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Development, evaluation, and optimization of an automated device for quality detection and separation of cowpea seeds

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ABSTRACT

Automation and Artificial intelligence has been used to solve the world''s most complex problems. The goal of this study is to develop, evaluate and optimize cowpea seeds quality detection and separating device to meet international export standards. The design of the device was divided into metering, automation, and conveyor belt outlet unit. An evaluation was done using samples made up of good and bad (impurity) portions. Response surface methodology was used to evaluate, model and optimize the device performance. The optimized results were validated using regression and prediction interval (PI) analysis test. The separating efficiency, throughput, maximum capacity, and actual utilization obtained; range from 68.966 - –94.118%, 0.5 – –3 kg/hr, 6–36 kg/12 h, 0.083–0.083(8.3%) respectively. These evaluating parameters were significantly affected by the operational factors at $P < 0.05$. Optimum values obtained are 92%, 2.689 kg/h, 32.781 kg/12 h for impurity separating: efficiency, throughput, and maximum capacity respectively. The prediction interval test shows that the validation experimental mean result lies within calculated prediction intervals. Regression analysis shows a 0.9(90%) coefficient of determination between the model predictions and the validation experimental results. The developed device was recommended to always operate at a metering speed of 20 rpm for optimum performance.

1. Introduction

Cowpea (*Vigna unguiculata (L.) Walp*) is one of the most ancient human protein food sources and has existed as a crop since Neolithic times. It is used for both consumptions and as industrial raw material for other products. The world produces over 8 million tones of dry cowpea seed yearly; with 90% percent of the production from Africa and Asia. America and Europe are the largest exporters, though being the least producers. This is because Asia and African producing countries can not meet international export standards (Henshaw, 2008, IITA, 2015, ACB, 2015, Snapp et al., 2018, Rawal and Navarro, 2019, FAOSTAT, 2020, FAO, 2021). This study's goal is to change that trend, by developing an automated cowpea seeds quality detecting and separating device for less developed producing countries.

Automation is the term used to describe an operation that requires less or no human involvement. In crop processing, a lot of the automation activity involves machine vision. According to tech brief (2019) machine vision automation is bring a never seen before solution to human problems. Machine vision involves the use of image sensors to detect materials and separate them. The use of machine vision to automate agricultural grains and seed processing operations has been carried out by various researchers. Casady and Paulsen (1989) developed a machine vision automated maize corn positioning system with an error-free of 99%. Georg et al. (1995) developed an automatic machine vision for broken and unbroken wheat kernel separating system with 95.8% accuracy. Wan (2002) developed an automatic image vision grain sorting system with 99% accuracy at 1296 kernels per minute using two cameras. The system was tested with rice, wheat, jobstear, and sorghum kernels. Pearson (2009) developed a hardware-based image processing damaged grain sorting device. It was tested with Maize and wheat kernels with a throughput of 40 kg/h and 8 kg/h, with an accuracy of 74 and 91% respectively. Pearson (2010) developed a low-cost high-speed machine vision grain damage sorter. The system was tested with wheat, barley, durum, and flax seeds. Its throughput was found to be 25 kg/h with an accuracy ranging from 92 to 96% depending on the grain being sorted. Kirilova et al., 2013 developed prototype image recognition and grading system for damaged maize seeds. The system was tested and found to have sensitivity, specificity, accuracy, and precision of 88.43, 93.88, 90.49, and 94.79%, respectively. Arkadiusz and Andrzej, 2018 developed, a 2D machine vision, automated machine for diseased rice sorting system using the rice shape and color. Injante et al., 2020 developed an automated image processing system for sorting lima beans to meet export standards. Test of the system shows an acceptance and

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rejection efficiency of 96.81 and 95.26% respectively. None of these researchers during evaluation used I-optimal experimental design to model and optimize the operational capability of their developments.

Modeling is the representation of concepts and happenings within our natural world, to study and predict future instances. Optimization is part of mathematical modeling (Zeigler et al., 2018). Dantzig (2014) and Al-Baali et al. (2018), define numerical optimization as choosing the best elements or factors among groups of elements considered. These choices must be done considering some sets of constraints or goals set for the selection. In order words, optimization is finding the best available choices under certain conditions. There are different mathematical approaches to achieve optimization. One of these approaches is Response surface methodology. Response surface methodology (RSM) is a mathematical technique that develops an experimental design that can put together all the independent variables or factors and use the experimental outcome or results to produce equations that can be used to reproduce or predict the experimental results or outcome again. Though complex calculations (well-designed regression analysis) are involved, it is one of the efficient ways of achieving optimization. Experimental designs developed during response surface optimization include Central Composite Design (CCD); Box-Behnken (BB); Optimal Designs (Stat-Ease, 2018; García and Peña, 2018; Makowski, 2020). The objective of this study is to develop, evaluate and optimize the operational capability of an automated device for quality detection and separation of cowpea seeds to meet international export standards.

2. Materials and methods

2.1. Design of the automated device

The design of the automated device was divided into three categories: metering unit, automation (artificial intelligence) unit, and conveyor belt unit. The detailed design parameters, calculations, and reasons for selections are displayed in Tables S1, S2, S3, and S4 (supplementary tables). Written materials consulted during design include (Boumans, 1985, Srivastava et al., 2006, Yalcin, 2007, Fenner Dunlop, 2009, Sharma and Mukesh, 2010, Dunlop, 2016, O'Keefe, 2017, Tech Briefs, 2019, Habasit Fabric Conveyor Belt Engineering Guide, 2021)

2.2. Automated device design components

2.2.1. Metering unit

This consists of an 11 kg/s capacity hopper having a 120 mm diameter wooden metering disc (with 4 holes bored at equal interval)

