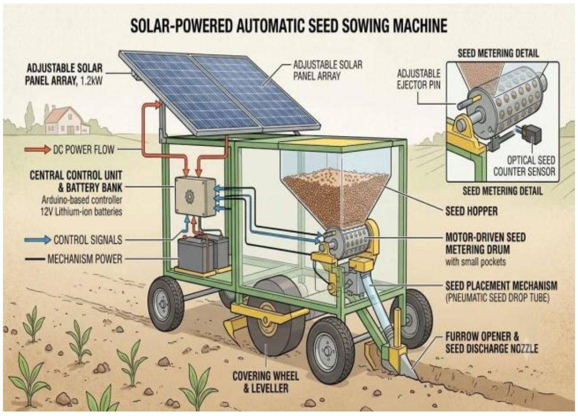

FIG:1.1

Traditional agronomic workflows exhibit severe mechanical and operational bottlenecks. Land preparation and seed sowing are historically executed via manual broad casting, rudimentary wooden/bullock-drawn ploughs, or fossil-fuel-powered internal combustion engine (ICE)tractors. Manual broadcasting and dibbling suffer from extensive human error, resulting in non-uniform seed-to-seed spacing, highly erratic furrow depths, excessive seed clustering, poor seed-to-soil compaction, and vulnerability to bird scavenging and wind erosion [3, 4, 8]. Consequently, seed emergence rates under traditional manual methods often stagnate between 60% and 75%, leading to substantial seed wastage and compromised plant population density [1, 6]. Concurrently, manual operations inflict severe musculoskeletal fatigue and occupational drudgery on smallholder farmers, while heavy ICE tractors emit copious particulate matter, CO2, and NOx, simultaneously burdening resource-poor farmers with volatile fossil fuel expenditures [1, 7].

In parallel with planting challenges, post-harvest crop residue management has emerged as an acute agro-environmental crisis. Across major cropping systems, billions of tons of lingo cellulosic crop residues including paddy straw, wheat straw, cotton stalks, sugarcane bagasse, and corn stover are generated annually. Lacking cost-effective recovery, collection, and processing infrastructure, farmers resort to in-situ open-field stubble burning. This uncontrolled combustion releases hazardous concentrations of particulate matter (PM2.5 and PM10), polycyclic aromatic hydrocarbons (PAHs), and carbon monoxide into the troposphere, triggering severe seasonal smog and depleting essential topsoil organic carbon and microbial diversity. Converting these bulky, low-density (50–100 kg/m^3) agricultural residues into high-density, energy-dense solid bio-pellets via thermo-mechanical densification offers a viable circular economy paradigm, transforming an environmental hazard into a standardized green fuel for rural decentralized power generation and industrial thermal applications.

Furthermore, agricultural water management poses another existential vulnerability. The agricultural sector consumes approximately 70% to 80% of global freshwater withdrawals [9, 10]. Traditional flood or wild furrow irrigation exhibits poor water application efficiencies (<40%), causing massive water wastage, nutrient leaching, deep percolation losses, and severe soil Stalinization [10]. Although modern micro-irrigation systems (drip and sprinkler) exist, their widespread adoption by smallholders is impeded by rigid piping networks, vulnerability to rodent damage, clogging, and the absence of intelligent, automated scheduling based on real-time soil moisture dynamics and local micro-climatic evapo transpiration [9, 10].

To surmount these multi-faceted challenges, an integrated engineering framework urgently required.

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To surmount these multi-faceted challenges, an integrated engineering framework urgently required.

This paper presents a holistic review of three converging technological vectors:

(1) Agricultural residue valorization through engineered pelletization;

(2) Renewable solar-photovoltaic automated seeding and furrow-opening machinery; and(3)Edge-IoT and

2. AGRICULTURAL RESIDUE PELLETIZATION TECHNOLOGY &VALORIZATION

Agricultural residues are inherently heterogeneous, anisotropic lignocelluloses matrices characterized by high moisture content (15–40%), extremely low bulk density(50–110 kg/m^3), low energy density by volume (1.0–2.5 GJ/m^3), poor grind ability, and irregular fibrous morphology. These raw properties make untreated biomass logistically challenging to transport, store, and feed uniformly into combustion or gasification systems. Pelletization is an advanced thermo-mechanical densification process wherein ground biomass particles are subjected to extreme compaction pressures (100–300 MPa) and elevated temperatures (80–140°C) inside cylindrical die channels, transforming loose residues into standardized, durable, high-density solid befouls.

