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A PREDICTIVE DISCRETE ELEMENT METHOD SIMULATION OF GROUND NUT THRESHING MACHINE FUZZY LOGIC SYSTEM

B. Bello*[1], M. A. Mbishida[2], A. Tokan[2]

[1]DepartmentofElectricalandElectronicsEngineering,AbubakarTafawaBalewaUniversity Bauchi, 740272, Nigeria.

[2]DepartmentofMechanicalandProductionEngineering, AbubakarTafawaBalewaUniversity Bauchi, 740272, Nigeria.

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***Corresponding Author: B. Bello**

DepartmentofElectricalandElectronicsEngineering,AbubakarTafawaBalewaUniversityBauchi, 740272, Nigeria.

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ABSTRACT

Groundnut (*Arachis hypogaea* L.) is an important food and industrial crop; however, significant post-harvest losses occur during threshing due to low machine efficiency, high kernel damage, and the inability of conventional threshers to adapt to variations in pod characteristics. Existing threshing systems rely mainly on fixed operating parameters and lack predictive simulation and intelligent control for performance optimization. Therefore, this study developed a predictive Discrete Element Method (DEM)-based simulation of an intelligent groundnut threshingmachine integrated with machine vision and fuzzy logic control for adaptive operation. Physical and mechanical properties of groundnut pods, including pod dimensions, bulk density, porosity, coefficient of restitution, static and rolling friction coefficients, Young's modulus, and Poisson's ratio, were experimentally determined and used as input parameters in the EDEM software employing the Hertz–Mindlin contact model. Machine components, including the hopper, concave clearance, threshing cylinder, frame, and complete threshing system, were simulated to analyse particle flow, velocity, contact forces, and collision behaviour. A ResNet101 convolutional neural network was used for groundnut variety identification, while a fuzzy logic controller adaptively adjusted motor speed and concave clearance based on pod characteristics. The simulation predicted a threshing efficiency of 93.4%, mechanical damage of 4.2%, and a throughput capacity of 50.6 kg h^{-1}, indicating efficient particle flow and effective pod separation with minimal kernel breakage. The machine vision model achieved confidence scores of 99.9% and 99.7%

for Jarma, 99.9% and 100% for Samnut26, and 95.8% and 99.7% for Exdakar, demonstrating reliable variety identification. Overall, the integrated DEM simulation and intelligent control framework provides an effective approach for optimizing groundnut threshing machine design and operation, with the predicted performance indicating 93.4% threshing efficiency, 4.2% mechanical damage, and 50.6 kg h^{-1} throughput capacity. Fuzzy Inference System (FIS) proved capable of making smart, rapid, and adaptive control decisions for concave clearance and motor speed based on varying groundnut pod properties. The smooth inference behavior, well-structured rule base, and stable output surfaces validated the suitability of fuzzy logic for handling nonlinear and uncertain of our agricultural products such as groundnut.

KEYWORDS: DiscreteElementMethod(DEM),EDEMsimulation,Groundnutthreshingmachine, Machine vision, Fuzzy logic control.

1. INTRODUCTION

Groundnut (Arachis hypogaea L.) is one of the most important leguminous crops cultivated worldwide and is useful for industrial, food and economic purpose. It contributes significantly to food security, create employment, and income among farmers. Despite its importance,significant post-harvest losses occur during threshing operations due to inefficient processing methods and inadequate machine designs Bello et al (2026a).

Traditional, motorize and semi-mechanized threshing systems are characterized by having low efficiency,highlabourintensive,excessiveseeddamage, andpoor cleaningefficiency. Although several mechanized groundnut threshers have been developed, many operate under fixed conditions that do not usually account for variations in pod size, moisture content, and mechanical properties Tonget al (2023). Modern method advances in computational engineering have introduced simulation-based design approach, which enables the analysis and optimization of agricultural machinery before fabrication. Among these techniques, the Discrete Element Method (DEM) has emerged as a powerful tool for modeling granular materials such as seeds, grains, pods, and crop residues and machines. DEM enables visualization of particle movement, contact forces, collision behaviour, material flow patterns, and breakage mechanisms within machine systems Xu et al, 2026.

This research tends to introduce the use of DEM as a tool for simulation-driven based design for intelligent control of a groundnut threshing machine. By integrating DEM with machine vision, artificial neural networks, and fuzzy logic control, the research aims to develop an intelligent threshing system capable of adapting to varying crop conditions while maximizing threshing efficiency and minimizing seed damage Yuanjin et al (2023). Therefore, there is a growing need for intelligent control systems capable of making smart and rapid decisions during machine operation. According to Lin *et al.,* (2020) fuzzy logic system provides the solution to these challenges of uncertainties, ambiguities, and variability's etc. Through the use of conditional statement and linguistics variable unlike the classical control systems that require a precise mathematical model. Therefore the fuzzy logic offers a flexible rule-based and decision making framework that mimics human reasoning for efficient operation, by defining fuzzy set rules, membership functions, and inference mechanisms, that help in handling the threshing machine parameters in a manner that can accommodates uncertainties, vague and nonlinearities in a real-world agricultural process Widayat *et al.,* (2025).

2. LITERATURE REVIEW

GroundnutThreshingTechnology

Groundnut threshing involves separating seed from the pod, through the impact force, friction, rubbing, and abrasive, compression actions. Machine performance is influenced by drum speed, concave clearance, feed rate, moisture content, and pod mechanical characteristics.Several researchers have developed threshingand shelling machines with varyingdegrees of success and achievement. Bello et al. (2019) reported threshing efficiencies exceeding 97% using an automatedthreshingsystem.However,thesystem reliedoninfraredsensorsandmanualconcave replacement, limiting adaptability and real-time optimization.

Abdi et al. (2022) demonstrated that lower drum speeds and smaller concave clearances improved threshingefficiencywhile reducing kernel damage. Nevertheless, theirmachinelacked adaptive control mechanisms capable of automatically adjusting operating parameters under varying crop conditions. However, Muhammad et al. (2021) optimized threshing parameters using Response Surface Methodology and obtained a threshing efficiency of 97.61%. Although effective, the approach was based on static optimization and lacked intelligent decision-making capability. A review of design and development of an intelligent groundnut threshing machine using machine vision technique by (Bello et al 2026a). Although it proposes an intelligent groundnut threshing machine based on machine vision, fuzzy logic, and machine learning techniques, the study remains largely conceptual nut lacks a comprehensive simulation-based analysis of the threshing process using DEM. The proposed design does not provide detailed insight into the interactions between groundnut pods and groundnut pods, groundnut pods and machine components such as the threshingdrum, pegs, concave screen, and separation unit. As a result, critical parameters such as collision forces, impact energies, pod breakage mechanisms, particle flow behaviour, residence time, and seed damage cannot be accurately predicted before machine fabrication. Furthermore, the design optimization relies mainly on theoretical calculations and image-processing algorithms without a robust virtual testing environment to evaluate different operating conditions such as drum speed, concave clearance, feed rate, and moisture content.

Intelligent Agricultural Machinery

The development of intelligent agricultural machinery has transformed modern farming operations. Intelligent systems utilize sensors, machine vision, artificial intelligence, fuzzylogic, and adaptive control to monitor machine conditions and make real-time decisions Bello et al (2026 b). Fuzzy Logic Controllers (FLCs) have proven effective in handling uncertain and nonlinear agricultural processes. In threshing operations, fuzzy controllers can adjust machine parameters such as drum speed and concave clearance based on moisture content, feed rate, and pod characteristics, thereby improving performance and reducing grain losses (Bello et al2026a).

