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Power Predicting for Power Take-Off Shaft of a Disc Maize Silage Harvester Using Machine Learning

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ABSTRACT

The relationship between the power consumed in the engine and the power take-off (P.T.O.) shaft of a maize silage harvester is critical to understanding the efficiency and performance of the harvester. The power consumed in the engine directly affects the power available for use on the P.T.O. shaft, which is the power source for the suspended silage harvesters. The research aimed to predict the power consumption of the P.T.O. shaft based on the power consumption of the tractor engine at different operating parameters, which are two applications of the P.T.O. shaft (540 and 540E rpm) and two forward speeds (1.8 and 2.5 km/h) using machine learning algorithms. The best results in terms of engine power consumption were achieved in the 540E P.T.O. application, and the forward speed was 1.8 km/h. The results also gave a correlation between the power consumed by the engine and the P.T.O shaft of 87%. Regarding prediction algorithms, the Tree algorithm gave the highest prediction accuracy of 98.8%, while the KNN, SVM, and ANN algorithms gave an accuracy of 98.1, 60, and 60%, respectively.

Keywords: power take-off shaft, forward speeds, maize silage harvester, machine learning techniques.

INTRODUCTION

Maize (*Zea Mays*) is a main crop in most countries of the world, including Iraq and Turkey. It is considered a major forage source for many livestock products. Whole plant silage is a feed source for dairy and beef production [1]. The maize production in Iraq and Turkey for the year 2022 amounted to 496,003 and 8,500,000 tons, respectively [2]. Cutting maize plants into silage using maize silage harvesters requires a lot of energy. The cutting process of plants consumes 85% of the total energy [3], and therefore a careful analysis of the cutting process is very important. The energy requirements for silage depend not only on the technical characteristics of the combined cutting unit of the combine but also on the initial compaction of the material by the feed rollers [4]. Disc-type harvesters are generally used to harvest maize silage. A single row of these harvesters requires tractor power of 40–80 Hp, two rows of 80–120 Hp, and four rows with more than 120 Hp [5]. After cutting the plant, it is thrown onto the agricultural trailer behind the tractor, and this process requires additional energy by increasing the speed of the cutting disc [6]. The power generated in a tractor engine is known as thrust power, hydraulic power, and power take-off shaft power. The power generated must be sufficient to meet the needs of agricultural equipment and machinery connected to the agricultural tractor. In contrast, more energy will be needed to complete the agricultural process, so fuel consumption will increase further to provide this energy [7]. The P.T.O. speeds close to the maximum engine speed must be provided, so that the machine can best meet the loads. However, running the engine at high speeds for low-power maize silage harvesters causes unnecessary energy and therefore high fuel consumption [8]. International companies have provided different P.T.O. shaft speeds, namely 540–540E and 1000–1000E rpm, which are considered standard with a higher transmission rate and lower engine speed [9].

The relationship between the energy consumed in the engine and the P.T.O. shaft is very important, as the energy consumed in the engine directly affects the energy available for use on the P.T.O. shaft, since the latter is considered the power source for the suspended silage harvesters. Efficient power transfer from the engine to the P.T.O. shaft is essential to improving the overall system performance and fuel consumption. The power consumed in the engine is usually greater than the power available at the P.T.O. shaft, due to friction, inefficiency in the transmission system, and other mechanical losses. These losses reduce the power available on the P.T.O. shaft compared to the power generated by the engine [10]. To calculate the power consumed on the P.T.O. shaft based on the power consumed by the engine, one needs to consider the efficiency of power transfer from the engine to the P.T.O. shaft. Efficiency may change with engine speed and load. An accurate calculation may require specific information about the engine and P.T.O. setting. More accurate predictions involve calculating efficiency at various speeds of the loads and engine using experimental data or mathematical models derived from experimental measurements [11]. Predicting the power consumed on the P.T.O. shaft includes various factors, such as engine speed, fuel consumption, forward speed, etc. Studies have developed equations and models to estimate tractor fuel consumption and the energy expended on the drawbar and P.T.O. shaft using laboratory and field tests. In addition, the efficiency of the transfer of power from the engine to the P.T.O. shaft plays a crucial role in accurately predicting the power consumed by the P.T.O shaft [12].