Pre-Treatment, Conditioning, and Extrusion Unit Operations

Feedstock Preparation Protocols: Achieving optimal pellet quality requires precise control over pre-pelletization unit operations:

Machine-learning-driven closed-loop irrigation systems. Fig. 1 illustrates the overall process cycle linking residue densification, renewable farm machinery, and smart cultivation.

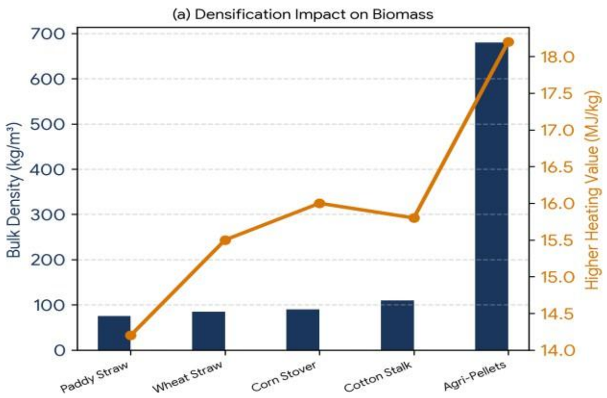

FIG1.2

2.1 Fundamental Physics of Biomass Densification

The densification mechanism progresses through three distinct physical stages within the extrusion die: (a) Particle rearrangement and elimination of inter-particle macro-voids under low-pressure; (b) Elastic and plastic deformation of biomass cellular structures under intermediate pressure, causing particle interlocking; and (c)Thermal softening and glass transition of native amorphous polymers (lignin, hemicelluloses, and pectin) under high friction-induced temperatures. Above its glass transition temperature (Tg ≈ 70–100°C under moisture), natural lignin plasticizes, flows across particle boundaries, and forms solid inter-molecular polymer bridges upon cooling. This natural thermosetting binding action eliminates the necessity for artificial chemical binders in well-conditioned feedstock.

Moisture Conditioning: Rawfeed stock moisture must be conditioned to a tight operational window of 8% to 12% (wet basis). Moisture below 8% generates excessive frictional resistance, leading to die clogging and thermal degradation; moisture exceeding 14% creates steam pockets during compaction, inducing extensive axial cracking and structural crumbling.

Thermal Preheating & Conditioning: Injecting low-pressure saturated steam (100–120°C) pre-activates lignin and reduces die drive electrical power consumption by up to 20–35%.

2.2 Mechanical Durability, Energy Density, and Emission Metrics

As synthesized in Table 1 and illustrated in Fig. 2(a), densification multiplies biomass bulk density by a factor of 6 to 9 (from ~75 kg/m^3 to >680 kg/m^3), while unit pellet density exceeds 1150–1250 kg/m^3. Volumetric energy density surges from 1.1 GJ/m^3 to over12.0GJ/m^3,revolutionizing logistics and storage

2.3 LITERATUREREVIEW:

To establish the current state-of-the-art across precision seeding, clean energy agricultural platforms, and automated robotics, a systematic analysis of foundational and contemporary literature was conducted across the source documents:

Pundkar & Mahalle (2015, 2021) conducted extensive reviews on pneumatic and mechanical seed sowing implements. They demonstrated that precision metering mechanisms are vital for uniform seed dispersion along travel paths, noting that intra-row spacing, seed rate control, and adequate furrow compaction are primary Economics. Mechanical durability index (evaluated via standard tumbling box tester ASAE S269.5) consistently surpasses 97.5% for well-compacted agro-pellets. When co-combusted in decentralized power boilers or gasifies, these pellets achieve thermal efficiencies exceeding 82% with an 85–90% reduction in unburned particulate emissions compared to open-field burning.Determinants of crop yield and field capacity [1, 4, 8].