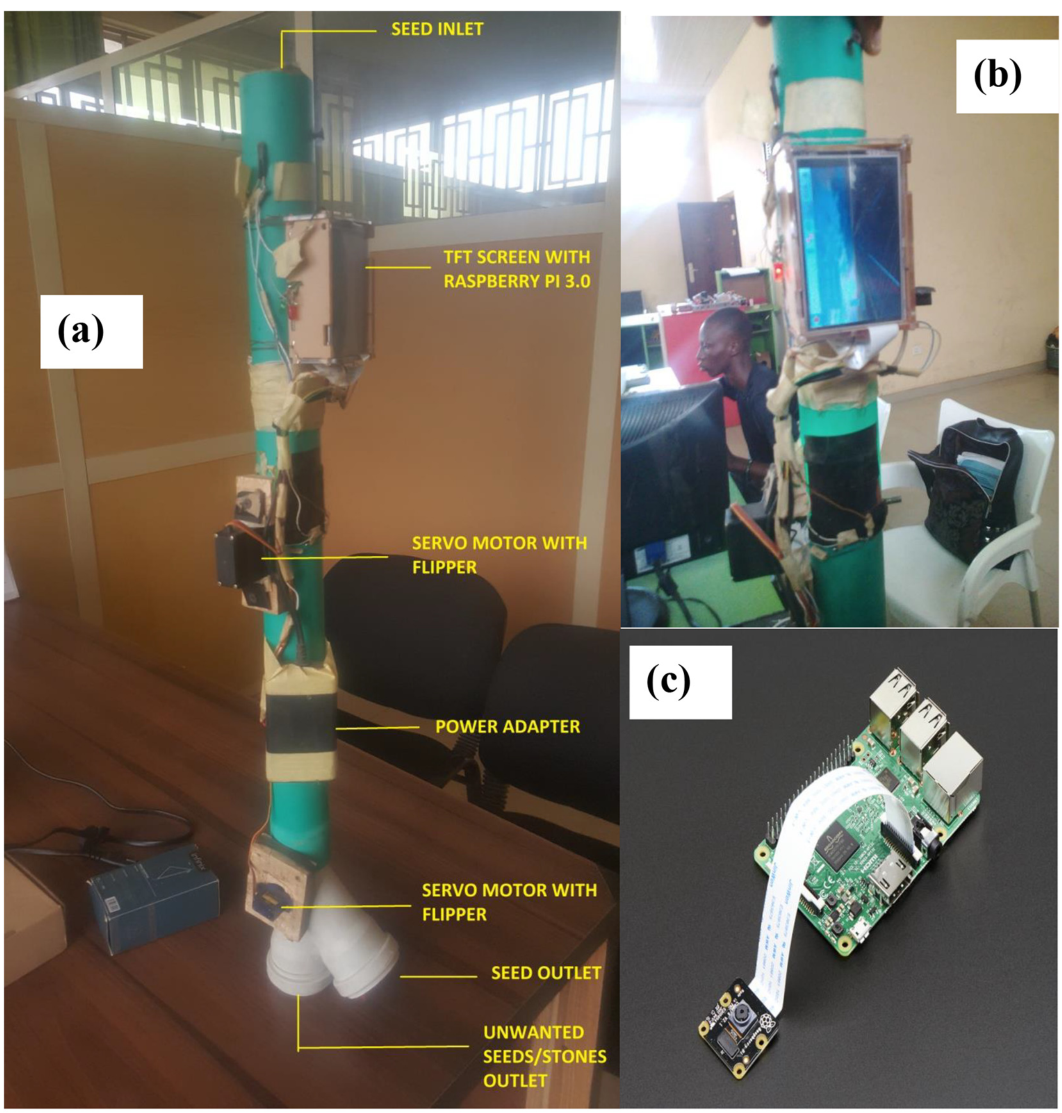

Fig. 1. Picture of (a) the whole automation unit (b) plastic box housing the raspberry pi board and camera with a TFT 5 in. screen (c) raspberry pi board with a pi camera board attached.

attached at the bottom (fig. S1 in the supplementary document). This metering disc was powered with 2 hp. motor revolving at 1450 rev/min and link to a reduction gear with ratio 1:80. This reduction gear allows the seeds and impurity to be metered one at a time into the automation unit. A 920 mm high standing frame was used to support the entire metering unit (Fig. S1a).

2.2.2. Automation unit

Fig. 1 displayed the automated unit. This consists of raspberry pi 3 board model B with a Pi camera board attached placed inside a rectangular plastic box (Fig. 1a). This box is covered with a 5 in. TFT screen which was also connected to the raspberry pi board (Fig. 1b and c). The box is then attached to a 90 mm length PVC pipe. The inside of the pipe is divided into two compartments separated with two circular plastic flippers forming the bases. Theses flippers are attached to two micro servo SG 90 motor which flip them 90^o inside the PVC pipe. The inside of the two (primary and secondary) compartments were lit up by LED lights also connected to the raspberry pi board. Adaptor power cable was used to power the raspberry pi board. The PVC pipe had two outlets at its end for rejected and accepted materials.

2.2.3. Conveyor belt outlet unit

This consists of belt carcass type of PN (polyester and Nylon) plain weave (DIN code EP) with strength range of 315–2000 kN/m (150–400 kn/m/ply). The belt has a carry capacity of 1000 kg/m^3, with length and width of 1300 mm and 250 mm respectively. The belt pulley dimensions are shown in fig. S1b (supplementary document).

2.3. Programming of automated unit

The Raspberry pi board operational system software was downloaded from the Raspberry pi organization website (https://www.raspberrypi.org/downloads/). The operating system software was installed as instructed by the company. After installation of the operating system, other devices like the Raspberry pi camera and the TFT screen was attached and their application software downloaded from their respective company websites. These applications software were also installed on the Raspberry pi board according to installation instructions. The Raspberry pi camera was now used to take 150,000 images each for good seeds and impurities (Program S1 in the supplementary document). Some pictures captured by the pi camera used for the automation are displayed in Fig. 2. These captured images was now saved on the Raspberry pi board and then uploaded into a laptop. These images were thereafter uploaded into python software. The program (which is the artificial intelligence part) that was developed by the python software; used for comparing incoming image with stored image on the Raspberry pi board are displayed in Program S2 in the supplementary document. After developing the python programs, it is then transferred into the Raspberry pi board.