Karwasra et al. [13] predicted the performance of the tractor power take-off shaft using twenty different parameters as inputs to predict the P.T.O. performance based on machine learning algorithms, and more accurately, the ANN algorithm was used. Rahimi-Ajdadi and Abbaspour-Gilandeh [14] also predicted fuel consumption using the Back Propagation Artificial Neural Network (ANN) algorithms. Jalilnezhad et al. [15] predicted tractor fuel consumption based on the data on tire pressure, plowing depth, tractor forward speed, dynamic load on the front axle, number of wheel passes, soil cone, and soil moisture index based on the convolutional neural network. Mohamed et al. [16] Predicted drawbar power as a ratio of engine power in different soil types (clay soil sandy clay soil, and concrete roads) by analyzing operating parameters and using predictive models, it is possible to effectively estimate the power consumed in the P.T.O. shaft. Tucki et al. [17] analyzed the possibility of using neural networks to determine the parameters of the chemical composition of exhaust gases as a function of engine performance parameters. The research aimed to predict the power consumption of the P.T.O. shaft based on the power consumption of the tractor engine at different operating parameters, which are two applications of the P.T.O. shaft (540 and 540E rpm) and two forward speeds (1.8 and 2.5 km/h) using machine learning algorithms.

MATERIALS AND METHODS

Measurement methodology

The measurement methodology consisted of three stages: The first stage was to study the effect of mechanical operating factors, both forward speed and P.T.O. shaft speed, on power consumption based on statistical analysis ($P < 0.05$). The second stage was to study the relationship between the power consumed by the engine and the power consumed by the P.T.O shaft. The final stage included determining the best machine learning algorithms for predicting the power on the power take-off shaft. Figure 1 shows a diagram of the measurement methodology.

Field experiment

The experiment was carried out at the Research and Applications Center of the Faculty of Agriculture, Selcuk University, where yellow maize plants (*Zea mays indentata*) were harvested. The distance between one line and another was 70 cm, the average moisture content of the plant was 70.56%, and the soil type was silty. The experiment was carried out for two applications of the P.T.O. shaft (540 and 540E rpm) and two different forward speeds V_1 and V_2 (1.8 and 2.5 km/h). Using a New Holland TD110D tractor equipped with a fuel consumption meter (Sea YF-S401), a torque meter (Datum brand Series 420 P.T.O. 1800 Nm model), and speed sensors. The 540-rpm