Shelke (2011) evaluated animal-drawn and mechanized planters for soybean cultivation, documenting that maintaining optimum plant population density and controlled row spacing increased grain yields by 15–22% while overcoming acute peak-season rural labor shortages [1, 3, 4, 6].

Iqbal et al. (2010) and Soomro et al. (2009) investigated wheat agronomic parameters under varying seeding techniques. They established that mechanical seed drilling at a calibrated rate of 125 kg/ha and uniform 3.0 cm depth significantly enhanced tailoring, root anchoring, and overall wheat yield compared to manual broadcasting [1,3, 5].

Joshua et al. (2010) and Swetha & Shreeharsha (2015) pioneered solar-photovoltaic agricultural implementations. Swetha et al. integrated a 10W–40W PV module, 12V/24V battery storage, and a DC shunt motor to drive automated furrow cutters and seeding mechanisms, employing peripheral infrared (IR) sensors and boundary posts for autonomous row maneuvering [1, 3, 7].

Dhandeet al. (2017) eliminated complex, failure-prone mechanical gear trains by integrating magnetic Hall Effect sensors with an ATmega16 microcontroller. This system converted wheel rotational counts into precise linear travel distances, actuating seed release solenoids at calibrated intervals formulti-crops pacing[1,3,5].

Kathiravan & Balashanmugam (2019) engineer eda multi-functional manually operated planter integrating a reciprocating piston pesticide pump driven by a slider-

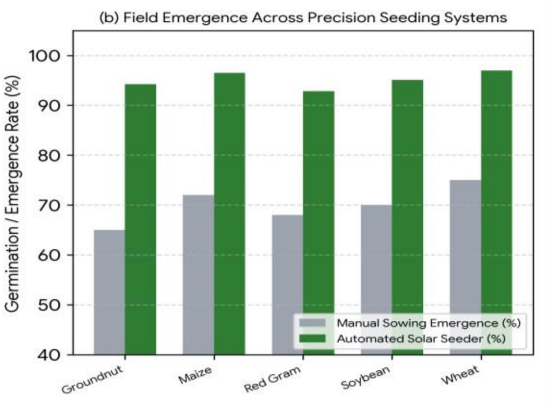

FIG:1.3 crank wheel mechanism. Their experimental results demonstrated a 69.96% reduction in human labor man-hours and a 13.02%yield increase compared to traditional methods [1, 4].

1. Kumar & Ashok (2020) developed an IoT-controlled smart seeding robot featuring an articulated 3D-printed robotic arm and ESP32 microprocessor. Utilizing ultrasonic sensors for obstacle avoidance and line-tracking sensors for lane following, the robotic arm picked and placed individual seeds for corn, groundnut, and red gram, achieving high seedling emergence [1, 6].
2. Kumar, Govil, Daga, Goel & Dewangan (2022) executed comprehensive CAD modeling and Finite Element Analysis (FEA) of automated seeders. Their structural simulations established that high-stress components (plough shear points and soil leveling sliders) operated well within permissible yield thresholds under continuous soil resistance [8].
3. Vij et al. (2020) and Kaur, Bhatt & Raja (2024) developed intelligent IoT-ML hybrid irrigation architectures. By networking DHT11, capacitive soil moisture, anemometer, and rain sensors to Thing Speak and Blynk cloud servers, they applied supervised ML algorithms (Random Forest, SVM, Naïve Bayes, and Logistic Regression), achieving 98.3%to99.8%precisioninautonomousirrigation scheduling [9, 10].