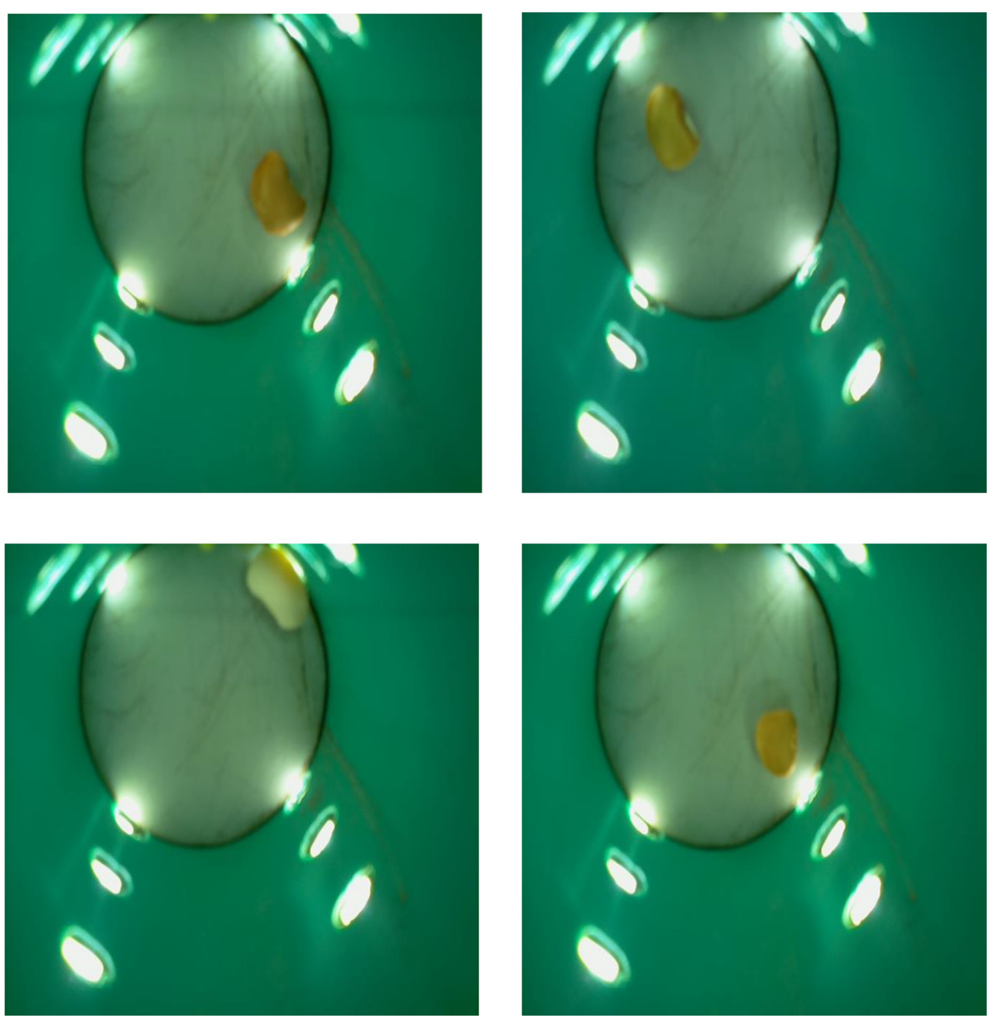

Fig. 2. Some captured images of cowpea seeds within the sorting chamber, taken by the raspberry Pi camera used for developing the sorting software programs.

2.4. Operational procedure of the automated device

The operational flow diagram of the separating procedures is displayed in Fig. 3. The device was first turned on. Then material to be detected and separated was introduced as input into the metering device hopper. Then metering drum at the end of the hopper, introduced it into the automation unit, one after the other. As the material passed into the automation units, motion and proximity sensors from the Raspberry Pi camera board detect its presence. When the material fell into the first detection chamber called the primary grain collector (compartment). This primary grain collecting chamber (compartment) was well illuminated by LED light bulbs (Fig. 2). The LED light bulbs were connected to the Pi camera board and come on when the automation device is turned on. The image photograph of the material was taken by the pi camera sensors in the primary collection chamber (compartment). This image was sent to the Raspberry pi board to be processed and compared it to previous images loaded into the board memory. The Raspberry pi board then activates the circular bottom plastic flipper (actuator) of the primary collection chamber (compartment) to rotate 90 degrees. This action allowed the material to move to the second chamber (compartment) called the secondary grain collection chamber (compartment). This chamber also was illuminated by LED light bulbs. In the secondary grain chamber (compartment), separation decisions are made. This decision was made using artificial intelligence program (see programs S1 and S2 in the supplementary material) developed by python program software, inputted into the Raspberry pi board. After comparing the taken image to the stored images, the Raspberry pi board automatically activates the actuator. The actuator here was the circular plastic flipper bottom of the secondary grain collecting chamber (compartment). This circular bottom flipped either flipped 90 degrees to the left or 90 degrees to the right. Each flipping of the bottom directs the material to either of the two outlet pipes. The outlet pipes are called the "Accepted and "Rejected" outlets. Materials move from the outlets onto the conveyor belt. These materials either fall to the right or left on the belt. The belt conveys them to another two outlets at the end of the conveyor belt. A well labeled diagram of the complete assembled setup of the cowpea quality detection and separation device is shown in Fig. 4.

2.5. Evaluation technique

Three good quality cowpea seed varieties namely: NG/AD/11/08/0033, NG/OA/11/08/063, and NGB/OG/0055 samples were obtained at the National Center for Genetic Resources and Biotechnology (NACGRAB), Ibadan, Nigeria. Quality assessment and selection of sample materials used for evaluation were carried out as displayed in

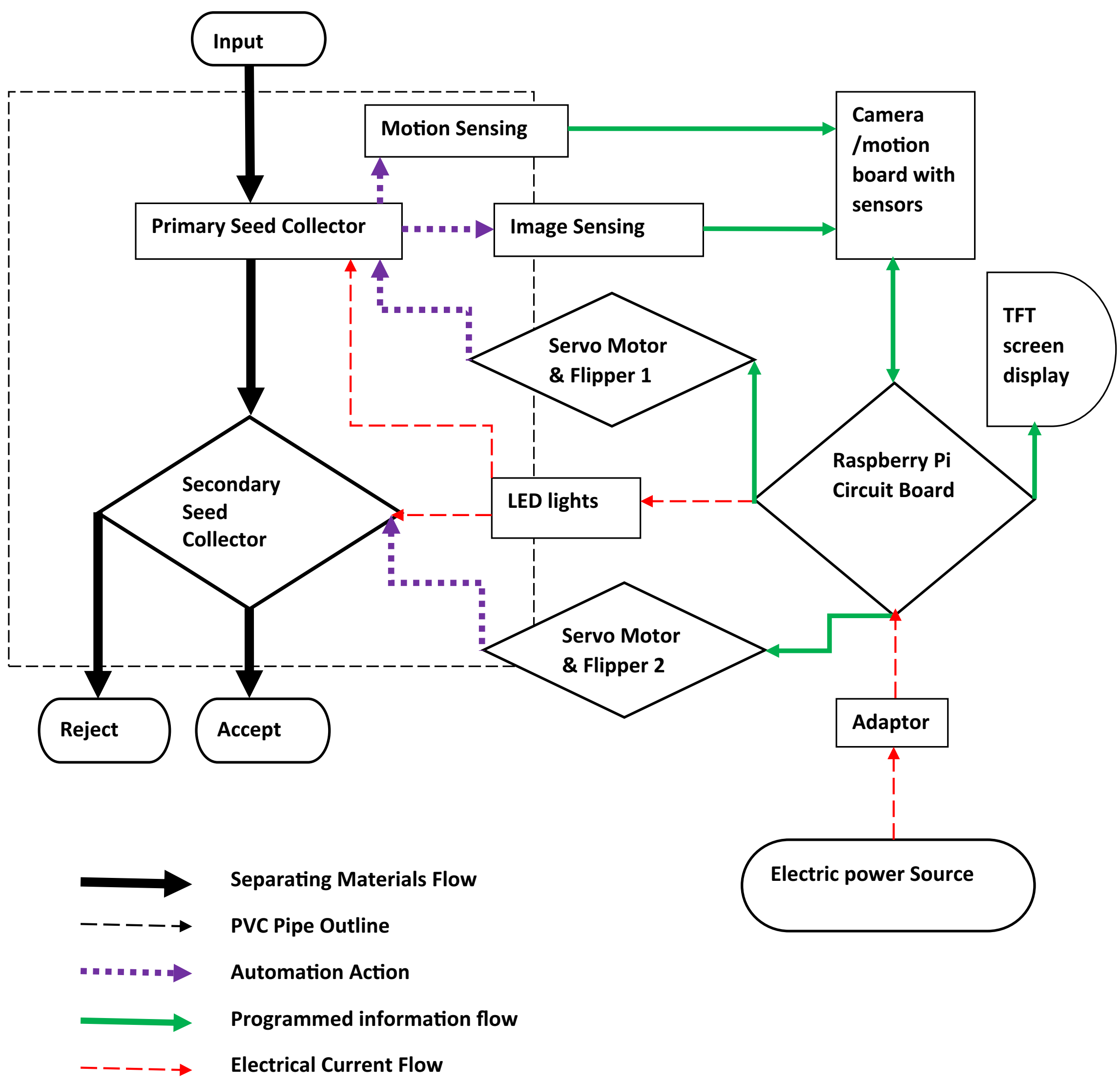

Fig. 3. Flow Chart of Automation unit of cowpea Seed/Impurity separation.