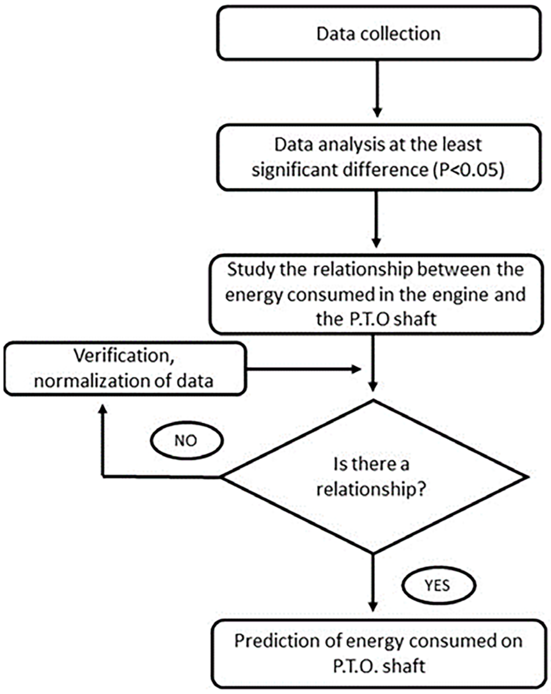

Figure 1. Measurement methodology diagram

speed for the 540 and 540E P.T.O applications is achieved at engine speeds of 2200 and 1600 rpm, respectively. The experiment also used a single-row suspension-type disc maize silage harvester (Figure 2). The machine takes its movement from the P.T.O. The silage material is cut using the cutting disc knives located on the two feeders of the machine. The plants are compressed between feed drums and transferred to chopping knives. The chopper knives consist of 12 pieces and are attached to a disc located on the cover. The cutting unit is of radial knife type and consists of a knife and a counter knife. The cut plants are transported to the trailer by the conveyor tube by the airflow generated by the chopper knives.

To calculate the power consumed on the P.T.O. shaft, the P.T.O. shaft torque is measured. Using the torque values obtained, the P.T.O. capacity of the harvester was calculated with the help of the following Equation [8].

$$N = \frac{M_d \times n}{9550} \tag{1}$$

where: N – power consumption in P.T.O. (kW), M_d – torque for P.T.O. (Nm), n – number of P.T.O. shaft revolutions (rpm).

The energy required to operate the harvester was estimated from fuel consumption data after each operation using the following Equation [18]:

$$P = \frac{Fc}{3600} \times \rho_f \times \eta_{mec} \times LCV \times \times \eta_{th} \times \frac{427}{75} \times \frac{1}{1.36} \tag{2}$$

where: P – power consumed by the engine (kW), F_C – fuel consumption (L/h), ρ_f – fuel density (kg/L) (for diesel = 0.85), LCV – calorific value of fuel (10,000 kcal/kg), 427 – mechanical thermal equivalent (J/kcal), η_{th} – engine thermal efficiency of the engine (~35% for diesel engines), η_{mec} – the mechanical efficiency of the motor (~80%).

Laboratory analysis

The relationship between the power values consumed in the engine and on the P.T.O. shaft was studied by calculating the correlation coefficient. Statistical analysis of the power consumed in the engine and on the P.T.O. shaft was performed for the data obtained from all applications. The LSD test was applied to the significant means with the least significant difference ($P < 0.05$) using the SPSS program.

MatlabR2022b installed on a Lenovo device with a 16 GB storage capacity and an Intel Core i7 processor with a clock speed of 2.3 GHz was used to predict the power consumed on the P.T.O. shaft. The data set contains 800 readings of the power consumed in the engine and on the P.T.O. shaft. In the research, 80% of the data were selected for training neural networks and 20% for testing. To predict power consumption on the P.T.O. shaft, inputs included engine power values and operating parameters at three forward speeds and two P.T.O. shaft applications. To compare different network architectures, the training, validation, and test sets were randomly selected to be used for all tests in this study.

The operating parameters used in the experiment, both forward speed and P.T.O. shaft speed, affect the performance of the machine learning algorithms, as shown in Table 1.

To determine the best algorithms to predict the energy consumed on the P.T.O. shaft, the following algorithms were used. The reason for this is that the performance of these algorithms would be better with the size of the considered research sample [19]:

Tree

The decision tree technique is like a tree structure, where each leaf node represents a classification, and the inner node is a test attribute while each branch represents possible test results [20, 21].

