



# Survey and Cost–Benefit Analysis of Sorting Technology for the Sweetpotato Packing Lines

Yuzhen Lu <sup>1,\*</sup> , Lorin Harvey <sup>2</sup>  and Mark Shankle <sup>2</sup>

<sup>1</sup> Department of Biosystems and Agricultural Engineering, Michigan State University, East Lansing, MI 48824, USA

<sup>2</sup> Pontotoc Ridge-Flatwoods Branch Experiment Station, Mississippi State University, Pontotoc, MS 38863, USA; lh1853@msstate.edu (L.H.); mws6@msstate.edu (M.S.)

\* Correspondence: luyuzhen@msu.edu

**Abstract:** Supplying high-quality fresh sweetpotato roots to the consumer requires sorting the roots by quality and removing culls deemed unsuitable for fresh markets at packing facilities. The sorting operation is traditionally performed by manual labor. This study surveyed the sorting lines of seven commercial sweetpotato packinghouses in Mississippi during the packing season of 2021. Sorting for defects entirely relied on labor, which accounted for up to 50% of the total labor in packinghouses. A cost–benefit analysis was conducted to determine the cost-effectiveness of implementing automated sorting technology as an alternative to manual sorting. The net benefits of automated sorting depended on labor savings and equipment costs. Machines at or less than USD 100,000 were economically beneficial with payback periods of less than three years when four or more workers could be replaced, while machines of USD 350,000 and higher would be not justifiable when quick economical returns were sought. Automated sorting promises to increase the profitability and competitiveness of fresh market sweetpotato packing industries.

**Keywords:** automation; economic analysis; machine vision; sorting; sweetpotato



**Citation:** Lu, Y.; Harvey, L.; Shankle, M. Survey and Cost–Benefit Analysis of Sorting Technology for the Sweetpotato Packing Lines. *AgriEngineering* **2023**, *5*, 941–949. <https://doi.org/10.3390/agriengineering5020058>

Academic Editor: Pankaj B. Pathare

Received: 8 March 2023

Revised: 4 May 2023

Accepted: 18 May 2023

Published: 22 May 2023



**Copyright:** © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

## 1. Introduction

In 2021, the United States (U.S.) produced 153,500 acres of sweetpotatoes, generating a farmgate revenue of over USD 680 million [1]. The major sweetpotato-producing states include North Carolina, Mississippi, and California, accounting for nearly 100% of the total production. Approximately 90% of the crop value is due to fresh market roots, with the remainder for processing. To optimize the marketing strategies of sweetpotatoes and deliver high-quality products to the consumer, harvested produce must be graded and sorted by quality at packing facilities, following harvesting and or storage. The U.S. quality grades for marketable sweetpotatoes encompass U.S. Extra No. 1, U.S. No. 1, U.S. No. 1 Petite, U.S. Commercial, and U.S. No. 2, defined according to appearance characteristics such as size, shape, color, and defects [2], determining the commodity price on the market.

In the packinghouse, sweetpotatoes, after storage, experience a series of packing operations, including dumping the roots in a water tank, washing, trash and undersize root elimination, grading and sorting, and box filling [3]. Among these operations, grading and sorting are traditionally performed manually. Human workers visually inspect the quality attributes of individual sweetpotato roots moving on a grading line and hand-sort inferior or defective roots that do not meet marketing requirements. Since the pack-out percentage of sweetpotatoes after months of storage is generally lower than 70% [4], there is a cullage removal rate of 30% or higher, requiring significant labor for grading and sorting. In addition to incurring labor costs, manual sorting may suffer from inconsistency and variability in quality assessment due to human subjectivity and physiological factors (e.g., vision acuity, fatigue, and stress). Moreover, static standing posture and repetitive

upper extremity motions during hand-sorting also increases the risk of musculoskeletal injuries [5].

To reduce labor dependence and costs while improving product quality and packing efficiency, the development of automated fruit sorting technology has been an active area of research for decades. Machine vision-based technology, which uses cameras and computers to interpret the scene, has received significant attention in automated grading and sorting of agricultural products. The technology offers significant advantages over human sorters because it is labor-saving, generally faster and more consistent, not prone to fatigue, more objective, and progressively lower in cost. Currently, machine vision-based sorting systems have been developed for a diversity of horticultural products (e.g., apples, citrus, nectarines, blueberries, etc.) and implemented at modern packing facilities [6].