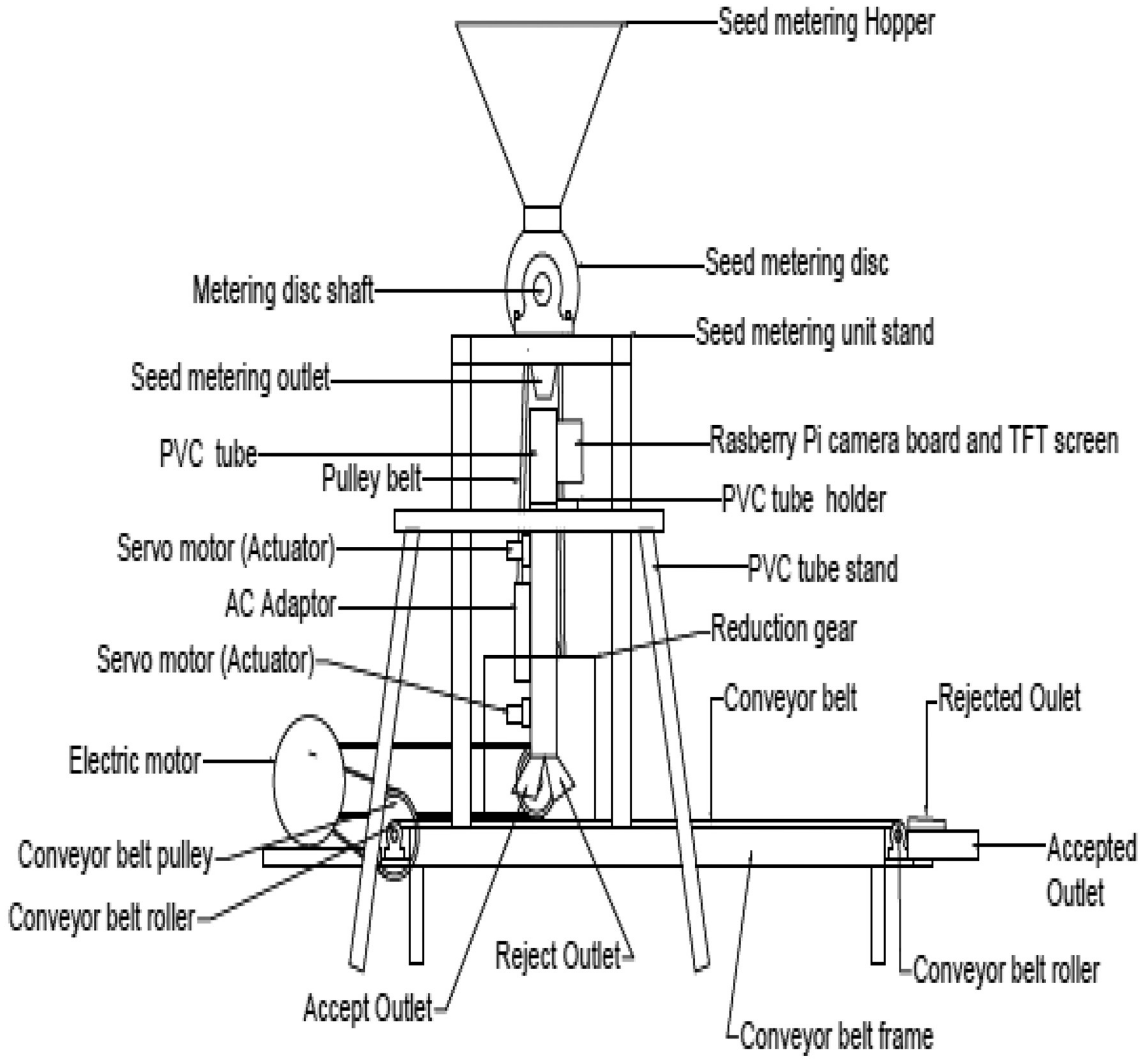

Fig. 4. Labeled diagram of the complete assembled setup of the cowpea quality detection and separation device.

Table 1. Images of impurities (bad portion) used in this study to mix with good seeds (good portion) are displayed in Fig. 5. These impurities are made up of:

Table 1
Quality assessment and selection of materials used for evaluation.

Quality parameters	Grade 1	Grade 2	Grade 3
Range of quality parameters limits of cowpea compile from international standards			
Broken Seeds (%)	2 – 3[a,b,c,f,g]	3 – 5[a,b,c,d,e]	6 -7[a,b,c,d,e,f]
Foreign Body (%)	0.5–0.8[a,b,d,e,g,i]	1[a,b,e,f,g,i]	2[a,b,c,d,e,f,g,h,i]
Damage Seeds (%)	4 – 6[a,b,d,e,f,g]	7 – 10[a,b,c,e,f,g]	15[a,b,c,d,e,f,g]
Bad portion (%)	6.5–10.8	11–16	23–24
Good portion (%)	93.5–89.2	89–84	77–76
Total (%)	100	100	100
Quality parameters used for preparing cowpea sample for this study			
Broken Seeds	3% (0.06 kg)	5% (0.1 kg)	7% (0.14 kg)
Foreign Body	0.8% (0.016 kg)	1% (0.02 kg)	2% (0.04 kg)
Damage Seeds	6% (0.12 kg)	10% (0.2 kg)	15% (0.3 kg)
Bad portion	9.8% (0.196 kg)	16% (0.32 kg)	24% (0.48 kg)
Good portion	90.2% (1.804 kg)	84% (1.68 kg)	76% (1.52 kg)
Total	100% (2 kg)	100% (2 kg)	100% (2 kg)

Sources: (a) African Standard, 2012; (b) United States Standards for Beans, 2008; (c) Draft Malawi Standard (2015); (d) AHCX Commodities Exchange, 2014; (e) Australian Pulse Standards, 2014/15; (f) EAC, 2010, Codex Standard 171–1989; (g) FDUS EAS 755., 2013 (i) Codex Standard 171-1989, n.d.

a) Damaged seeds - cowpea seeds exposed to natural environment for six months for it to be both insect and fungal affected (Fig. 5a and b)
b) Broken seeds – Crushed cowpea seeds (Fig. 5c)
c) Foreign body - Stones (ranging from 6 to 10 mm in diameter) (Fig. 5d)