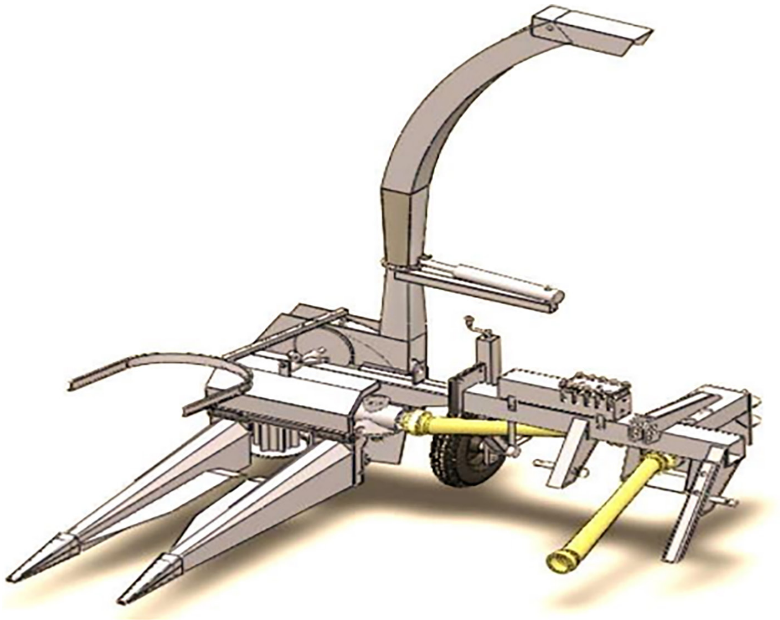

Figure 2. Maize silage harvester

K–Nearest neighbor (KNN)

The basis of this algorithm is to identify a query point that belongs to a certain class (the distance in the feature space is a measure of similarity) if many samples like this query point in the feature space do so [22, 23].

Support vector machines (SVM)

This algorithm classifies points by comparing them with each other at two different distances. The algorithm identifies the hyperplane of data that can be linearly separated, which maximizes the distance between the training samples [24, 25].

Artificial neural network (ANN)

Mathematical programs that collect data and index it according to a specific design (neurons) are called neural networks. The layers in the neural network are connected through nodes, so the operation of this algorithm is similar to that of the neuron network [26, 27]. To determine the performance measure for the employed machine learning algorithms, the Precision, Recall, and F-Measure metrics were used (Table 2) [28].

RESULTS AND DISCUSSION

The results show that the power consumption values decrease when applying the P.T.O shaft speed at 540E and lower forward speeds (Table 3). The average power consumption when applying the 540 P.T.O is 19.06 kW and when applying the 540E is 17.61 kW. The average power consumption at the first forward speed is 17.32 kW, and at the forward second speed, it is an average of 19.35. The interaction between the first forward speed (1.8 km/h) and the 540E application of the P.T.O. shaft gave the lowest power consumption value of 16.44 kW. The amount of energy consumption decreased by 8.23% when applying 540E and by 11.72% when reducing forward speed. When forward speed increases, the engine power consumption also tends to increase [29]. The power consumption also decreases with the number of revolutions, which is related to the application of the P.T.O. shaft [30]. According to the results of the analysis of variance applied to the values of the engine power consumption, it was found that there is no significant effect of the change in the P.T.O. application and the average forward speed on the engine power consumption ($P < 0.05$) (Table 3). Since the P.T.O. speed remained constant at 540 rpm in both P.T.O. applications in the experiment, the power requirements of the P.T.O. shaft were also changed at similar rates (Figure 3). The highest power consumption was achieved for the P.T.O. shaft with a forward speed (2.5) of 17.93 kW, while the lowest power consumption was

Table 1. The effect of operating parameters on the performance of machine learning algorithms

Operating parameters	Effect of operating parameters on the performance of machine learning algorithms
Forward speed	Forward speed directly affects the feed rate and engine speed when harvesting maize silage, which affects the energy required to cut the silage. Therefore, forward speed is a critical factor that affects the accuracy and effectiveness of the error diagnosis method and thus affects the performance of machine learning algorithms.
P.T.O shaft speed	The P.T.O shaft rotates at different speeds, with rotation proportional to the speed of the tractor engine. Higher PTO shaft speeds can impact the performance of machine learning algorithms by affecting the efficiency and energy consumption of the maize silage harvester.