Sofu et al. [7] reported on a two-lane automatic apple sorting system with color cameras to sort fruit for size, color, and weights as well as surface defects. The system used a roller conveyor to rotate the fruit during imaging and a transporter conveyor consisting of bowls for sorting graded fruit, which achieved sorting accuracy of 79% to 89% at the speed of 0.05–0.2 m/s. Fan et al. [8] reported on a four-lane color vision-based apple sorting system for defect detection at a speed of 5 apples/s, which the system acquired six images from each fruit and achieved an accuracy of 92% based on a conventional neural network-based classification model. Deep learning-based techniques were also used for detecting and tracking defective citrus fruit on a roller conveyor system toward online sorting [9]. Mohi-Alden et al. [10] presented a conveyor belt-based color sorting system for bell peppers, which achieved 93% accuracy for size and maturity by a five-class multilayer perception model at a conveyor speed of 0.2 m/s. Advanced imaging modalities such as hyperspectral/multispectral imaging have also been widely researched for enhanced fruit quality assessment [11], despite limited commercial success for real-time online sorting compared with color/panchromatic imaging. Recent years have seen growing interest in developing machine vision systems for automated in-field grading and sorting of harvested crops [12]. Zhang et al. [13] developed an apple grading system with hardware designs (e.g., compact conveyor, computer vision, and sorting systems) optimized for in-orchard application, which achieved 99% sorting accuracy at a throughput of 10.5 fruits/s during laboratory tests. Lu et al. [14] advanced the sorting system into an integrated harvest-assistive in-field sorting machine and conducted field tests and demonstrations of its performance in commercial apple orchards. This machine promised to find practical applications in the years to come.

Although machine vision has achieved remarkable success in automated grading and sorting of many other horticultural commodities, sweetpotato industries, especially in Mississippi, are yet to adopt machine vision-based technology at packing facilities for enhanced quality control efforts and packing efficiency while reducing labor needs. To date, there has been scant research into the development of machine vision-based technology for quality assessment and automated sorting of sweetpotatoes, with the exception of a few studies that investigated the use of image-based analysis for determining the size and shape of sweetpotato storage roots [15–17]. To guide the efforts to develop machine vision-based technology for sweetpotato grading and sorting, there is a need to assess the current sorting practice and labor demand at commercial sweetpotato packing facilities. Since labor reduction is the main driver to the development of automated sorting technology, it is important to assess the cost-effectiveness of implementing automated technology as opposed to manual sorting for sweetpotato industries.

Ball and Folwell [18] conducted an economic analysis of different commercially available electronic graders versus manual sorting for fresh-market asparagus, which demonstrated the increased profitability by adopting electronic graders in place of manual labor. Mizushima and Lu [19] analyzed the costs and benefits of in-field sorting technology for the apple industry, suggesting that in-field sorting would be economically beneficial compared with the practice without field sorting, if the sorting machinery costs were equal to or less than USD 30,000. In an updated analysis of in-field sorting machines for ap-

ples, Zhang et al. [20] showed that the net annual benefits would range from USD 13,500 to USD 78,400 for fresh-market apple growers and from USD 23,900 to USD 81,700 for processing apple growers, assuming the sorting machine price was between USD 100,000 and USD 160,000. These studies provide good examples of the economic evaluation of automated sorting technology for harvested produce. To the best of our knowledge, similar research has not been carried out for sweetpotatoes. This study was, hence, to survey the sweetpotato sorting lines of commercial packinghouses in Mississippi and thereby perform a cost–benefit analysis of automated sorting versus manual sorting for sweetpotato packing lines.

## 2. Materials and Methods

### 2.1. Packinghouse Survey

Site visits to seven commercial packinghouses in major sweetpotato growing regions (four in Vardaman, two in Houston, and one in Senatobia in Mississippi) were conducted during the packing season of 2021 to survey the sorting technology for sweetpotatoes. These packinghouses represented a cross section of packers that served the vast majority of sweetpotato growers in Mississippi. The survey was conducted by the authors through in-person observations of sorting operations and meetings with technical personnel of packing lines to obtain key information on the quality grading criteria, sorting equipment and mechanisms, packing capacity, labor costs, and attitude toward automated sorting. Because packhouses were busy with sweetpotato packing, no formal questionnaire was conducted for the survey.