To evaluate the device (machine) performance, a 2 kg of an experimental sample (good + bad portion), made up of different varieties and quality grades (percentage of impurity: grade 1, 2, and 3) was poured into the metering hopper. This was metering at speeds of 12, 16, and 20 rpm. Separated samples were collected at the rejected and accepted outlets of the belt conveyor. Both separated samples that were collected from the outlets at the end of each run (experiment). Were further hand sorted into good seeds, broken seeds, foreign body, and damaged seeds. They were then weighed and recorded. The time for each experimental run was also taken and recorded. Evaluation parameters were calculated as displayed by eqs. (1)–(5):

A. The separating efficiency of Automation device (E)(%) is the Impurity removal efficiency

$$E = \frac{weight\ of\ impurity\ collect\ at\ the\ reject\ outlet}{Tatal\ weight\ of\ impurity\ used\ for\ experiment}\ x\ 100 \qquad (1)$$

Fig. 5. Pictures of (a) diseased seeds (b) insect infected seeds (c) broken seeds and (d) stones; used for preparing impurity.

$$\text{Total weight of impurity} = \text{weight of (Broken seeds + Foreign bodies + Damage seeds)} \quad (2)$$

B. Throughput of Automation device (T) (kg/h) is the Impurity removed in one hour

$$T = \textit{weight of impurity coming out of the rejected outlet in one hour} \quad (3)$$

C. Maximum Capacity of Automation device (MC) (kg/12 h) is the impurity removed in 12 h (assuming the device is only allowed to operate for only 12 h a day)

$$MC = \textit{Throughput rate x operation time} = T \textit{ x } 12 \textit{ hours} \quad (4)$$

D. Actual utilization of Automation device

$$\textit{Actual Utilization } (AU) = \frac{\textit{Throughput } (T)}{\textit{Maximum Capacity } (MC)} \quad (5)$$

Machine utilization is a measure of how intensively a machine is being used. Machine utilization compares the actual machine time (setup and run time) to available time.

Operational factors used for evaluating were speed of metering device, seeds varieties and seed grades.

2.6. Modeling, optimization, and validation

The experimental design used for modeling and collection of data was response surface I-optimal design. Software used for both modeling and optimization was “Design Expert” version 10. The goals of the optimization were to achieve device settings that will produce maximum impurity separation efficiency, throughput, and capacity. Validation on the device was done using two statistical analyses: The regression analysis test and the Prediction interval test.

3. Results and discussion

3.1. Evaluation

The experimental results obtained during the evaluation are shown in Table 2. Summary of the modeling activity were displayed in Table 3. Impurity separation efficiency obtained during evaluation range from 68.966–94.118% with a mean result of 82.758%. The standard deviation of the experiment was 7.479%. A low standard deviation value of 7.479% shows that majority of the impurity separation efficiency results obtained are close to the mean result of 82.752%. This is good, owning to the fact that constant operational high separating efficiency is a desirable characteristic for a quality control device. Similar separating accuracies ranges had been achieved by Casady and Paulsen (1989), Georg et al. (1995), Wan (2002), Pearson (2009), Pearson (2010), Kirilova et al. (2013), Arkadiusz and Andrzej (2018) and Injante et al. (2020) for other grains and seeds. Impurity separating throughput results obtained range from 0.5–3 kg/h with a mean result of 1.352 kg/h. The standard deviation of the experiment was 0.777 kg/h. A low standard deviation also signifies that the majority of the results obtained do not spread along with the range but concentrate around the mean throughput of 1.352. This is also a good quality for predicting device performance. Similar throughput results ranges for other grains and seeds were reported by Wan (2002), Pearson (2009), and Pearson (2010). The maximum impurity separation capacity results obtained range from 6 to 36 kg/12 h. The mean value obtained was 16.404 kg/12 h with an experimental mean deviation of 9.473 kg/12 h. A low standard deviation value of 9.473 kg/12 h shows that majority of the maximum impurity separation capacity results obtained are close to the mean result of 16.404 kg/12 h. This knowledge can help the operator schedule his working hours and cost of operation. The actual Utilization capacity results obtain for the device were 0.083 (8.3%) all through the experiments. This is because a constant sample weight of 2 kg was used throughout the evaluation experiments. 2 kg represent 8.3% of the device material carrying and processing capacity at a time. From this information, this study deduced that the device can carry and process 24 kg (100% utilization) at a time.

3.2. Effects of operational factors on evaluation parameters

The effects of operational factors like speed of metering, variety, and grade of the sample used; on evaluation parameters like separating efficiency, throughput, and maximum capacity are displayed graphically in Fig. 6 and 7. A 2D plot of separating efficiency on metering speed shows a quadratic relationship (Fig. 6a). This plot shows that an increase in seed metering speed reduced the separating efficiency to a point. Then further increments start to increase the efficiency. This phenomenon can be attributed, to the image processing time. The programmed image comparing time was set for five second (Program S2). So, increasing the speed of seed metering (feed rate) will lead to having more seeds in the separating chambers. This can lead to wrong decision during comparing acquired image to stored image, therefore reducing separation efficiency. Similar observation was mentioned by Pearson et al., 2008 during his evaluation of a developed color image based sorter for separating red and white wheat. They also notice that increasing the federate affected the sorting accuracy of wheat seeds from its impurity. So therefore, this study recommends that to increase separation efficiency the metering speed should be reduced from its design metering speed of 15 rpm. A 3D graph of separating efficiency on variety and grade shows that; NG/AD/11/08/0033 (small white seeds) has the highest separating efficiency and NGB/OG/0055 (red seeds) the lowest (Fig. 7a). This trend can be explained to be caused by the bright white colors and the small sizes of NG/AD/11/08/0033 variety. Its color makes it easier to detect by the pi camera while its size allows it to be metered faster. The NGB/OG/0055 (red seeds) variety color delay during its detection, which could be due to colour spectrum band differences. Similar condition was reported by Pasikatan and Dowell (2003), during evaluation of a high speed sorter for separating impurity in white and red wheat. The sorting sensitivity and accuracy was less for

Table 2
Automation device evaluation results.

Run	Factors			Responses			
	Speed of Metering	Grade	Variety	Separating Efficiency	Separating Throughput	Maximum separating capacity	Actual Utilization
	rpm			%	kg/h	kg/12 h	
1	16	1	33	91.892	0.680	8.160	0.083
2	16	3	33	90.909	1.818	21.818	0.083
3	12	2	33	90.615	0.875	10.500	0.083
4	16	3	55	72.727	1.333	16.000	0.083
5	20	1	63	80.973	2.257	30.542	0.083
6	20	2	63	81.579	2.583	31.000	0.083
7	20	3	63	81.818	2.647	31.765	0.083
8	16	1	55	70.000	0.784	11.000	0.083
9	20	2	55	76.923	3.000	36.000	0.083
10	16	3	63	82.353	2.100	25.200	0.083
11	12	1	55	73.171	0.500	6.000	0.083
12	12	3	63	85.739	1.045	12.674	0.083
13	16	1	33	91.892	0.680	8.160	0.083
14	16	3	55	72.727	1.333	16.000	0.083
15	20	3	33	90.000	2.647	31.765	0.083
16	16	3	33	90.909	1.818	21.818	0.083
17	20	1	55	77.295	1.231	14.769	0.083
18	12	2	63	82.143	0.852	10.222	0.083
19	12	1	63	80.645	0.577	6.923	0.083
20	12	2	63	82.000	0.810	10.000	0.083
21	12	1	33	94.118	0.571	6.857	0.083
22	16	2	33	89.286	1.190	14.286	0.083
23	12	2	55	68.966	0.606	7.273	0.083
24	16	1	63	82.353	0.700	8.400	0.083
25	16	2	33	87.923	1.154	12.978	0.083

Table 3
Summary of modeling of automation device evaluation parameter.