Table 2. Metrics for measuring the accuracy of the performance of the algorithms used

Metrics	Equations	
Precision	$TP1 / (TP1 + FP1)$	*TP*1 – positive true, *FP*1 – positive false, *TN*1 – negative true, *FN*1 – negative false.
Recall	$TP1 / (TP1 + FN1)$	
F-Measure	$\frac{TP1 \cdot TN1 - FP1 \cdot FN1}{\sqrt{(TP1+FP1)(TP1+FN1)(TN1+FP1)(TN1+FN1)}}$	

Table 3. LSD test results for engine power consumption values

P.T.O application	Forward speeds (km/h)		Average
	V1	V2	
540	18.19	19.93	19.06
540E	16.44	18.77	17.61
	LSD = 3.05		LSD = 2.15
Average	17.32	19.35	
	LSD = 2.15		

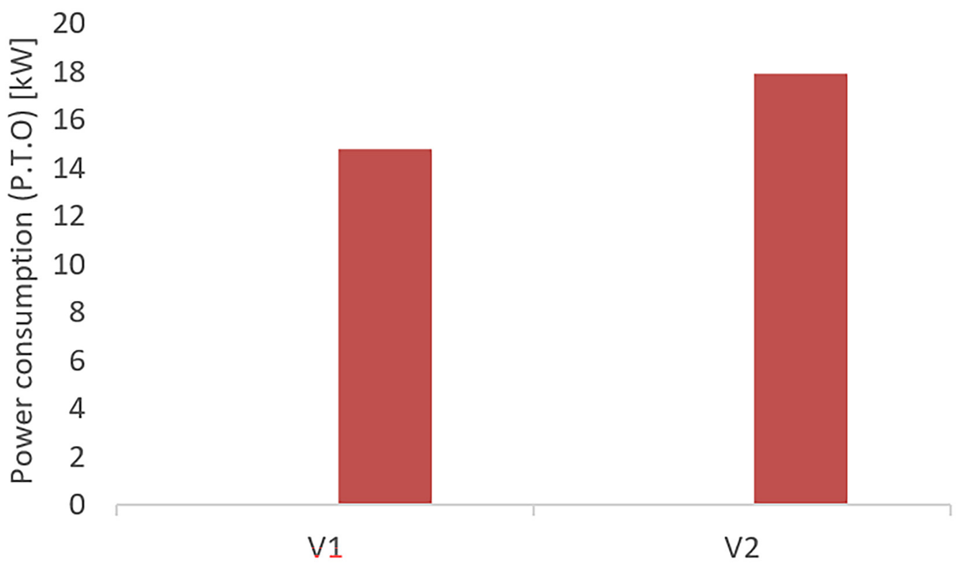

Figure 3. The power consumption depends on the forward speed

achieved for the P.T.O. shaft with a forward speed (1.8) of 14.79 kW. P.T.O. power consumption increases along with the combine's operating speed. Increasing the forward speed increased the average P.T.O. shaft power consumption by 21.23%. The power consumption on the P.T.O. shaft increases along with the working speed [6]. After determining the effect of the operating parameters of both the P.T.O. shaft application and the forward speeds on the power consumption of the tractor engine and the P.T.O. shaft, the relationship between the