### 2.2. Cost–Benefit Analysis

Automated sorting technology aims to remove or reduce the manual labor required in the packing line of fresh sweetpotatoes. The net benefits would depend on the cost savings of sorting labor at packing lines in comparison with the costs of sorting equipment. The following analysis assumed other packing operations (e.g., washing and packaging) remained unchanged regardless of whether manual or automated sorting was implemented. The equipment cost, including the ownership and operation costs, was calculated using the American Society of Agricultural and Biological Engineers (ASABE) EP496.3 standard for agricultural machinery [21] as described below.

The total annual ownership costs ( $C_o$ ) of a machine (also called fixed costs) reflect equipment depreciation, interest charges, and the costs for taxes, housing, and insurance. The ownership costs were estimated by multiplying the purchase price of the machine by the ownership cost percentage as follows:

$$C_o = P_M \left[ \frac{1 - S_V}{L} + \frac{1 + S_V}{2} i + K \right] \quad (1)$$

where  $P_M$ ,  $S_V$ ,  $L$ ,  $i$ , and  $K$  represent the machine price, the salvage value factor for equipment depreciation at the end of the machine life, the machine life (in year), the annual interest rate, and the ownership cost factor for taxes, housing, and insurance, respectively. Several assumptions were made for the parameters in Equation (1), as summarized in Table 1. A 10-year machine life was considered, with the salvage value of 6.55%, which was in line with the modified accelerated cost recovery system depreciation schedule [22]. It was assumed that the machine was purchased by a loan to fully finance the acquisition value at an interest rate of 8.5%. The interest was chosen based on the current rates for purchasing agricultural machinery under a 10-year term (AgDirect.com). The ownership cost factor was set to 2%, as recommended by the ASABE standard [21], accounting for taxes (1%), housing (0.75%), and insurance (0.25%).

**Table 1.** Parameters used in cost–benefit analysis of automated sorting technology.

Machine Life	Salvage	Interest Rate	Ownership Factor	Working Hours	Machine Power	Labor Wage
10 years	6.55%	8.5%	2%	600 h/year	10 kW	USD 13.67/h

The annual operation cost includes the costs for repair and maintenance ( $RM$ ) and energy consumption. The  $RM$  cost ( $C_{RM}$ ) is necessary to keep a machine operable due to wear, part failures, accidents, and natural deterioration, and it is affected by the purchase price ( $P_M$ ) and the amount of use ( $h$ , accumulated hours of machine use). The cost  $C_{RM}$  was also estimated according to the ASABE Standard DP496.3 using the following equation:

$$C_{RM} = P_M \times RF1 \times \left[ \frac{h}{1000} \right]^{RF2} \tag{2}$$

where  $RF1$  and  $RF2$  are the repair and maintenance factors that were given in the ASABE D497.7 standard. However, the standard does not provide data for the two factors for fruit sorting machines. Instead,  $RF1 = 0.3$  and  $RF2 = 1.6$  were used in the study, as in the cost analysis for an in-field fruit sorting machine [19], although they may have overestimated the cost. The machine was assumed to run for 8 h/day for 5 days/week over a 15-week packing season (corresponding to 600 packing hours) annually.

For energy consumption, the cost calculation assumed a 10 kW electronically powered sorting machine at an electricity rate of USD 0.07/kWh [the averaged industrial electricity rate in Mississippi at the time of writing; see <https://www.eia.gov/electricity/monthly> (accessed on 1 March 2023)]. The power was reasonable as it was comparable to or higher than that of commercial optical sorting machines (e.g., the TOMRA 3A and NEWTEC Celox sorters) for potatoes. The annual energy cost ( $C_E$ ) was hence estimated as follows:

$$C_E = 0.7 \times h \tag{3}$$

The sweetpotato packing lines in Mississippi relied on a mix of domestic workers and the labor hired through the H-2A Temporary Agricultural Worker Visa program [23]. Since the exact percentage of H-2A or domestic labor in Mississippi was unknown, an estimated national average of 10% for H-2A labor for agriculture [24] was chosen for the labor cost analysis. A further assumption was that hired labor was paid on an hourly basis at the adverse effect wage rate (AEWR) [25], which is the mandatory minimum wage agricultural employers pay workers under the H-2A program. The 2023 AEWR of USD 13.67/hour for Mississippi was used in the calculation for the first year. Additional costs of USD 3.69 (27% of the AEWR) were included for domestic labor for social security, Medicare, and worker’s compensation [26]. The hourly labor cost was increased annually by 3%. Hence, the annual labor savings were estimated as follows:

$$S(y) = (13.67 \times 10\% + 17.36 \times 90\%) \times N \times h \times 1.3^{(y-1)} = 16.991 \times N \times h \times 1.03^{(y-1)} \tag{4}$$

where  $N$  is the number of workers removed from the packing line due to automated sorting, and  $y$  is the year ranging from 1 to 10. It is noted that the calculation above does not factor miscellaneous costs in hiring H-2A workers (e.g., worker petition, visa application, transportation, housing, etc.). Then, the annual benefit was the labor savings minus the equipment costs discounted at a rate of 8% (commonly used in a cash flow analysis) to obtain the present value (PV) of net benefits in year one:

$$PV(y) = [S(y) - C_o - C_{RM} - C_E] / (1.08)^y \tag{5}$$

Further, the summation of PVs over the machine life (10 years) yielded the net present value (NPV). NPV is an important metric used in decision-making of capital investment, which was used for assessing the benefits of adopting new agricultural technologies [27,28]. A positive NPV indicated that the economic benefits exceeded the anticipated costs, and

hence, the investment was profitable. The payback period (PP) was computed using the discounted cash flows. The PP was the time needed to recover the investment or break even, and the shortest PP was considered the most acceptable. In addition, a modified internal return rate (MIRR) was calculated for the cash flows over 10 years at a reinvestment rate of 8%. The MIRR was also a measure of profitability and reported as a percentage return on the investment, which was used in a similar study on the economic analysis of grading machines for asparagus [18].

The cash flow analysis for NPV and MIRR in this study was performed in Matlab 2022a with the Financial Toolbox (The MathWorks, Inc., Natick, MA, USA).

### 3. Results

#### 3.1. Sorting Line Survey

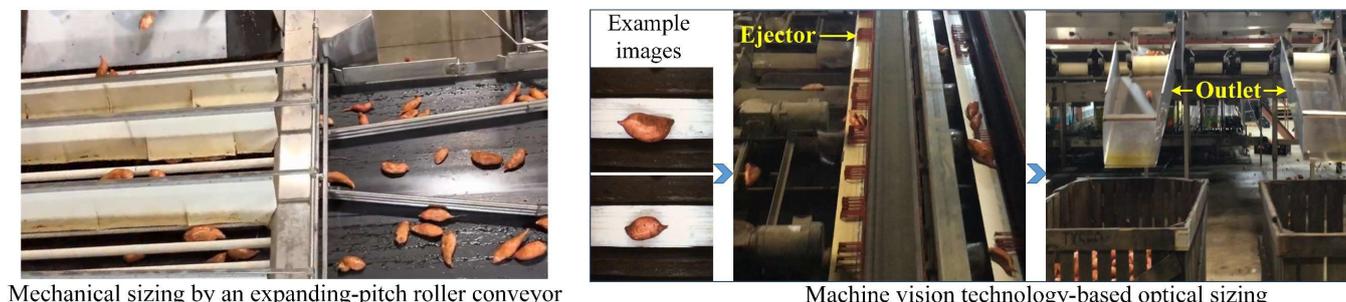
All seven packinghouses surveyed relied on manual labor for the grading and sorting of sweetpotato roots for the fresh market. Depending on the labor availability and the needed packing throughput, a sweetpotato sorting line consisted of a crew of four to 10 workers arranged on two sides of a mechanized inspection table of roller conveyors (Figure 1). Human sorters visually inspected the sweetpotato roots traveling on the roller conveyor table, hand-segregated low-quality roots from good ones, and picked out decayed or unmarketable roots from the packing line. The rollers of the conveyor table were typically translated and rotated, and chains attached to both ends of the roller effected translation along closed loop paths; such features enabled transporting and rotating fruits for quality inspection and grading.



**Figure 1.** Photographs of hand-sorting at sweetpotato packing facilities. The photographs were taken by the authors in six different packinghouses in Mississippi in December of 2021.