Software:	Design Expert Version 10
Study Type:	Response Surface
Design Type:	I-optimal
Subtype:	Randomized
Blocks:	No Blocks

Factor	Units	Type	Subtype	Mi*	Max*	Coded	Values	Mean	Std. Dev.*
Speed of Metering	rpm	Numeric	Discrete	12	20	1 = 12	1 = 20	15.68	3.038
Grade		Categorical	Nominal	1	3		Levels:	3	
Variety		Categorical	Nominal	055	063		Levels:	3	

Response	Units	Obs*	Analysis	Min*	Max*	Mean	Std. Dev.*	Ratio	Trans*	Model
Separating Efficiency	%	25	Polynomial	68.966	94.118	82.758	7.479	1.365	None	Quadratic
Separating Throughput	kg/h	25	Polynomial	0.500	3.000	1.352	0.777	6	None	Linear
Maximum separating capacity	kg/12 h	25	Polynomial	6.000	36.000	16.404	9.473	6	None	Linear
Actual Utilization		25	Polynomial	0.083	0.083	0.083	2.83E-17	1	None	Linear

*Obs is Observation, Min is Minimum, Max is maximum, Trans is Transformation, Std. Dev. is Standard Deviation.

the red wheat blend than for the white. This study had therefore shown that the developed device separate white cowpea better than red. A plot of the device throughput with metering speed shows a linear relationship (Fig. 6b). Throughput increases as metering speeds are increased. This behavior can be explained from the point of view that increasing the metering speed increase the number of material introduced into the automated unit in one hour. So therefore, more impurities are likely to be a separation in one hour. Kawusara (2019) and Injante et al. (2020) also reported similar observation during evaluation and testing of their image processing devices for cowpea and lima beans respectively. Although throughput range of 0.5–3 kg/h obtained is low compare to that obtained by previous researchers for other grains and seeds. To improve this, then the use of a higher version of the raspberry board with lesser decision time (processing speed) with HD camera is recommends. A 3D plot of throughput on variety and grade shows that; NG/OA/11/08/063 has the highest throughput and NGB/OG/0055 the lowest; grade 3 has the highest throughput and grade 1 the lowest (Fig. 7b). This could be because NG/OA/11/08/063 variety has a very

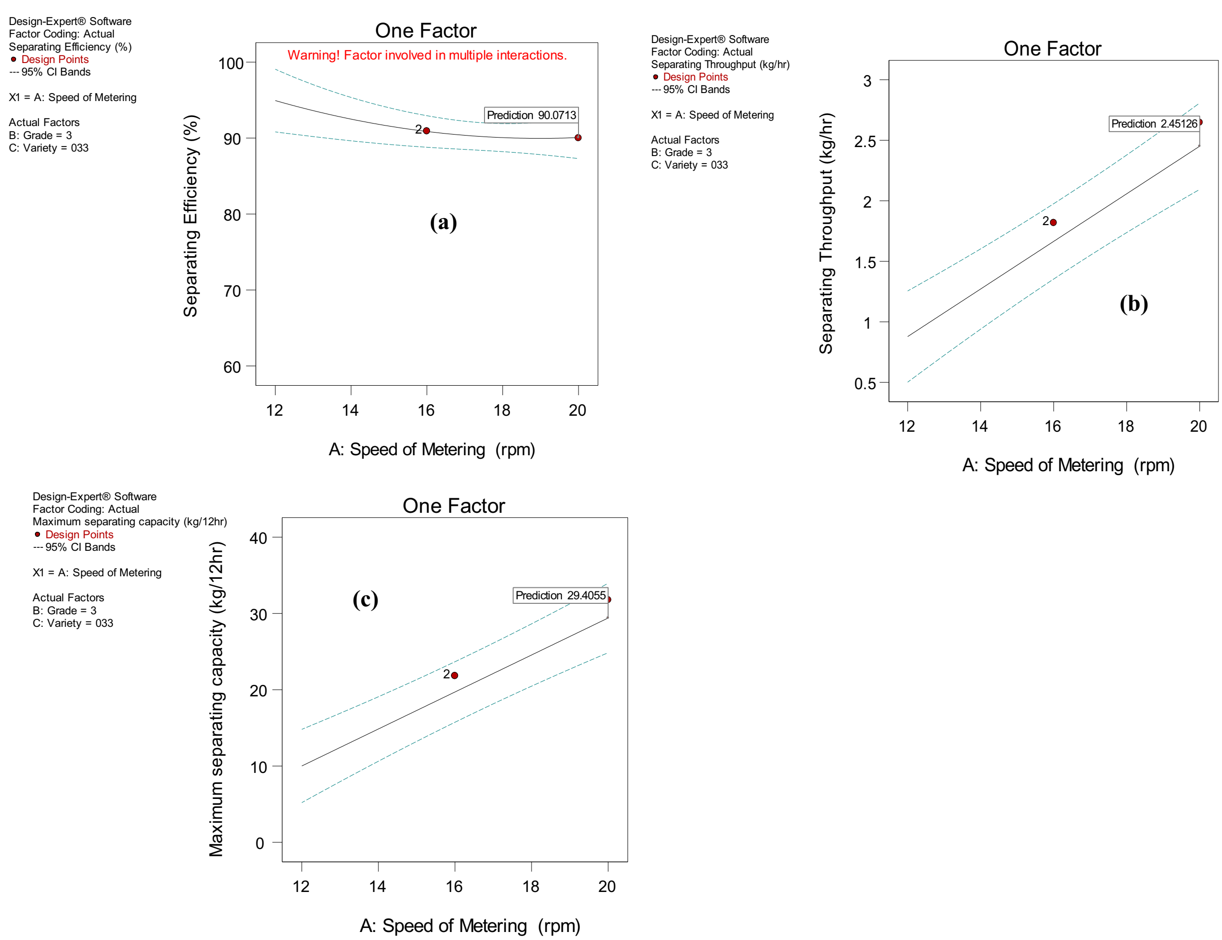

Fig. 6. 2D graphs on effect of speed of metering on (a) Separating Efficiency (b) Separating Throughput (c) Maximum separating capacity.