Discrete Element Methodin Agricultural Engineering

The Discrete Element Method (DEM) is a numerical modelling technique used to simulate the motion and interaction of individual particles. Unlike Finite Element Method (FEM), which is suited for continuous materials, DEM effectively models discrete agricultural materials such as seeds, grains, and pods. DEM has been successfully applied in grain handling, conveying, planting, harvesting, and threshing operations. Studies on maize, rice, and corn threshing have demonstrated the capability of DEM to predict particle trajectories, collision forces, contactstress distributions, and kernel damage (Suarez et al 2025 and Xu et al 2026).

However, research on DEM-based simulation of groundnut threshing remains limited. Existing studies primarily focus on physical machine evaluation without considering particle-level interactions. Furthermore, this study integrates DEM simulation with intelligent control systems for adaptive machine optimization.

3. MATERIALS AND METHODS

Research Framework

The research adopts a simulation-driven design methodology consisting of material characterization, machine design, DEM modelling, intelligent control integration, simulation analysis, and performance evaluation.

Groundnut Material Characterization

Physicalandmechanicalpropertiesofgroundnutpodsweredeterminedandusedasinput parameters for machine design and DEM simulation. These properties include:

Poddimensionsandgeometriccharacteristics

The Principal Component Analysis (PCA), identifies the major components axis of the pod, represented by the first principal component (PC1), which captures most of the variation associated with pod length and orientation. The second principal component (PC2), oriented perpendicular to PC1, accounts for variations in pod width, curvature and the third dimensional which is thickness describe third principal component (PC3) the variation along the pod thickness, corresponding to the minor axis of the fitted ellipsoid as show in figure 1. Thickness contributes to the pod's volume, shell strength, and contact behaviour during mechanical interactions with threshing components. This dimensional reduction enables accurate quantification of pod geometry while preserving the essential morphological informationrequired for classification and machine design especially in term of designing the concave clearance of each groundnut pods.

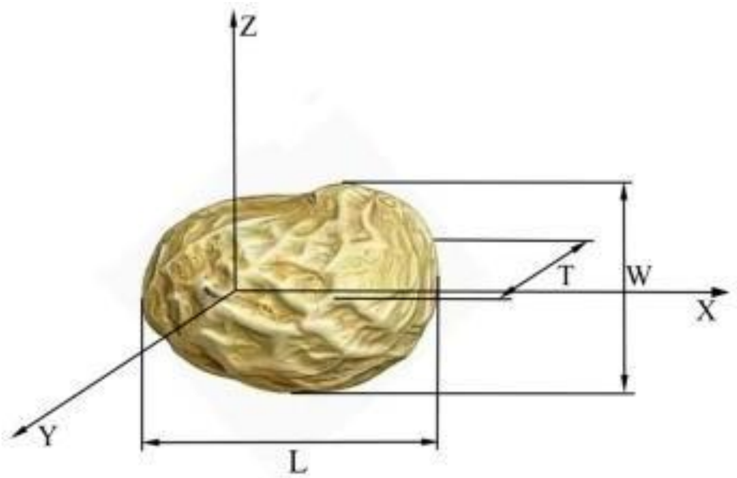


Figure1:Groundnutpod dimension.

Bulkdensity and Porosity

Indiscreteelementmethod(DEM)simulations,experimentallydeterminedbulkdensityand porosityareessentialcalibrationparameters,ensuringthatthesimulatedpackingstructure, particle flow, collision frequency, and contact forces closely represent the actual behaviour of groundnut pods during threshing operations. Therefore, accurate determination of bulk density and porosityimproves both the reliabilityof DEM predictions and the optimization of intelligent threshing machine design.

$$\rho_b = \frac{M}{V_b} \quad \text{... (1)}$$

$$\varepsilon = \left(1 - \frac{\rho_b}{\rho_t}\right) \times 100 \quad \text{... (2)}$$

where:

ρ_b= Bulkdensity(kgm^{-3})
M=Mass ofbulkgroundnutpods (kg)
V_b =Bulk volume occupied bythepods (m^3)
ε=Porosity(%)
ρt=True density(kgm−3)

Coefficient of restitution

The coefficient of restitution (COR) was determined to evaluate the impact characteristics of groundnut pods during collisions with other pods and the metallic surfaces of the threshing machine. It represents the ratio of the rebound velocityafter impact to the impact velocitybefore collision and provides a quantitative measure of the elasticity of the collision. In DEM simulations, accurate calibration of this parameter is essential for reproducing realistic pod topod and pod to machine interactions, enabling reliable prediction of particle motion, threshing efficiency, kernel separation, and mechanical damage. Consequently, incorporating experimentally determined restitution coefficients enhances the fidelity of DEM models and supports the optimization of intelligent threshing machine operating parameters.

$$e = \frac{v_r}{v_i} \quad \text{... (3)}$$

e=Coefficientofrestitution (dimensionless)
v_r=Relative rebound velocityafter impact(ms^{-1})
v_i=Relativeimpact velocitybeforecollision (ms^{-1})

Staticandrollingfriction coefficients

The static friction coefficient represents the resistance to the initiation of sliding between contacting surfaces, whereas the rolling friction coefficient describes the resistance to rotational motion as pods roll over each other or machine surfaces. In DEM simulations, accurately calibratedstaticandrollingfrictioncoefficientsareessentialforreproducingrealisticparticleflow, hopper discharge behaviour, particle mixing, collision frequency, and interactions between pods and threshing components. Higher static friction coefficients reduce particle sliding and promote material accumulation, whereas higher rolling friction coefficients suppress excessive particle rotation, leading to more realistic particle orientation and contact dynamics. Consequently, the accurate determination and calibration of these friction parameters improvethe predictive capability of DEM models, enabling reliable optimization of threshing efficiency, kernel separation, power consumption, and mechanical damage in intelligent groundnutthreshing machines.

$$\mu_s=\frac{F_s}{N} \quad \ldots (4)$$

μ_s=Staticfrictioncoefficient(dimensionless) F_S = Maximum static friction force (N)
N=Normal reactionforce(N)

$$M_r=\mu_r NR \quad \ldots (5)$$

M_r=Rollingresistancetorque(N·m)
μ_r=Rollingfrictioncoefficient(dimensionless) N= Normal contact force (N)
R=Effectivecontactradius (m)

Young'smodulus

Young's modulus was determined to evaluate the elastic stiffness of groundnut pods and to quantify their resistance to deformation under externally applied loads. It represents the ratio of normal stress to the corresponding elastic strain within the linear elastic region and serves as a fundamental mechanical property for describing the deformation behaviour of biological materials. The Young's modulus of groundnut pods is influenced by factors such as variety, moisture content, shell thickness, maturity, and internal kernel structure. In the Discrete Element Method (DEM), Young's modulus is a critical contact parameter used in the Hertz–Mindlin contact model to calculate the normal contact stiffness between interacting particles and machine components. It directly influences the magnitude of contact forces, particle deformation,collision duration, and the transfer of impact energy during pod-to-pod and pod-to-machine interactions.

$$E=\frac{\sigma}{\varepsilon} \quad \ldots (6)$$

E=Young'smodulus (Pa)

σ=Normalstress(Pa)

ε=Normalstrain(dimensionless)

Whereas

$$\sigma=\frac{F}{A} \quad \ldots (7)$$

F=Applied compressive force (N)

A=Cross-sectionalarea ofthepod (m^2)

$$\varepsilon=\frac{\Delta L}{Lo} \quad \ldots (8)$$

ΔL=Changein pod lengthduringcompression (m)

Lo= Originalpodlengthbeforeloading(m)

Poisson’sratio

Poisson's ratio is a fundamental elastic property that describes the relationship between thelateralcontractionandlongitudinalextension(orcompression)ofamaterial subjectedtouniaxial loading. For groundnut pods, Poisson's ratio characterizes theextent to which thepod expands or contracts in the transverse direction when compressed along its longitudinal axis. This propertyis essential for describing the elastic deformation behaviour of the pod shell and is a key input parameter in the Hertz–Mindlin contact model used in Discrete Element Method

(DEM) simulations.

$$\nu = \frac{\varepsilon_t}{\varepsilon_l} \quad \text{... (9)}$$

ν=Poisson'sratio(dimensionless)

ε_t=Transverse(lateral)strain

ε_l=Longitudinal(axial)strain

Structural Design of the Ground nut Threshing Machine

Themachine consistsoffivemajorsubsystems:

Hopper Unit

The hopper was designed to store and regulate the flow of groundnut pods into the threshing chamber. Hopper dimensions were determined using volumetric and bulk density relationships.