The full capacity of a sorting line would require 12 or more workers for a daily throughput of 70 bins (a bin can hold 800–900 pounds of sweetpotatoes) packed in about 1500 40-pound corrugated boxes. Hand-sorting alone accounted for about 30–50% of the total labor at packinghouses, which varied with the automation level of the packing operations. All the surveyed packing lines installed automated sizing machines (Figure 2) to separate sweetpotato roots into three or more grades. Four packinghouses only used a mechanical sizer, while three others used more advanced optical technology for sweetpotato sizing. The mechanical sizer, which sorted the roots by diameter, was typically made of an expanding-pitch roller conveyor where smaller roots were first dropped out from the spacings of adjacent rollers, and larger roots were carried further before being deposited from larger roller spacings to a different destination. The optical sizing equipment used imaging technology for the size measurement of the roots that were traveling on a conveyor belt, followed by the mechanical ejection of the sized roots to the corresponding channels, which

was capable of finer size grading and higher efficiency compared with the mechanical sizer. None of the surveyed packinghouses implemented automated sorting of sweetpotatoes for quality factors such as surface defects.



**Figure 2.** Photographs of automated mechanical (left) and optical (right) sizing of sweetpotatoes. The photographs were taken by the authors during the packinghouse visits in December of 2021.

All the surveyed packers expressed interest in adopting or enhancing automated sorting technology to reduce labor costs and dependence and improve product quality and uniformity. One large packer was experimenting with advanced imaging and AI (artificial intelligence) technologies for quality sorting. Due to perceived cost concerns, smaller packers were more interested in investing in cost-effective machine vision technology to supplement or replace human sorters. Hence, there is a real need to conduct a cost-benefit analysis to determine the extent to which packers would economically benefit from implementing automated sorting as opposed to manual sorting.

### 3.2. Cost-Benefit Analysis

The cost-effectiveness of replacing human sorters with automated sorters depends on machine costs and the number of employees that can be eliminated due to automated sorting. Table 2 depicts the economic benefits for machine prices ranging from USD 50,000 to USD 350,000 and the reduction of four to 12 sorting workers. The machine price range reflected what could be potentially acceptable for even small-scale sweetpotato packers, and the labor reduction agreed with the sorting labor needed at existing sweetpotato packing facilities according to the packinghouse survey above.

**Table 2.** Estimated economic benefits of automated sorting as opposed to manual sorting for sweetpotato packing lines in different scenarios of machine price and worker reduction.

# Workers Reduced	Metrics	Machine Price (USD)						
		50,000	100,000	150,000	200,000	250,000	300,000	350,000
4	NPV (USD)	199,317.6	93,796.5	–	–	–	–	–
	PP (years)	0.63	2.78	–	–	–	–	–
	MIRR (%)	40.9	24.6	–	–	–	–	–
5	NPV (USD)	276,288.2	170,767.1	65,246.0	–	–	–	–
	PP (years)	0.45	1.49	5.54	–	–	–	–
	MIRR (%)	45.3	30.8	18.3	–	–	–	–
6	NPV (USD)	353,258.8	247,737.7	142,216.6	36,695.5	–	–	–
	PP (years)	0.35	1.01	2.73	9.01	–	–	–
	MIRR (%)	48.8	35.1	24.7	13.4	–	–	–
7	NPV (USD)	430,229.4	324,708.3	219,187.2	113,666.1	8145.0	–	–
	PP (years)	0.29	0.76	1.75	4.43	9.81	–	–
	MIRR (%)	51.6	38.5	29.1	20.3	9.1	–	–
8	NPV (USD)	507,200.0	401,678.9	296,157.8	190,636.7	85,115.6	–	–
	PP (years)	0.24	0.61	1.28	2.71	6.56	–	–
	MIRR (%)	50.5	41.2	32.5	24.8	16.7	–	–