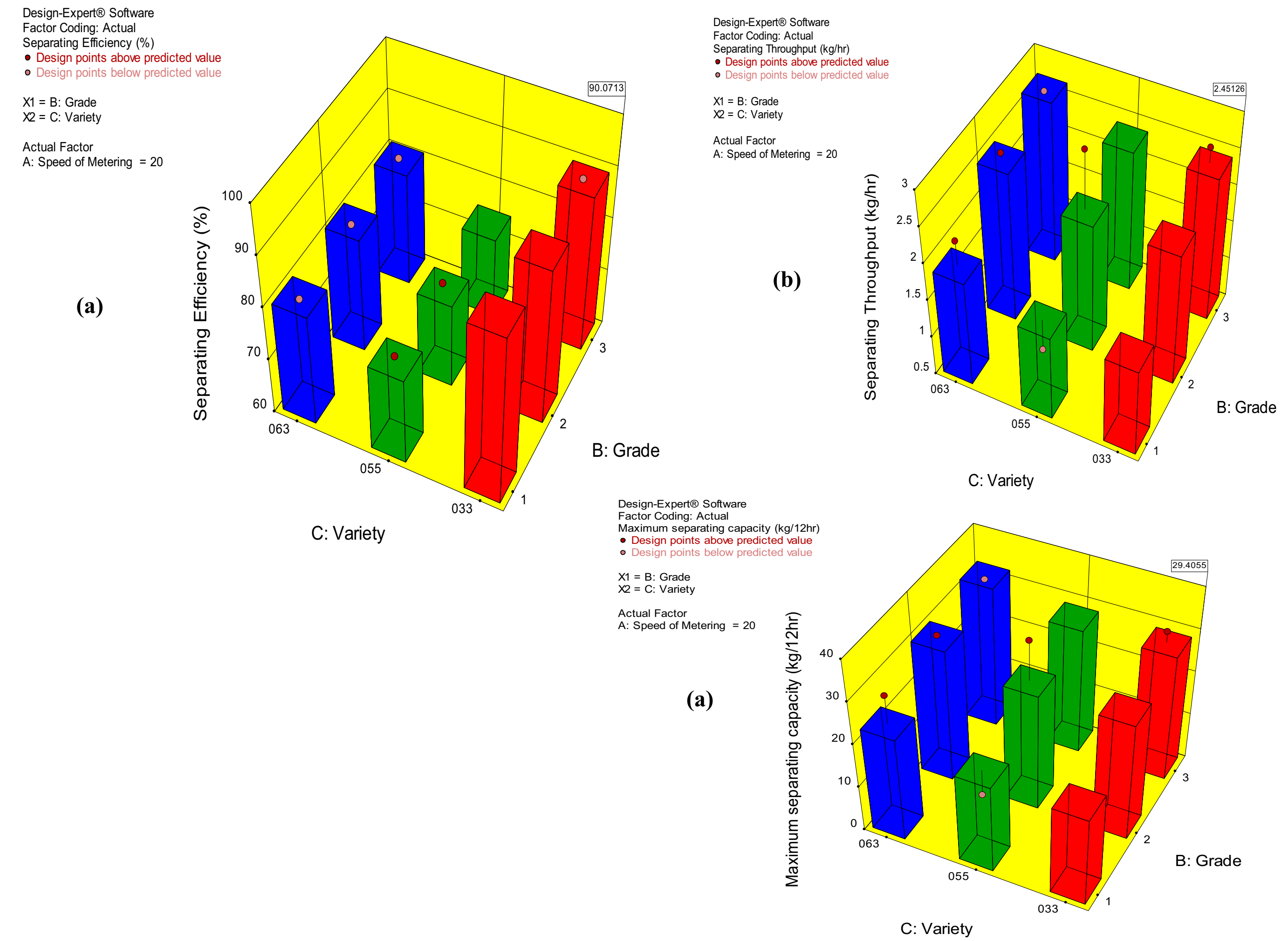

Fig. 7. 3D graphs on effect of seed variety and grade On (a) Separating efficiency (b) Separating throughput (c) Maximum separating capacity.

bright white color which is easier to detect than NGB/OG/0055 which has red coloured seeds. Also, grade 3 having more impurity must separate more impurity per time. Similarly throughput behavior had been observed by Pearson et al. (2008), Pearson (2009) and Pearson (2010). A graph of maximum capacity plotted on metering speed, behavior similar to that of throughput graph (Fig. 6c). Also, 3D plot of

Table 4
Optimized results of evaluation of operational performance on automation device.

Constraints						
Name	Goal	Lower Limit	Upper Limit	Lower Weight	Upper Weight	Importance
Speed of Metering	In range	12	20	1	1	3
Grade	In range	1	3	1	1	3
Variety	In range	055	063	1	1	3
Efficiency	Maximize	68.966	94.118	1	1	3
Throughput	Maximize	0.5	3	1	1	3
Maximum capacity	Maximize	6	36	1	1	3
Actual Utilization	none	0.083	0.083	1	1	3

Solution Number	Speed of Metering	Grade	Variety	Efficiency	Throughput	Maximum capacity	Actual Utilization	Desirability
1	20	3	033	90.071	2.451	29.405	0.083	0.799
2	20	2	033	90.054	2.287	27.445	0.083	0.754
3	20	3	063	81.852	2.689	32.781	0.083	0.737
4	20	2	063	82.183	2.525	30.821	0.083	0.706
5	20	1	033	92.598	1.694	20.926	0.083	0.607
6	20	1	063	81.464	1.932	24.302	0.083	0.558
7	20	3	055	75.484	2.413	29.185	0.083	0.535
8	20	2	055	76.270	2.249	27.224	0.083	0.524
9	20	1	055	76.748	1.656	20.705	0.083	0.412

maximum capacity on variety and grade behaviors similar to that of throughput plot on variety and grade (Fig. 7c). Similar explanations given to throughput graphs can also be used for the maximum capacity.

3.3. Modeling and optimization

Five polynomial equations were considered for modeling and optimization of evaluation parameters as shown in table S5 (Supplementary table). These equations were: linear, 2 factors interaction (2FI), quadratic (2 order polynomial), and cubic (3 order polynomial). A quadratic equation model was chosen for separating efficiency. This choice was base on the fact that among the model equations tested. The quadratic equation had the highest: lack of fit *p*-value (a value that describes whether the equation adequately describes the relationship between the variables); adjusted R-square (how close are the data results close to the regression line adjusted for the predictors) and predicted R-square (how well are predicted values close to the experimental values). Linear equation models were chosen for modeling and optimization of separating throughput and maximum separating capacity. This choice was base on the fact that among the polynomials tested. The linear equation had the highest sequential p-value (the probability that the terms are not modeling noise) and predicted R-square. These two model equations were used to optimize the evaluation parameters, but first the Analysis of Variance (ANOVA) and statistic parameters were calculated. The ANOVA, statistical parameters, and model equation terms for the evaluation parameters are displayed in tables S6, 7, and 8 (supplementary tables). ANOVA shows that all developed models for evaluating parameters were all significant at $P < 0.05$ while their lack fit were not significant at $P < 0.05$ (table S6). These are good indication of a very good predictive model. Table S7 shows the statistical quality of the developed equations. These statistic range are standard deviations (0–4.306), coefficient of variation (CV) (0–26.249), PRESS (0–654.111), −2 Log Likelihood (9–137.087), R-Squared (0.8–0.985), Adjusted R-Squared (0.7–0.965), Predicted R-Squared (0.5–0.876), Adequate Precision (14–22.924), Bayesian information criterion (BIC) (29–156.401) and Akaike information criterion (AIC) (26–153.754). These modeling statistic ranges show that the developed models can be used to accurately optimize the evaluation parameters of the developed device at 95% confident level. Model equations are displayed in table S8 (supplementary table).