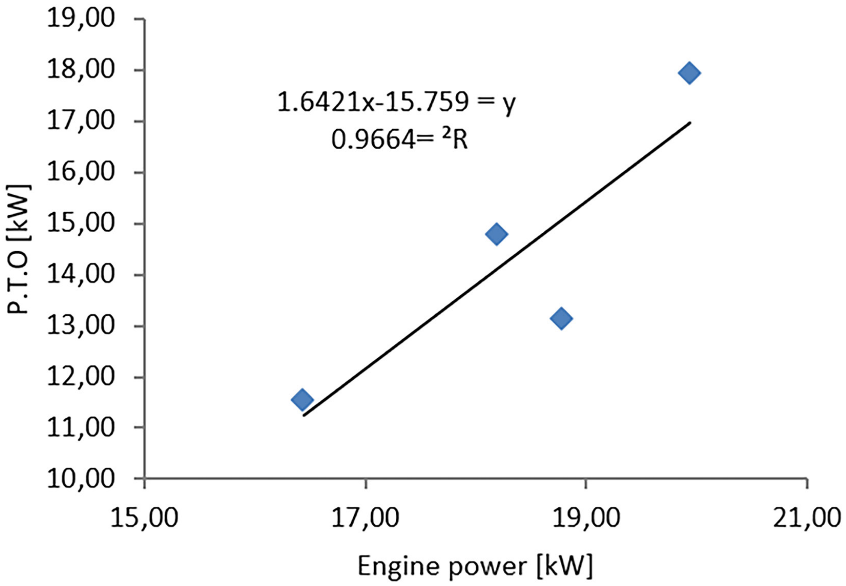

Figure 4. The relationship between the power consumed in the engine and on the P.T.O. shaft

power consumed in the engine and the P.T.O. shaft was determined (Figure 4).

The power consumed in the engine directly affects the power available for use in the P.T.O. shaft, and the power consumed in the engine is usually greater than the power available at the P.T.O. shaft [10]. Therefore, there is a very important relationship between the energy consumed at the two places above. The correlation coefficient between the energy consumed in the engine and the P.T.O shaft reached 87% based on the data obtained.

After determining the relationship between the energy consumed in the engine and the P.T.O. shaft, used machine learning algorithms, and more specifically the KNN, Tree, SVM, and ANN algorithms to predict the amount of energy consumed on the P.T.O. shaft based on data on the values of the energy consumed in the engine and various operating factors (two applications of P.T.O. shaft and two forward speeds). Figure 5 shows the accuracy of the algorithms used in the prediction. It can be seen from Figure 5 that the algorithm with the highest classification accuracy is the Tree algorithm with an accuracy of 98.8% and that the algorithm with the least accuracy in prediction is the SVM and ANN algorithm with an accuracy of 60%. In comparison, the KNN algorithm gave a prediction accuracy of 98.1%. To further analyze the accuracy, the precision, recall, and F-Measure were calculated. On the basis of the data in Table 4, the Tree algorithm gave the

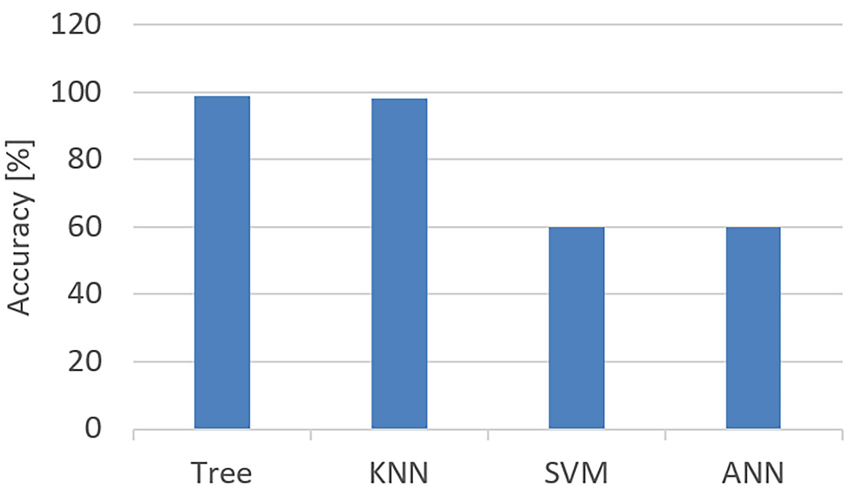

Figure 5. Accuracy of algorithms used in prediction

Table 4. Precision, recall, and F-Measure values for the algorithms used

Algorithm name	Precision	Recall	F-Measure
Tree	0.8030	0.8068	0.8049
KNN	0.8	0.8	0.8
SVM	0.7114	0.7823	0.7452
ANN	0.7114	0.7823	0.7452

highest values in Precision, Recall, and F-Measure. However, SVM and ANN algorithm gave the lowest values in the measured parameters. As a result of the training and testing of the data given as input to the machine learning algorithms, a confusion matrix was obtained. Figure 6 shows the confusion matrix of the algorithms used in the prediction. The blue values in the figure above indicate positive or accurate results, while the red values indicate negative or false results. Total cost (validation) shows the amount of prediction error for the above algorithms (Table 5).