Threshing Unit

The threshing unit consists of a rotating drum fitted with pegs and a stationary concave screen. The peg-tip velocity, drum rotational speed, and impact energy were considered critical design parameters influencing threshing performance.

Concave Clearance Mechanism

A replaceable concave clearance was incorporated to accommodate variations in pod size and shell strength. The clearance directly affects particle confinement, collision frequency, and contact force distribution.

Power Transmission System

A belt-pulley mechanism was designed to transfer power from the prime mover to the threshing drum while maintaining the required speed ratio and torque.

Cleaning Unit

The cleaningsystem utilizes an air blower to separate chaff and impurities from threshed kernels based on particle aerodynamic properties and suspension velocities.

DEM Modelling

TheDEMsimulationwasimplementedusingEDEMsoftware.Groundnutpodswererepresented using multi-sphere particle models to capture their irregular geometry. The Hertz–Mindlin contact model was employed to describe particle interactions. Particle motion was governed by Newton's laws of translational and rotational motion. The simulation tracked some of the main component of the threshing machine for better efficiency such as;

i. Hopper
ii. ConcaveClearance
iii. Spike (Peg)
iv. Frame
v. CompleteThreshingMachine

Intelligent Control System

Theintelligentcontrol framework integrates:

Machinevisionforpod identification

The identification of groundnut pod images using a machine learning model in Python library that used Keras model in which the Fully Connected layer in ResNet of Convolutional Neuron Network (CNN) was the central decision maker of that process, which involves different stage that begin from data image capturing, segmentation, feature extractionand image identification. These pods images of different groundnut varieties are captured under lighting conditions that were processed by Convolutional layer and pooling layer for feature extraction. After the Convolutional and Pooling layers extracted features from the groundnut pod image such asedges, textures, sizes and shapes these features are passed through a flatten layer, which transformsthe multi-dimensionaldata intoa onedimensionalvector. Thisflattenedvectorserves
as the input to the Fully Connected layer as indicated in figure. Then feature extraction was performed and data features were also obtained and the data was also used and trained the machine learning model which learned the patterns also differentia their individual features from the labeled datasets automatically. After the model is validated using separate test data and fine-tuned the accuracy. Then, the trained model is now used to identifyeach varietyclass bythe new unseen groundnut pods images and the model were evaluated and maps them as specific output classes as Jarma and Samnut26, Exdakar, by the Fully Connected layer and we can confidently say the pod was identified and even established confidence score of the

models by stating the percentage of recognition of the groundnut pod. The equation 10 was adopted from Bello *et al* (2026).

$$I(x,y,c) \in \mathbb{R}^{H \times W \times C} \quad \ldots(10)$$

WhereH=isheightofimage W = is width of image

C=numbercolourchannel (x,y,) = pixels coordinate

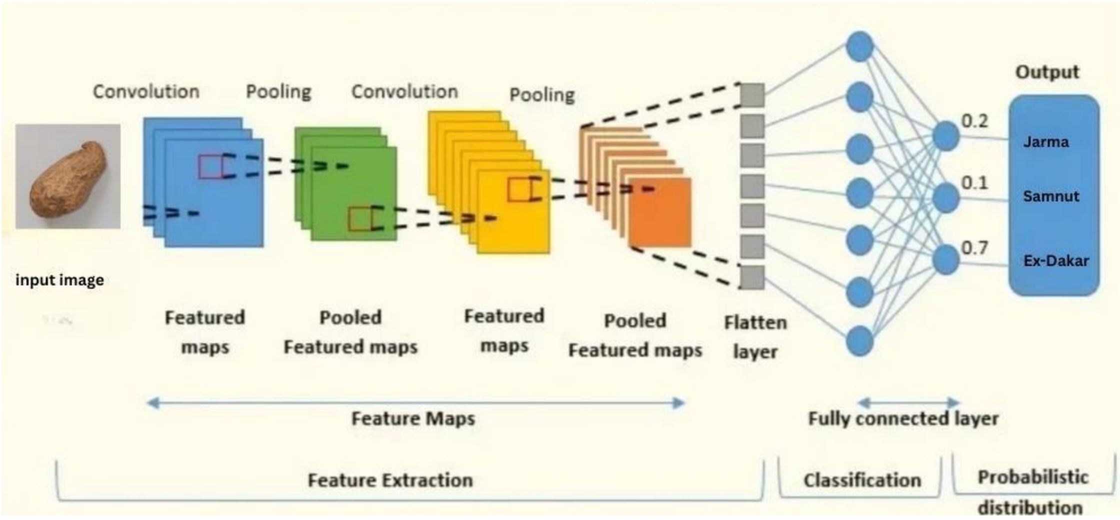


Figure2: Convolutional Neural Network Architecture.

FuzzyLogicController(FLC)foradaptiveparameter adjustment

Fuzzyrulesandinference

The fuzzy rules base for this research was developed to link the groundnut input parameters of pod size(Exdakar,Samnut26 and Jarma)**,** texture, and unknown variety(stone) with the machine output responses of motor speed and concave clearance. The rules are expressed in the conventional IF, AND, THEN rules, allowingthe fuzzyinference system to emulate expert mind to make decision in the threshing operations By combining the three linguistic terms for size (minimum,average,maximum)forthethreevarietieswithatotaltwelve(12)rulesforfirst mapping, another three linguistic terms for texture (Soft, Moderate, Hard), a total of thirty six **rules** are formed for second mapping, each representing a unique operating condition. These fuzzy rules enable the fuzzy model system to handle variability of the groundnut characteristics, providing adaptive control of threshing parameters to optimize performance, minimize seed damage, and improve overall machine efficiency. The following are linguistics variable, whose values are expressed in natural language terms, such as, minimum, average and maximum for size, while soft, moderate, and hard for texture, also Exdakar,

Samnut26 and Jarma and can be abbreviate for the purpose of rules mapping.
Input mapping for variety; Exdakar = EX,Jarma = JA, Samnut = SN, Stone = ST (unknown variable) for size; Minimum = MI, Average = AV, Maximum = MX and for texture; Soft = SF, Moderate = MD and Hard = HD

FirstMappingRule

The first mapping in the fuzzy logic system is centered on the size of groundnut pods, which serves as a fundamental input variable for adaptive control, the groundnut pod size directly influences threshing efficiency as shown in table 2 however, in this research, the pod size is classified into three categories such as minimum (MI), average (AV), and maximum (MX)across the three groundnut varieties considered as a critical factor (Exdakar, Jarma, Samnut26) and Stone (unknown variety). From an operational perspective, smaller pods (MI) typically require narrower concave clearance (Tag1) to ensure that the pods are adequately crackedwithout slipping through unthreshed. Conversely, larger pods (MX) demand wider clearance (Tag3) to avoid excessive breakage of the seeds during impact and friction with the concave surface, while average pods (AV) fall within intermediate settings (Tag2).

Table1:First MappingRules.