The optimum solutions obtained from optimizing the device operations are displayed in Table 4. The goals of the optimization were to achieve maximum separating: efficiency, throughput, and capacity. This was done within the experimental ranges of metering speed, variety, and grades used in this study. Nine optimum solutions were achieved. The automation device achieved its highest separating efficiency (92%) when processing NG/AD/11/08/0033 variety of grade 1 with a metering speed of 20 rpm (solution 5 in Table 4). Maximum separating throughput (2.689 kg/h) was achieved when processing NG/OA/11/08/063 variety of grade 3 with a metering speed of 20 rpm (solution 3 in Table 4). Maximum separating capacity (32.781 kg/12 h) was achieved when processing NG/OA/11/08/063 variety of grade 3 with a metering speed of 20 rpm (solution 3 in Table 4). More

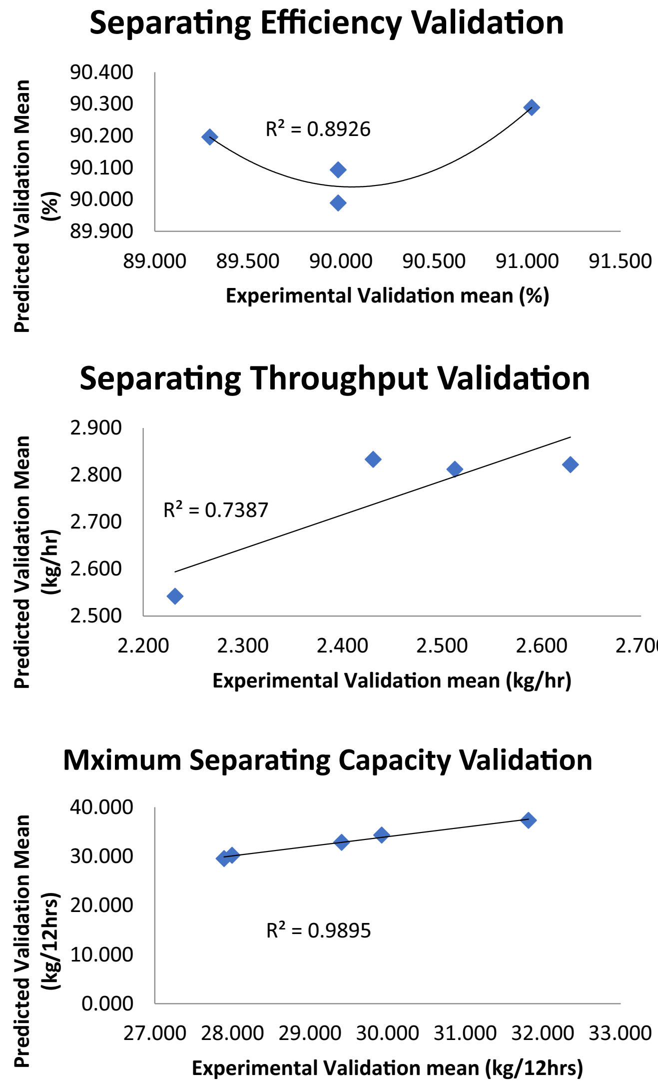

Fig. 8. Regression analysis for validation of automation device operation.

Table 5
Validation results for the automation device.

Two-sided Confidence = 95%									
Factor		Level used for validation	Low Level			High Level		Std. Dev.*	Coding
Speed of Metering		20	12			20		0	Actual
Grade		3	1			3		N/A	Actual
Variety		033	055			063		N/A	Actual
Response	Predicted Validation Mean	Predicted Median Validation	Evaluation Data Mean	Std Dev*	N*	Pred Std* Error	95% PI* low	Validation Experimental mean	95% PI* high
Efficiency	90.071	90.071	82.758	1.389	5	1.863	85.920	90.142	94.223
Throughput	2.451	2.451	1.352	0.338	5	0.378	1.659	2.752	3.244
Maximum capacity	29.405	29.405	16.404	4.306	5	4.824	19.309	32.836	39.502
Actual Utilization	0.083	0.083	0.083	1.36×10^{-17}	5	0	0.083	0.083	0.083

*n is Number of Experimental observation, PI is Prediction interval, Std Dev. is Standard Deviation, Pred Std is Predicted standard.

choices can be made from Table 4, depending on operational goals. All optimal results were obtained at a metering speed of 20 rpm. This means that the automated device should not be operated below or above a metering speed of 20 rpm.

3.4. Validation

Prediction interval (PI) statistical analysis test was done to validate the prediction ability of the models used; for optimizing separating efficiency, separating throughput, and maximum separating capacity. The mean validation results were displayed in Table 5 (full results are displayed in table S9 in supplementary material). The analysis shows that the mean validation experimental results obtained; for separating efficiency, separating throughput, and maximum separating capacity all lay between calculated low 95% prediction intervals (95% PI) and calculated high 95% prediction intervals (95% PI). This indicates that the models are predicting within a statistically expected range. Furthermore, a regression analysis was also done to validate the predictive ability of the models (Fig. 8). A regression graph between the predicted results was plotted against validation experimental results. This graphs show coefficient of determination (R^2) value of 0.892 (89.2%) for separating efficiency, 0.738 (73.8%) for separating throughput, and 0.989 (98.9%) for maximum separating capacity. These values show that the developed models used for optimization predictions were within the range of 73–93% accurate and precise.

4. Conclusions

An automated (artificially intelligent) quality separating device was developed with three units. These units are the metering, automating, and belt conveying outlet. To evaluate the device; its separating efficiency, throughput, and maximum capacity were modeled and optimized. An optimal: impurity separating efficiency of 92%, impurity separating throughput of 2.689 kg/h, and maximum impurity separating capacity of 32.781 kg/12 h were achieved. The effects of operating factors like cowpea variety, cowpea export grades, and metering speed on device evaluation parameters like impurity separating: efficiency, throughput, and maximum capacity were established. It was also established that the metering speed of the device should not go below or above 20 rpm for optimal impurity separating results. This artificially intelligent (smart) device can also be used in cowpea seeds grading processing line to achieve cowpea seeds export grade quality.

Declaration of Competing Interest

There is no conflict of interest what so ever between co-author and me. This research was not funded by any cooperation or institution. This research was part of my PhD research work.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.aiia.2021.10.003.

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