2.4 MATHEMATICAL DESIGN,POWER KINEMATICS, AND FINITE ELEMENTS TRUCTURAL ANALYSIS

To ensure optimal operational stability, power efficiency, and long-term mechanical reliability under aggressive field conditions, a rigorous mathematical kinematic model coupled with static finite element structural verification was formulated

KINEMATICS, ANDFINITE

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Power Transmission Kinematics & Belt-Pulley Drive Design

Velocity Ratio & Rotational Kinematics: The primary motive torque for driving the rotary soil-furrow cutter is derived from a 24V High-Torque DC motor operating at an initial rated speed N=25RPM geared down from 1800 RPM). Power is transmitted to the high-carbon steel cutter tool via an open flat/V-belt pulley configuration [1, 4]:

(geared down from 1800 RPM). Power is transmitted to the high-carbon steel cutter tool via an open flat/V-belt pulley configuration [1, 4]:

2.5 Finite Element Structural & Stress-Deformation Analysis (FEA)

Structural Simulation Results: During furrow creation, the cutter teeth and soil deflector blades endure continuous resistive shear forces from compacted soil (draft force F_draft ≈ 500 N). Static structural FEA simulations conducted in ANSYS/Cero[8] reveal critical stress concentrations and directional

EXPERIMENTAL FIELD PERFORMANCE & MULTI-CROP AGRONOMIC VALIDATION

Experimental field trials were conducted across five major crop varieties: Groundnut (Peanut), Maize (Corn), Red Gram (Pigeon Pea Dal), Soybean, and Wheat Grain

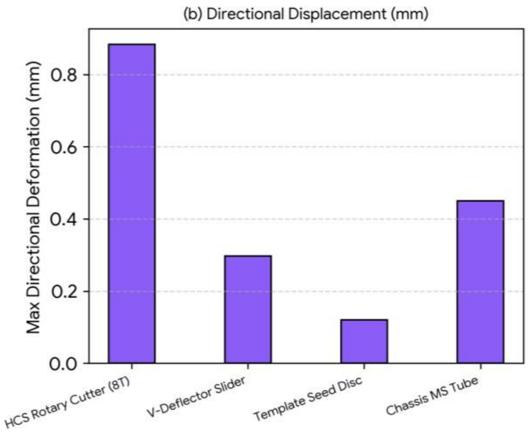

Fig.3. Structural Finite Element Analysis (FEA) Verification: Peakvon Mises Stressvs.Allowable Material Yield Strength;

Maximum Directional Displacements Across Critical Mechanical Components.

under tilled loamy soil conditions [1, 4,6]. Sowing depth, discharge speed, seed rate, and field emergence rates were systematically logged.

As compiled in Table 3 and depicted in Fig. 2(b), the automated solar seeder achieved outstanding germination emergence rates exceeding 92.8% to 97.0% acrossalltested **FIG:1.4**High-Carbon Steel Rotary Cutter (8 Sharp Teeth, 220 mmDia,20mmShaft):The peak equivalent on Misses stress reached 312.11 MPa at the tooth root fillet, remaining safely below the material yield strength(σ_y= 450 MPa), resulting in a safety factor of 1.44. Maximum directional deformation was 0.883mm [8].

V-Shaped Mild Steel Soil Deflector Slider: Peak von Mises stress reached 181.90 MPa, well below structural MS yield strength (σ_y = 250 MPa), with a negligible maximum elastic deflection of 0.297 mm[8].

Mild Steel Hollow Chassis (450 x 915 x 450 mm, 22 kg): Endured a maximum bending stress of 115.4 MPa under full payload (solar panel, battery, water tank ,and seed hopper), exhibiting high tensional rigidity and vibration damping [1, 8].

2.6 EXPERIMENTAL FIELD PERFORMANCE & MULTI-CROP AGRONOMIC VALIDATION

1. Experimental field trials were conducted across five major crop varieties: Groundnut (Peanut), Maize (Corn), Red Gram (Pigeon Pea Dal), Soybean, and Wheat Grain
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5. under tilled loamy soil conditions [1, 4,6]. Sowing depth, discharge speed, seed rate, and field emergence rates were systematically logged.