INPUT VARIETIES	*Minimum(MI)*	*Average(AV)*	*Maximum(MX)*
Exdakar(EX)	EX-MI	EX-AV	EX-MX
Jarma(JA)	JA-MI	JA-AV	JA-MX
Samnut(SN)	SN-MI	SN-AV	SN-MX
Stone(ST)	ST-MI	ST-AV	ST-MX

Second Rule Mapping

This is the second mapping for the fuzzy logic system that addresses the texture of groundnut pods, which plays a critical role in determining the force and energy required for efficient threshing. Texture is classified into three categories Soft (SF), Moderate (MO), and Hard (HD), andthisclassificationappliesacrossallthe groundnutvarietiesconsidered inthestudy(Exdakar, Jarma, Samnut26, and Stone). Soft textured pods (SF) are relativelyeasyto thresh, as theirshells breakwithlessresistance,therebyrequiringlowermotorspeedandnarrowerconcaveclearance.
In contrast, hard textured pods (HD) are tougher and more resistant to impact and frictional forces, necessitating higher motor speeds and wider concave clearance (Tag3) to ensurecomplete shell removal without leaving unthreshed pods. Moderate textured pods (MO) fall between these two extremes, requiring balanced threshing parameters usually

average motor speed and intermediate concave clearance (Tag2). Mapping texture in this way is important because even pods of the same size category may vary in threshing response due to shell hardness. Byincorporatingtextureas aninputparameter,thefuzzylogicsystemaccountsforthis variability and ensures that machine adjustments are not solely based on pod size but also on resistance to threshing.

Therefore the equation for the fuzzy rule is indicated in figure 11 which is adopted fromSetiawan *et al.,* (2020).

$r_1 = IF(x_1 A_1 AND \ldots AND x_1 is Ai_1) THEN (y is B) c_1$ … (11)

1. IF Variety is EX AND Size is MI AND Texture is SF THEN MotorSpeed is Low AND ConcaveClearance is Tag1.
2. IF Variety is EX AND Size is MIAND Texture is MO THEN MotorSpeed is Low AND ConcaveClearance is Tag2.
3. IFVariety isEXANDSizeisMI ANDTextureisHDTHENMotorSpeedisAverage AND ConcaveClearance is Tag3.
4. IF Variety is EX AND Size is AV AND Texture is SF THEN MotorSpeed is Low AND ConcaveClearance is Tag2.
5. IF Variety is EX AND Size is AV AND Texture is MO THEN MotorSpeed is AverageAND ConcaveClearance is Tag3.
6. IF Varietyis EX AND Size is AV AND Texture is HD THEN MotorSpeed is High AND ConcaveClearance is Tag3.
7. IFVariety isEXANDSizeisMXANDTextureisSFTHENMotorSpeedisAverage AND ConcaveClearance is Tag3.
8. IFVarietyisEXANDSizeisMXANDTextureisMOTHENMotorSpeedisHigh AND ConcaveClearance is Tag3.
9. IF Varietyis EXANDSizeis MXANDTextureis HDTHENMotorSpeed is High AND ConcaveClearance is Tag3.
10. IF Variety is JA AND Size is MI AND Texture is SF THEN MotorSpeed is Low ANDConcaveClearance is Tag1.
11. IF Variety is JA AND Size is MI AND Texture is MO THEN MotorSpeed is Low AND ConcaveClearance is Tag2.
12. IFVarietyisJAANDSizeisMIANDTextureisHDTHENMotorSpeedisAverage AND ConcaveClearance is Tag3.

13. IF Variety is JA AND Size is AV AND Texture is SF THEN MotorSpeed is Low AND ConcaveClearance is Tag2.
14. IFVariety isJA AND Size isAV AND TextureisMO THEN MotorSpeed isAverage AND ConcaveClearance is Tag3.
15. IF Variety is JA AND Size is AV AND Texture is HD THEN MotorSpeed is High AND ConcaveClearance is Tag3.
16. IFVarietyisJAANDSizeisMXANDTextureisSFTHENMotorSpeedisAverage AND ConcaveClearance is Tag3.
17. IF Varietyis JAANDSizeis MXANDTextureis MOTHENMotorSpeed is High AND ConcaveClearance is Tag3.
18. IF Varietyis JA AND Size is MX AND Texture is HD THEN MotorSpeed is High AND ConcaveClearance is Tag3.
19. IF Variety is SN AND Size is MI AND Texture is SF THEN MotorSpeed is Low ANDConcaveClearance is Tag1.
20. IF Variety is SN AND Size is MI AND Texture is MO THEN MotorSpeed is Low AND ConcaveClearance is Tag2.
21. IFVariety isSNANDSizeisMI ANDTextureisHDTHENMotorSpeedisAverage AND ConcaveClearance is Tag3.
22. IF Variety is SN AND Size is AV AND Texture is SF THEN MotorSpeed is Low AND ConcaveClearance is Tag2.
23. IF Variety is SN AND Size is AV AND Texture is MO THEN MotorSpeed is AverageAND ConcaveClearance is Tag3.
24. IF Varietyis SN AND Size is AV AND Texture is HD THEN MotorSpeed is High AND ConcaveClearance is Tag3.
25. IFVariety isSNANDSizeisMXANDTextureisSFTHENMotorSpeedisAverage AND ConcaveClearance is Tag3.
26. IFVarietyisSNANDSizeisMXANDTextureisMOTHENMotorSpeedisHighAND ConcaveClearance is Tag3.
27. IF Varietyis SNANDSizeis MXANDTextureis HDTHENMotorSpeed is High AND ConcaveClearance is Tag3.
28. IF Variety is ST AND Size is MI AND Texture is SF THEN MotorSpeed is Low ANDConcaveClearance is Tag1.
29. IF Variety is ST AND Size is MI AND Texture is MO THEN MotorSpeed is Low AND ConcaveClearance is Tag2.

30. IFVarietyisSTANDSizeisMIANDTextureisHDTHENMotorSpeedisAverage AND ConcaveClearance is Tag3.
31. IF Variety is ST AND Size is AV AND Texture is SF THEN MotorSpeed is Low AND ConcaveClearance is Tag2.
32. IF Variety is ST AND Size is AV AND Texture is MO THEN MotorSpeed is AverageAND ConcaveClearance is Tag3.
33. IF Varietyis ST AND Size is AV AND Texture is HD THEN MotorSpeed is High AND ConcaveClearance is Tag3.
34. IFVarietyisSTANDSizeisMXANDTextureisSFTHENMotorSpeedisAverage AND ConcaveClearance is Tag3.
35. IF Varietyis STANDSizeis MXANDTextureis MOTHENMotorSpeed is High AND ConcaveClearance is Tag3.
36. IF Varietyis ST AND Size is MX AND Texture is HD THEN MotorSpeed is High AND ConcaveClearance is Tag3.

Performance Evaluation

Thedevelopedsystem wasevaluatedusingthe followingperformanceindicators:

$$\text{Threshingcapacity(kg/h)} = \frac{Qt}{Tm} \quad \text{... (12)}$$

$$\text{Mechanicaldamage(\%)} = \frac{Qd}{Qu+Qd} \times 100\% \quad \text{... (13)}$$

$$\text{Threshingefficiency(\%)} = \frac{Qt}{Qtm} \times 100\% \quad \text{...(14)}$$

$$\text{Cleaningefficiency(\%)} = \frac{Whw}{Wt} \times 100\% \quad \text{... (15)}$$