**Table 2.** *Cont.*

# Workers Reduced	Metrics	Machine Price (USD)						
		50,000	100,000	150,000	200,000	250,000	300,000	350,000
9	NPV (USD)	584,170.5	478,649.4	373,128.3	267,607.2	162,086.1	56,565.0	–
	PP (years)	0.21	0.51	1.00	1.91	3.94	8.92	–
	MIRR (%)	56.2	43.5	35.2	28.2	21.4	13.5	–
10	NPV (USD)	661,141.1	555,620.0	450,098.9	344,577.8	239,056.7	133,535.6	28,014.5
	PP (years)	0.19	0.44	0.82	1.47	2.70	5.42	9.54
	MIRR (%)	58.1	45.6	37.5	31.0	24.9	18.5	10.6
11	NPV (USD)	738,111.7	632,590.6	527,069.5	421,548.4	316,027.3	210,506.2	104,985.1
	PP (years)	0.17	0.39	0.70	1.19	2.03	3.65	7.10
	MIRR (%)	59.8	47.4	39.5	33.3	27.6	22.1	15.9
12	NPV (USD)	815,082.3	709,561.2	604,040.1	498,519.0	392,997.9	287,476.8	181,955.7
	PP (years)	0.15	0.34	0.61	1.00	1.61	2.69	4.78
	MIRR (%)	61.4	49.0	41.3	35.3	30.0	24.9	19.6

Note: #, NPV, PP, and MIRR represent “number of”, net present value, discounted payback period, and modified internal return rate, respectively. “–” indicates negative NPVs, and the corresponding investment is not financially beneficial.

The lower the price of a sorting machine and the larger the worker reduction, the more economically beneficial and the shorter the payback period. The machine price at USD 50,000 was beneficial in all the scenarios, generating NPVs of hundreds of thousands of dollars with payback periods of less than 1 year. For the minimum reduction of four workers, it had a payback period of 0.63 years and a 10-year MIRR of 40.9%, while in the case of the maximum reduction of 12 workers, the payback period decreased to the shortest time, 0.15 years, with the MIRR increasing to 61.4%, although such profitable sorting machines may be not developed in the near future. The machine price at USD 100,000 also consistently yielded positive NPVs by saving four to 12 workers. The reduction of four workers resulted in a payback period of 2.78 years, which was still considered attractive for packers seeking short-term economic returns within 3 years, and even quicker returns within 1 year could be achieved by eliminating seven or more workers.

A sorting machine priced at USD 150,000 and higher would not be financially beneficial if they could not replace five or more workers to generate positive NPVs. To achieve profitability for the machines priced at USD 150,000, USD 200,000, USD 250,000, and USD 300,000 would require replacing a minimum of five, six, seven, and nine workers, respectively, while for a payback period within 3 years, machines at these prices would need to eliminate a minimum of 6, 8, 10, and 12 workers, respectively. However, machines at an even higher price could not be economically rewarding because of long payback periods, unless more than 12 workers could be removed from sorting lines. Such expensive sorting equipment could pose great challenges to the adoption by small-scale sweetpotato packers.

**4. Discussion**

Sweetpotato packers in Mississippi are facing challenges with the shortage of labor at packing facilities, especially for such labor-intensive tasks as sorting storage roots for quality. All surveyed packers have relied on a mixture of H2-A workers and domestic labor for packing operations, but they expressed concerns about the rising costs and uncertainty of labor, which are eroding the sustained profitability of sweetpotato industries. There is a need for automated innovations to reduce packing labor and improve packing efficiency. The cost–benefit analysis of this study showed that automated sorting in place of manual sorting could generate sufficient economic benefits exceeding investment costs due to substantial labor savings. This justifies the need to develop automated sorting technology for sweetpotatoes and advance its adoption at packing facilities.

The machine price is a key factor influencing profitability. Higher machine prices would take longer times to recover equipment costs, but they might offer larger long-term savings if the machine allowed for the elimination of more employees. In choosing

among sorting machines, sweetpotato packers would need to decide whether short-term or long-term savings are more important. It should be noted that the economic benefits presented here (see Table 2) were specific to assumptions and simplified analysis procedures (Section 3.2) used in this study, which may not reflect well the actual costs/benefits at sweetpotato packing facilities. Sweetpotato packers interested in adopting automated sorting technology need also to examine a diversity of other factors on an individual basis, such as the space for installing a sorting machine and the associated installation and maintenance fees, the sorting performance including throughput and effectiveness/accuracy of defect sorting, packing hours, and pack out percentages. Nonetheless, the cost–benefit analysis of this study does provide guidance for R&D activities in developing cost-effective automated sorting technology and for packers to evaluate the economics of implementing automated sorters as an alternative to human workers.