As compiled in Table 3 and depicted in Fig. 2(b), the automated solar seeder achieved outstanding germination emergence rates exceeding 92.8% to 97.0% across all tested crops. This represents a marked improvement over manual broadcasting and dibbling (65–75%). Comparative operational analysis against conventional practices confirms a 69.96% reduction in human man-hour labor **FIG1.5** requirements, 55.17% savings in animal/bullock hours, and a net crop yield improvement of 13.02% [1, 4]. These enhancements are directly attributable to uniform furrow depth control, consistent intra-row spacing, and optimal compaction by the V-deflector slider.

2.7 IoT, MACHINE LEARNING, AND CLOSED-LOOP SMART RESOURCE OPTIMIZATION

To achieve complete operational autonomy, modern farm mechanization interfaces seamlessly with distributed Internet of Things (IoT) wireless sensor networks (WSN) and edge-based Machine Learning (ML) decision engines [9, 10]. Fig. 4 illustrates the four-layer closed-loop architecture.

2.8 Multi-Layer IoT Hardware and Communication Architecture

1. Perception / Physical Sensing Layer: Integrates analog capacitive soil moisture probes (operating across a 0–1023 digital scale; threshold = 40%), DHT11 digital ambient temperature and relative humidity sensors (accuracy ±2°C, ±5% RH), cup anemometers for wind velocity, optical rain sensors, and ultrasonic tank level sensors[9,10].
2. Edge Processing & Transport Layer: Dual-tier edge processing utilizing Arduino Uno R3 for real-time sensor polling and Node MCU ESP8266 (Wi-Fi 802.11 b/g/n) / Raspberry Pi 3B+ as local gateway nodes. Telemetry packets are transmitted via MQTT/HTTP protocols to Thing Speak cloud servers and the Blynk mobile dashboard [9,10].

3. Actuation Layer: Relay modules (5V/12V) actuate high-torque DC cutter motors, solenoid directional valves (1A/1B for Zone 1; 2A/2B for Zone 2), and micro-irrigation submersible pumps based on automated algorithmic triggers [10].

2.9 Supervised Machine Learning Algorithms for Predictive Irrigation

Algorithmic Comparative Evaluation: Continuous sensor streams (3,000 real-world data instances) were evaluated using supervised classification and regression pipelines (80% training, 20% testing) to predict exact soil moisture depletion and water actuation needs [9, 10]:

- Random Forest (RF) Classifier: Constructed an ensemble of 100 uncorrelated decision trees, achieving the highest overall classification accuracy of 99.8% with an ultra-low Mean Squared Error (MSE) of 0.16 [10].
- Naïve Bayes (NB): Evaluated Gaussian conditional probability distributions (P(A|B) = [P(B|A)*P(A)] / P(B)), delivering 98.8% accuracy and 0.16 MSE with minimal computational overhead, ideal for low-power edge microcontrollers [10].
- Support Vector Machine (SVM): Implemented non-linear kernel transformations(RBF kerne l:K(x_i,x_j)=exp(-γ||x_i-x_j||^2)),yielding99.3%accuracy and 0.66MSE[9, 10].
- Logistic Regression(LR):Modeled binary pump state activation (P(x) = 1 / [1 + e^(-(x-μ)/s)]), reaching 99.5% accuracy and 0.50 MSE [10].

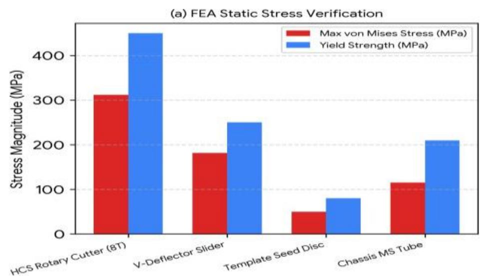
3. RESEARCH GAPS

Despite significant technological progress across biomass densification, solar mechanization, and IoT precision agriculture, systematic synthesis of the literature reveals several critical engineering bottlenecks:

1. Feedstock-Specific Densification Dynamics: Existing pelletization models lack adaptive multi-die control capable of compensating for real-time variations in residue moisture, silica ash content, and lignin ratios across mixed biomass blends (e.g., paddy straw blended with cotton stalk).
2. Robotic Seeding Throughput Constraints: While 3D-printed robotic arm seeders provide flexible single-seed pick-and-place capabilities, their cycle times remain excessively slow (26–36 sec per 2 ft) when handling irregular, micro-sized seeds (suchas sesame, mustard, or onion) compared to high-speed mechanical frustum discs (7–10 sec per 2 ft) [6].
3. Fixed-Architecture Micro-Irrigation Limitations: Contemporary T-shaped and sprinkler setups are structurally constrained to low-canopy crops (<4 ft), lacking height-adjustable gantries or modular drop nozzles suitable for mature sugarcane, maize, or orchard crops [10].
4. Severe Environmental Degradation of Field Hardware: Low-cost edge sensors (especially resistive/capacitive soil probes and DHT11 units) suffer rapid electrochemical corrosion, biological fouling, and calibration drift under prolonged field exposure to high soil salinity, agrochemical residues, and severe temperature swings [9, 10].
5. Computational Latency & Edge-AI Constraints: High-performing deep learning models and Model Predictive Control (MPC) algorithms demand significant memory and floating-point computation, making real-time execution challenging on resource-constrained microcontrollers (NodeMCU/AT mega) without relying on persistent cloud connectivity [2, 9].

3.1 FUTURE ENGINEERING SCOPE & DEVELOPMENT ROADMAP

To address the identified research gaps, future investigations should pursue the following development trajectories:



Integrated Soil Drill Tillage: Replacing high-speed rotary cutters with low-disturbance hollow core drills or ultrasonic vibrating coulters to minimize topsoil displacement and enhance conservation tillage [1, 3].

Autonomous RTK-GPS and Vision AI Navigation: Implementing Real-Time Kinematic (RTK) GPS, LiDAR SLAM, and embedded YOLOv8 machine vision models on Edge-AI processors (e.g., NVIDIA Jetson Orin Nano) for autonomous obstacle avoidance, weed identification, and micro-dosed spot weeding [1, 4, 6].

Multi-Hopper Modular Gang Planters: Developing modular, multi-row seeder attachments with interchangeable 3D-printed metering cassettes to support variable-rate companion planting across large acreage 8].

Closed-Loop IoT Soil Geochemistry & Fustigation: Integrating ion-selective field-effect transistor (ISFET) sensors for continuous real-time monitoring of soil nitrogen-phosphorus-potassium (NPK) and pH, dynamically co-injecting liquid bio-fertilizer during automated seed placement [9, 10].

Circular Bio-Energy Integration: Coupling agricultural residue pellet gasifiers with Stirling engine micro-generators to recharge robotic seeder battery banks directly on off-grid farm premises, establishinga self-sustaining circular bio-economy.

4. CONCLUSION

This comprehensive engineering review establishes that the convergence of agricultural residue pelletization, solar-photovoltaic automated farm machinery,and IoT-machine learning precision control provides a powerful, multi-dimensional solution for modernizing global agriculture. Densifying loose crop residues into high-density bio-pellets (>680 kg/m^3,18.2 MJ/kg) eliminates open-field stubble burning, reduces carbon emissions, and generates localized economic value. Simultaneously, solar-powered multi-crop seeders equipped with high-carbon steel rotary cutters, calibrated seed drums, and V-deflector sliders eliminate direct fossil fuel consumption, lower human labor requirements by 69.96%, and increase crop germination emergence to >92–97% across diverse crops (groundnut, maize, red gram, soybean, and wheat). Furthermore, integrating distributed IoT sensor networks with supervised machine learning algorithms (Random Forest achieving 99.8% classification accuracy) automates precision irrigation dosing, preventing over-watering and saving up to 60% of precious freshwater resources. With total prototype fabrication costs maintained below INR 10,000 (~$120 USD), this integrated technological paradigm offers an accessible, scalable, and environmentally sustainable pathway for empowering smallholder farmers and securing the future of global food and energy systems.

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