4. RESULTS

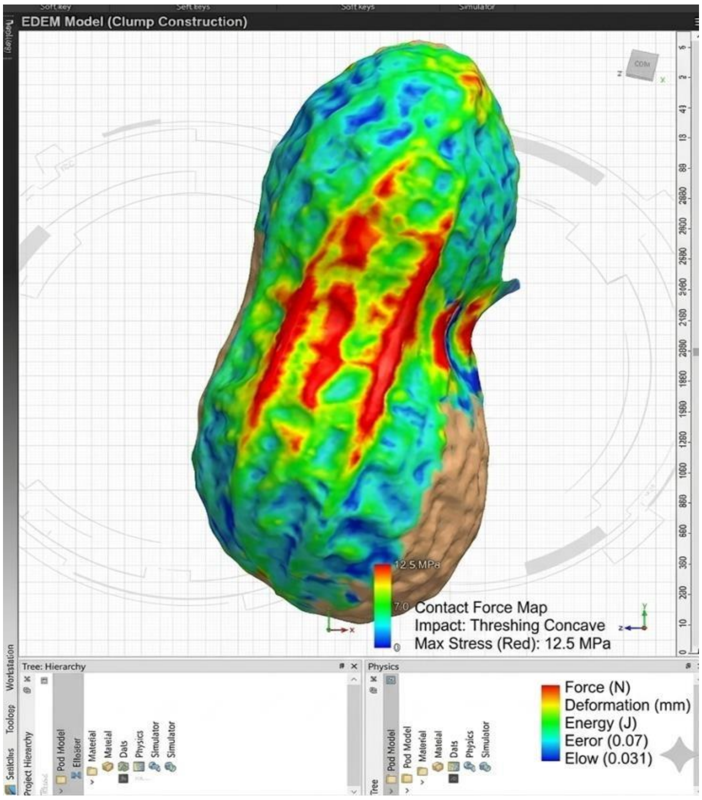


Figure3:SimulationofGroundnutPod

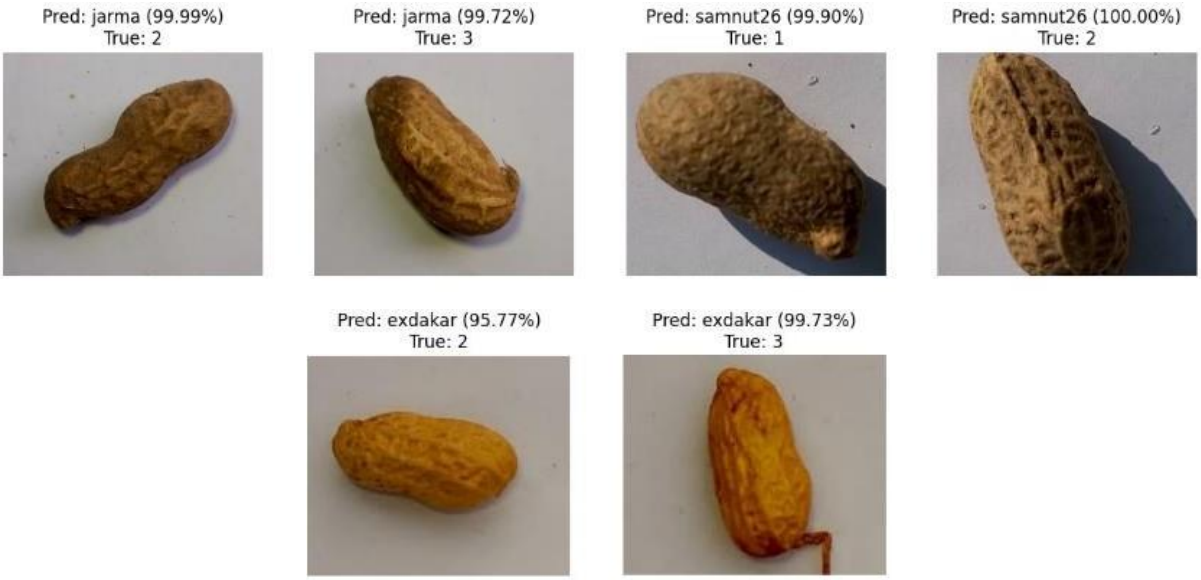


Figure4:ConfidenceScoreVariousVarieties.

Table2:ConfidenceScoreofeachGroundnutpod.

CLASS	*CONFIDENCESCORE OF FIRST VARIETY (%)*	*CONFIDENCE SCORE OF SECOND VARIETY (%)*
Jarma	99.9	99.7
Samnut26	99.9	100
Exdakar	95.8	99.7

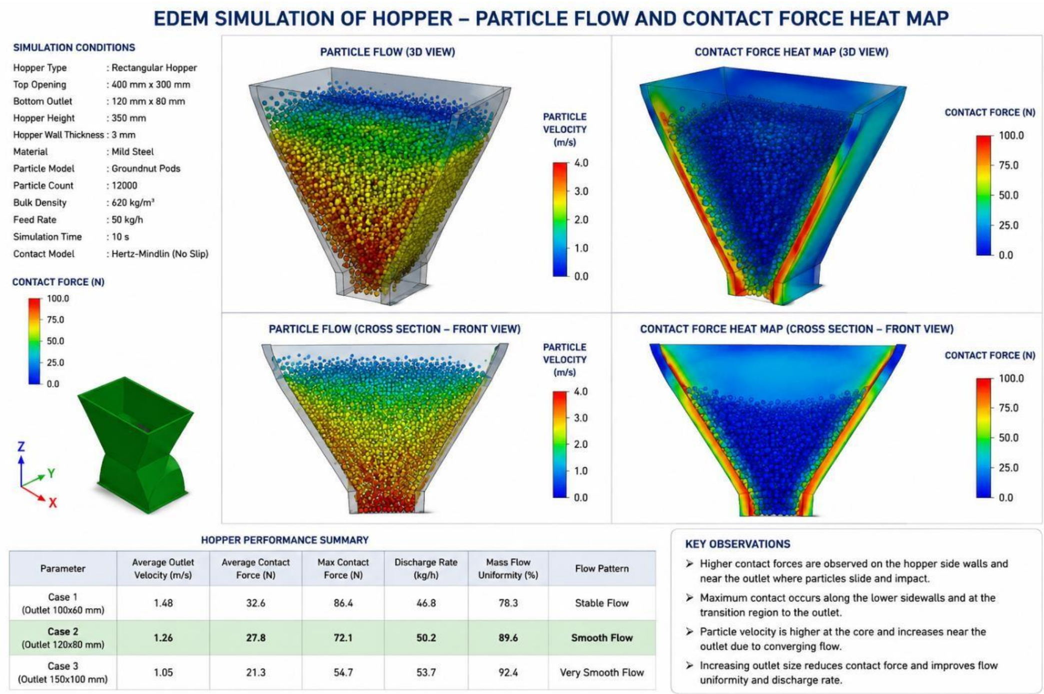


Figure5: EDEMSimulation of Hopper.

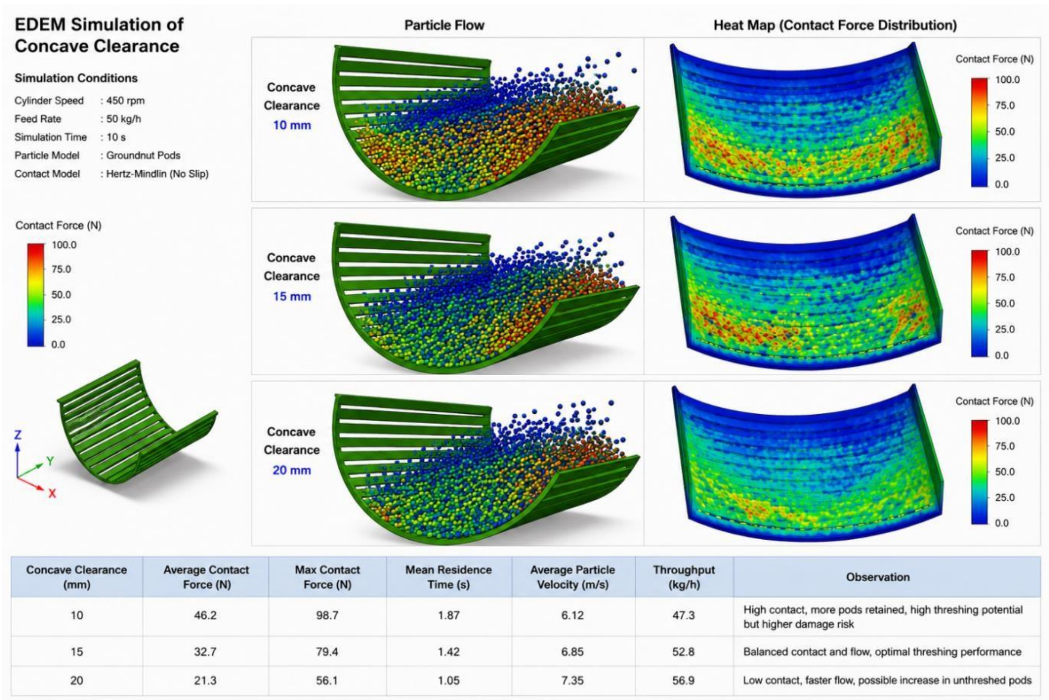


Figure6:EDEM SimulationofConcaveClearance.