## 5. Conclusions

Sorting is an important operation at sweetpotato packing lines to segregate storage roots by quality grades. This study conducted a survey of seven commercial sweetpotato packers across Mississippi and found that although sorting sweetpotato roots for size was mechanized or automated, sorting for quality factors such as defects was still performed entirely by hand. Manual sorting accounted for 30–50% of the total labor at sweetpotato packing facilities. Automating sorting in place of manual sorting for quality could be potentially beneficial to sweetpotato packers. The net benefits depended on the specific labor reductions and sorting equipment and associated installation and maintenance costs. Machines of USD 100,000 or lower could achieve substantial economic benefits within a payback period of 3 years if a minimum of four workers are eliminated due to automated sorting. More expensive sorting machines would require longer payback periods and might not be economically beneficial if labor savings were not significant. Machine vision-based automated sorting systems are yet to be developed for sweetpotatoes and implemented at commercial packing lines. Research is needed to develop dedicated cost-effective automated quality sorting technology for sweetpotatoes.

**Author Contributions:** Conceptualization, Y.L.; methodology, Y.L.; formal analysis, Y.L.; investigation, Y.L. and L.H.; writing—original draft preparation, Y.L.; writing—review and editing, Y.L., L.H., and M.S.; supervision, Y.L. All authors have read and agreed to the published version of the manuscript.

**Funding:** This work was supported in part by the U.S. Department of Agriculture Mississippi Department of Agriculture and Commerce Specialty Crop Block Grant Program (G00006341).

**Data Availability Statement:** Not applicable.

**Acknowledgments:** The authors thank the sweetpotato packers in Mississippi for supporting the survey of their packing facilities.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

1. USDA-NASS, United States of Department of Agriculture National Agricultural Statistics Service. *Vegetables 2021 Summary*; United States of Department of Agriculture National Agricultural Statistics Service: Washington, DC, USA, 2022.
2. USDA, U.S. Department of Agriculture. *United States Standards for Grades of Sweet Potatoes*; U.S. Department of Agriculture: Washington, DC, USA, 2005.
3. Edmunds, B.A.; Boyette, M.D.; Clark, C.A.; Ferrin, D.M.; Smith, T.P.; Holmes, G.J. *Postharvest Handling of Sweetpotatoes*; North Carolina Cooperative Extension Service: Raleigh, NC, USA, 2008.
4. Boyette, M.D. The investigation of negative horizontal ventilation for long-term storage of sweetpotatoes. *Appl. Eng. Agri.* **2009**, *25*, 701–708. [\[CrossRef\]](#)
5. Simcox, N.; Flanagan, M.E.; Camp, J.; Spielholz, P.; Synder, K. *Musculoskeletal Risks in Washington State Apple Packing Companies*; Field Research and Consultation Group, University of Washington Department of Environmental Health: Seattle, WA, USA, 2001.
6. Bollen, A.F.; Prussia, S.E. Sorting for defects. In *Postharvest Handling: A Systems Approach*, 4th ed.; Florkowski, W.J., Banks, N.H., Shewfelt, R.L., Prussia, S.E., Eds.; Academic Press: London, UK, 2022; pp. 377–398.

7. Sofu, M.M.; Er, O.; Kayacan, M.C.; Cetisli, B. Design of an automatic apple sorting system using machine vision. *Comput. Electron. Agri.* **2016**, *127*, 395–405. [[CrossRef](#)]
8. Fan, S.; Li, J.; Zhang, Y.; Tian, X.; Wang, Q.; He, X.; Zhang, C.; Huang, W. On line detection of defective apples using computer vision system combined with deep learning methods. *J. Food Eng.* **2020**, *286*, 110102. [[CrossRef](#)]
9. Chen, Y.; An, X.; Gao, S.; Li, S.; Kang, H. A deep learning-based vision system combining detection and tracking for fast on-line citrus sorting. *Front. Plant Sci.* **2021**, *12*, 622062. [[CrossRef](#)] [[PubMed](#)]
10. Mohi-Alden, K.; Omid, M.; Firouz, M.S.; Nasiri, A. A machine vision-intelligent modeling based technique for in-line bell pepper sorting. *Info. Proc. Agri.* **2022**, in press. [[CrossRef](#)]
11. Lu, Y.; Saeys, W.; Kim, M.; Peng, Y.; Lu, R. Hyperspectral imaging technology for quality and safety evaluation of horticultural products: A review and celebration of the past 20-year progress. *Postharvest Biol. Technol.* **2020**, *170*, 111318. [[CrossRef](#)]
12. Blasco, J.; González, M.G.G.; Chueca, P.; Cubero, S.; Aleixos, N. Advances in automated in-field grading of harvested crops. In *Robotics and Automation for Improving Agriculture*; Billingsley, J., Ed.; Burleigh Dodds Science Publishing: Cambridge, UK, 2019; pp. 215–232.
13. Zhang, Z.; Lu, Y.; Lu, R. Development and evaluation of an apple infield grading and sorting system. *Postharvest Biol. Technol.* **2021**, *180*, 111588. [[CrossRef](#)]
14. Lu, Y.; Zhang, Z.; Lu, R. Development and preliminary evaluation of a new apple harvest assist and in-field sorting machine. *Appl. Eng. Agri.* **2022**, *38*, 23–35. [[CrossRef](#)]
15. Boyette, M.D.; Tsimnikas, A.L. *Evaluating the Shape and Size Characteristics of Sweetpotatoes Using Digital Image Analysis*; 2017 ASABE Annual International Meeting Paper No. 1700038; ASABE: St. Joseph, MI, USA, 2017.
16. Haque, S.; Lobaton, E.; Nelson, N.; Yencho, G.C.; Pecota, K.V.; Mierop, R.; Kudenov, M.W.; Boyette, M.D.; Williams, C.M. Computer vision approach to characterize size and shape phenotypes of horticultural crops using high-throughput imagery. *Comput. Electron. Agri.* **2021**, *182*, 106011. [[CrossRef](#)]
17. Wright, M.E.; Tappan, J.H.; Sistler, F.E. The size and shape of typical sweet potatoes. *Tran. ASAE* **1986**, *29*, 0678–0682. [[CrossRef](#)]
18. Ball, T.; Folwell, R.J. Economic analysis of alternatives to manual sorting using selected electronic graders in asparagus fresh packing. *J. Food Proc. Pres.* **2004**, *28*, 405–416. [[CrossRef](#)]
19. Mizushima, A.; Lu, R. Cost benefits analysis of in-field presorting for the apple industry. *Appl. Eng. Agri.* **2011**, *27*, 33–40. [[CrossRef](#)]
20. Zhang, Z.; Pothula, A.K.; Lu, R. Economic evaluation of apple harvest and in-field sorting technology. *Trans. ASABE* **2017**, *60*, 1537–1550. [[CrossRef](#)]
21. *ASAE EP496.3 FEB2006 (R2020)*; ASABE Standards. Agricultural Machinery Management. ASABE: St. Joseph, MI, USA, 2022.
22. Internal Revenue Service. How to depreciate property Department of the Treasury Internal Revenue Service. Available online: <https://www.irs.gov/publications/p946> (accessed on 23 April 2023).
23. Castillo, M.; Martin, P.; Rutledge, Z. *The H-2A Temporary Agricultural Worker Program in 2020*; U.S. Department of Agriculture Economic Research Service: Washington, DC, USA, 2022.
24. Casta, D.; Martin, P. *Coronavirus and Farmworkers Farm Employment, Safety Issues, and the H-2A Guestworker Program*; Economic Policy Institute: Washington, DC, USA, 2020.
25. DOL, Department of Labor. Labor certification process for the temporary employment of foreign workers in Agriculture in the United States: Adverse effect wage rates for non-range occupations in 2023. *Fed. Regist.* **2022**, *87*, 77142–77143.
26. Guidry, K.; Smith, T.; Sistrunk, M. *Projected Costs and Returns Crop Enterprise Budgets for Sweet Potato Production in Louisiana, 2019*; The LSU AgCenter: Baton Rouge, LA, USA, 2019.
27. Julian, J.W.; Seavert, C.F. AgProfit: A net present value and cash flow-based decision aid for agriculture producers. *Agri. Financ. Rev.* **2011**, *71*, 366–378. [[CrossRef](#)]
28. Zhang, Z.; Heinemann, P.H. Economic analysis of a low-cost apple harvest-assist unit. *HortTechnology* **2017**, *27*, 240–247. [[CrossRef](#)]

**Disclaimer/Publisher’s Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.