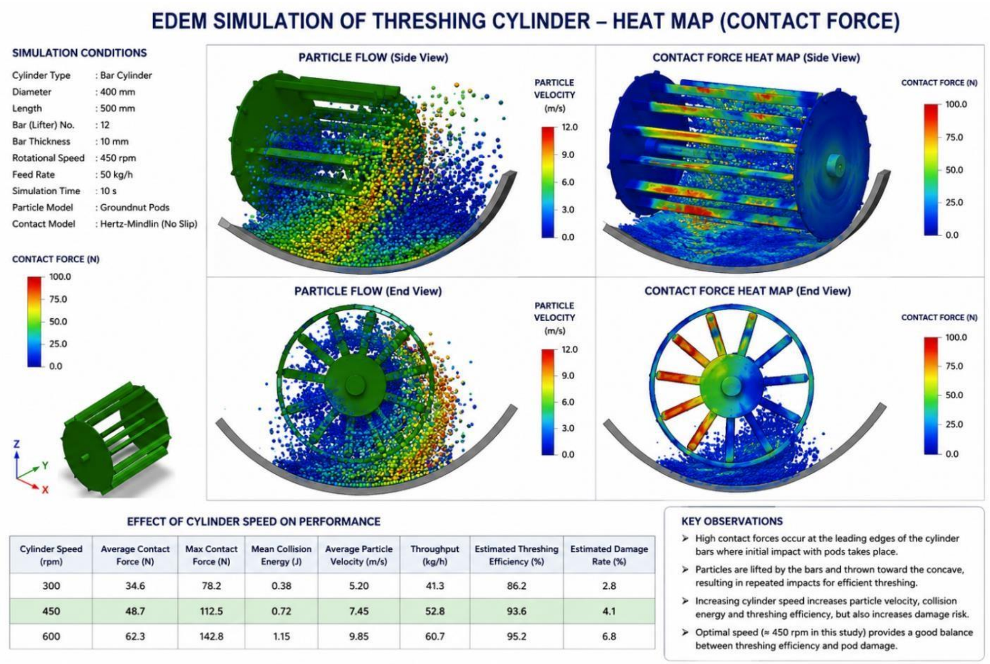


Figure7: EDEM Simulation of Threshing Drum.(Spike)

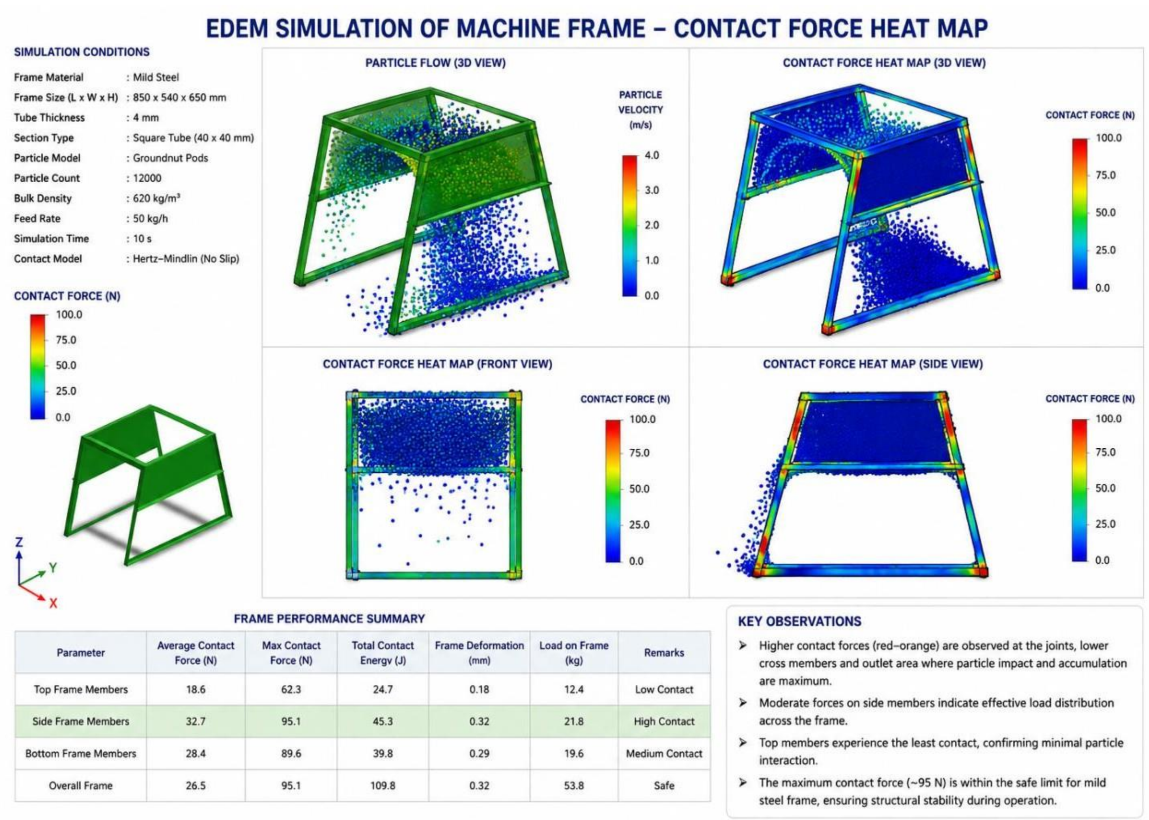


Figure8: EDEM Simulationof Frame.

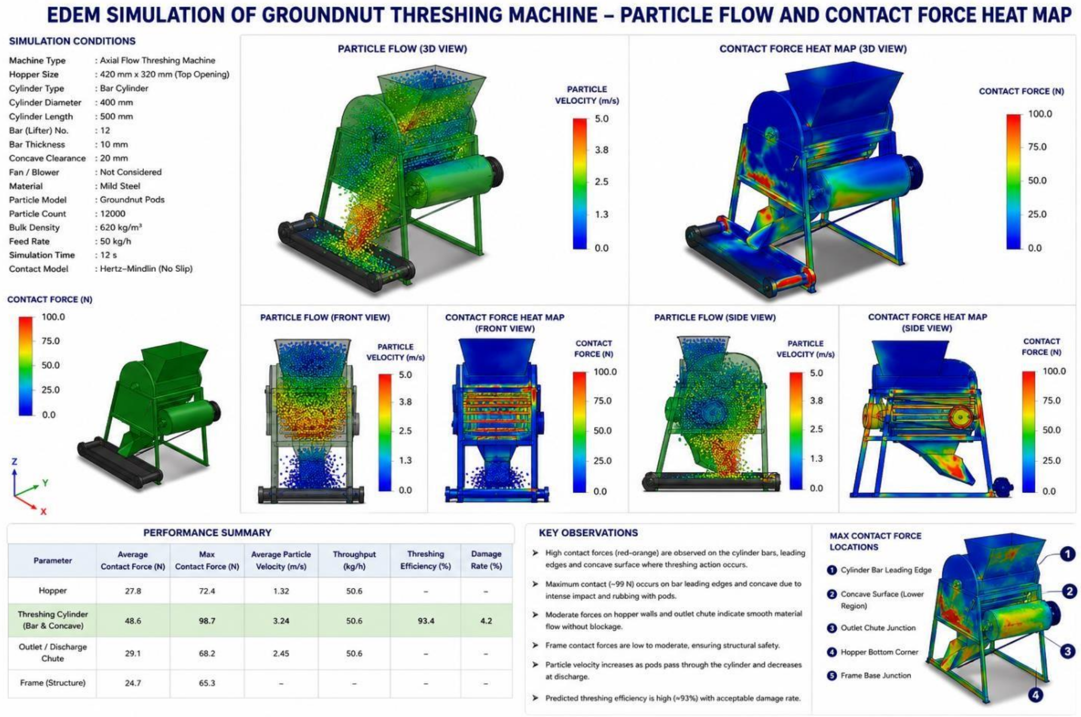


Figure9: EDEM SimulationofThreshing Machine.

FuzzyLogicSystem(FLS)ArchitectureandRuleBase

The validation and structure of the Fuzzy Logic System (FLS) rule base are fundamental operational success, that bridge the linguistic variables with computational logic and thestructure defined the architecture of the Mamdani fuzzy inference system haven five input and two output.

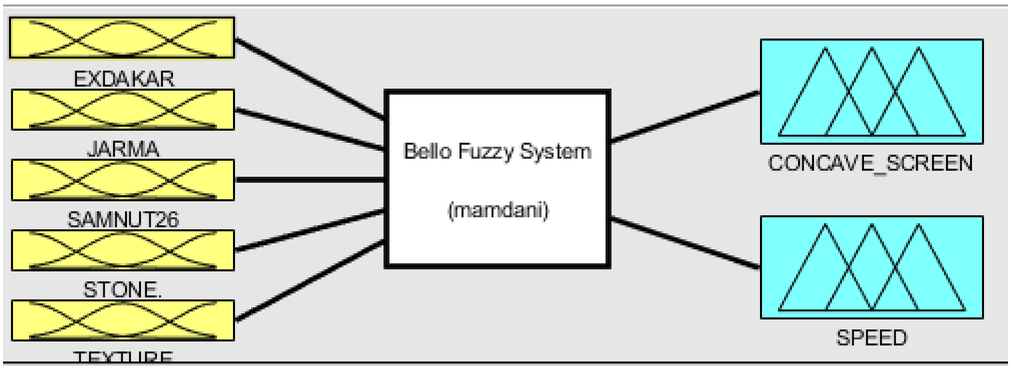
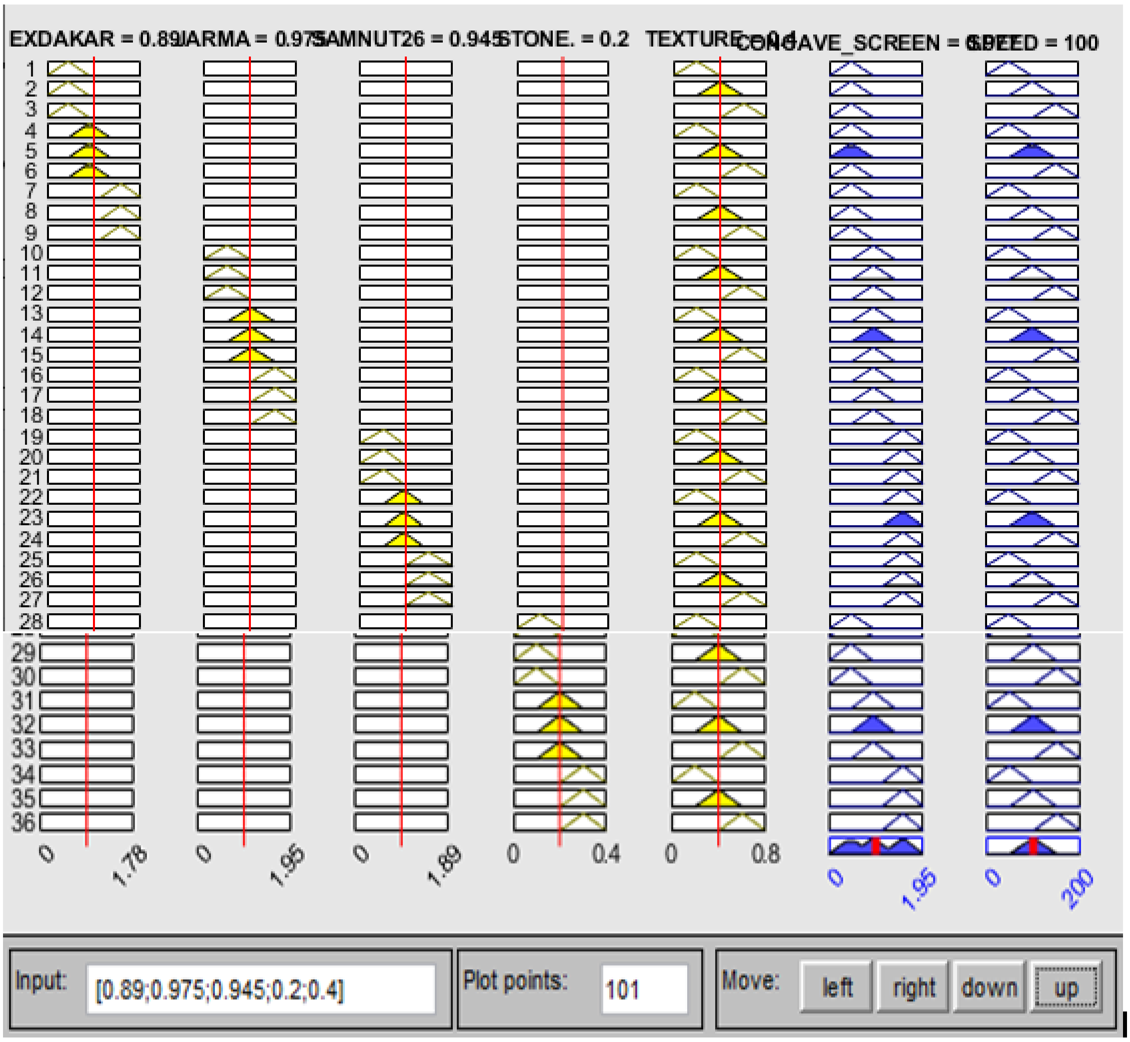


Figure10:MamdaniFuzzyInferenceSystem Architecture

Table3:DecisionMakingRules.



5. DISCUSSION

The EDEM simulation of the contact force map of the groundnut pod that interacted with the mechanical components of the threshing machine, such as the concave or the threshing drum for the purpose of threshing is been explained with the use of colour as shown in figure 3. The red areas indicate the regions of highest contact force, peaking at 12.5 MPa in this simulation these aretheprimaryimpactzoneswherethethreshingdrumortheconcaveribs strikethepod. Forthe threshing to be successful these forces must exceed the fracture toughness of the shell. However, if these red zones appear consistently on the waist of the pod, it might indicate a higher risk of seed damage. Furthermore the yellow and green transitions represent a force range of approximately 7.0 to 10.0 MPa. This suggests secondary contact or friction. It shows where the pod is being squeezed between the drum and the concave rather than being hit directly. This is the ideal zone for adaptive concave replacement there is need to have enough green or yellow force to maintain friction for hulling without reaching the destructive red levels too frequently. Also the blue to purple regions represent minimal contact force (near 0 MPa). These are the "free"surfacesofthepodthatarenotcurrentlyunderpressureorincontactwiththemachine walls. If a pod is predominantly blue during its entire residence time, it suggests that the motor speed is too low or the concave clearance is too wide, leading to poor threshing performance.The ResNet101 of Convolution Neural Network was the model used for the feature extraction, identification as indicated in figure 2, due to its ability and strength of handling complex image for analysis. During the training, the groundnut pod images undergoes different transformations that improved its generalization such as flipping, scalable, rotation of0^0, 90^0, 180^0 and 270^0 degrees,resizing, blowing and cropping to a dimension of 224x224 pixels especially when dealing with imbalanced or limited data set for model performance. Traditional machine relied based on operator selection feature of their physical and engineering properties using their domain skill knowledge which is seen as a setback engineering practice, time consuming and error prone due to worker fatigue that led to more minor error resulting to misalignment and misclassification during operation . However, for confidence score represents the certaintyof the model about the groundnut identification and its prediction on all the three varieties Exdakar, Jarma and Samnut26 images as shown in figure 4, the model identified the groundnut pod with the following confidence score Jarma have 99.9, 99.7%, Samnut26 have 99.9, 100% andExdakarhad95.7,99.7%,respectively, whichindicated averyhigh certaintyinitsidentification. Therefore for this research the model had attended its threshold. Where the confidence score is below 50% the model is said to be unreliable and uncertainty while table 2 summarized the confidence score that were assigned by softmax in ResNet 101 of Convolutional NeuralNetwork.

The EDEM simulation of the hopper demonstrates a stable gravitational flow of groundnut pods from the inlet to the outlet as shown in figure 5. The contact force heat map indicates that the highest contact forceswithredand orangeregions areconcentratedalongthelower hopper walls and around the outlet, where the groundnut convergence and the groundnut interactions most at the wall. While, the central region of the hopper is dominated by blue and green colors, representing lower contact forces and smoother particle flow. As groundnut approached theoutlet their velocity increases due to the converging geometry, resulting in efficient discharge with minimal groundnut accumulation. Overall, the heat map analysis confirms that the hopper geometry promotes uniform groundnut flow, minimizes the blockage, and ensures a consistent feed rate into the threshing chamber, thereby improving the overall performance of thegroundnut threshing machine. The EDEM contact force heat map shows that the highest impact forces red and orangeregionsareconcentrated atthe leadingedges ofthethreshingcylinder bars and within the cylinder concave interaction area as shown in figure 6, where groundnut pods experience repeated collisions necessary for effective threshing. The green and blue regions indicate lower contact forces as the pods move away from the impact area and particle interactions decrease. The relatively uniform distribution of high force regions around the cylinder suggests balanced loading and consistent threshing action. The overall heat map confirmsthatthecylinderdesigneffectivelytransfersimpactenergytothepods,whileindicating that cylinder speed and bar geometry should be optimized to maximize threshing efficiency and minimize pod damage. The EDEM contact force heat map shows that the highest impact forces red and orange regions are concentrated at the leading edges of the threshing cylinder bars and within the cylinder concave interaction region**,** where groundnut pods experience repeated collisions necessary for effective threshing as shown in figure 7. The green and blue regions indicate lower contact forces as the pods move away from the impact zone and particle interactionsdecrease.Therelativelyuniformdistributionofhighforceregionsaroundthe cylinder suggests balanced loading and consistent threshing action. Overall, the heat map confirmsthatthecylinderdesigneffectivelytransfersimpactenergytothepods,whileindicating that cylinder speed and bar geometry should be optimized to maximize threshing efficiency and minimize pod damage.

The EDEM simulation of the machine frame evaluates the distribution of contact forces transmitted from the flowing groundnut pods to the supporting structure during operation. The contact force heat map reveals that the highest stresses red and orange regions are concentratedat the frame joints, lower cross members, and the hopper support region, where groundnut pods impact and load transfer are greatest as seeing in figure 8. Moderate contact forces green and yellow regions are distributed along the side members, indicating effective load distribution acrosstheframe,whiletheupperframemembersremainpredominantlyblue,signifyingminimal particle interaction. The uniform distribution of contact forces and the low predicted frame deformation indicate that the frame possesses adequate structural rigidity to withstandoperational loads without significant stress concentration. Overall, the simulation confirms that the frame design provides sufficient mechanical stability and effective load bearing capacity, ensuring reliable support for the threshing unit and associated components during continuous operation.The EDEMsimulationdemonstratestheflow of groundnutpods through thethreshing machine and the distribution of contact forces during operation as shown in figure 9. The heat map indicates that the highest contact forces red and orange regions are concentrated at the threshing cylinder bars and concave, where repeated particle impacts produce effectivethreshing. Moderate contact forces green and yellow regions occur around the hopper and discharge chute, indicating smooth material transfer with minimal flow obstruction, while the frame experiencespredominantlylowcontact forcesblueregions,confirmingadequatestructural support and stability. Particle velocity increases as the pods pass through the threshing chamber and decreases at the outlet during discharge. Overall, the simulation confirms that the machine provides uniform particle flow, efficient threshing, and stable structural performance, with the cylinder concave assembly serving as the primary threshing region.

The EDEM simulation predicts that the groundnut threshing machine achieves a threshing efficiency of 93.4% with a relatively low mechanical damage of 4.2%, indicating efficient pod separation while minimizing kernel breakage. The throughput capacity of 50.6 kg h^{-1} confirms stable particle flow through the hopper, threshing chamber, and discharge outlet under the selected operating conditions. However, cleaning efficiency was not evaluated because themodel does not include the blower and cleaning mechanism required to separate kernels from chaff and other impurities. Consequently, the simulation demonstrates good threshing performance and acceptable product quality, while the cleaning performance would require an extended DEM. The model in figure 10 illustrates the overall architecture of the Mamdani Fuzzy Inference System (FIS) that is used for development of intelligent groundnut threshing machine that integrates five different input variables coming from convolution neural network (CNN) as discussed in the previous research that showcased the groundnut pods properties such asExdakar, Jarma, Samnut26, Stone (unknown varieties) and texture with two output control actions, such as concave screen clearance and motor speed. Through which linguistic input variables rules baseare transformedintoprecise control decisions made,thedesignedFISwas able handle nonlinear characteristics of the groundnut Pods as well as it output, thereby enhancing adaptive control performance. Table 3 explained the formulated fuzzy rule base that regulates the decision-making process of the system. The rules are derived from the physical propertiesofgroundnutpods asstatedinthepreviousresearch,suchassize, texture, etcthatmap the characteristics for optimal concave clearance and motor speed settings for effectiveoperation.

6. CONCLUSION

The predictive DEM-based intelligent groundnut threshing machine demonstrated satisfactory operational performance by integrating EDEM simulation, machine vision, and fuzzy logic control for adaptive threshing. The simulation achieved a threshing efficiency of 93.4%**,** mechanical damage of 4.2%**,** and a throughput capacity of 50.6 kg h^{-1}**,** confirming efficient pod separation with minimal kernel damage. In addition, the ResNet101 model accurately identified groundnut varieties with confidence scores of up to 100%**,** enabling reliable adaptive control of motor speed and concave clearance. Furthermore the developed Mamdani Fuzzy Inference System proved capable of making smart, rapid, and adaptive control decisions for concave clearance and motor speed based on varying groundnut pod properties. The smooth inference behavior, well-structured rule base, and stable output surfaces validated the suitability of fuzzy logic for handling nonlinear and uncertain of our agricultural products such as groundnut. These findings demonstrate that the proposed simulation-driven intelligent system can enhancemachine performance, reduce post-harvest losses, and provide a practical framework for the design and optimization of next-generation groundnut threshing machines.

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