The ANN algorithm gave the least accuracy. The reason for this is that the ANN algorithm has a high accuracy for samples of more than 1000 [31]. The other algorithms outperformed it because the number of samples was close to 100 [32, 33].

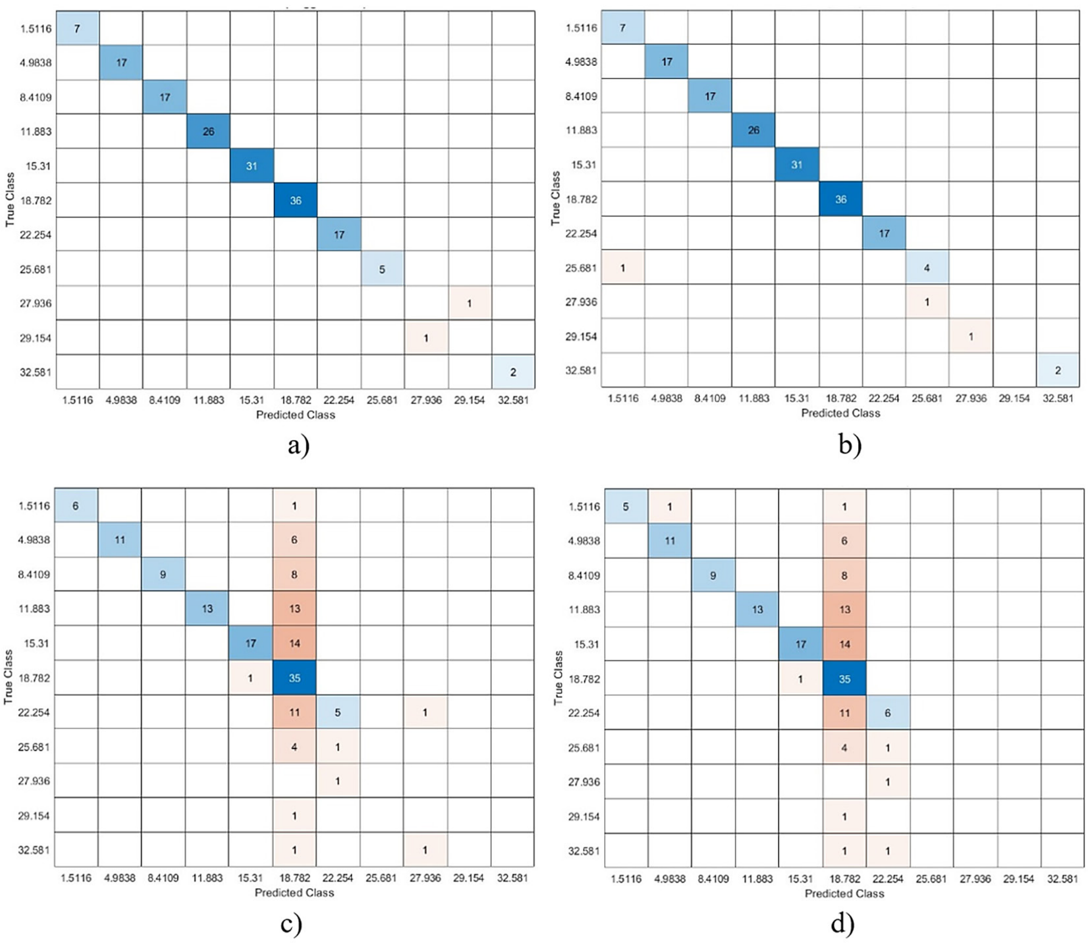

Figure 6. Correlation matrix of the machine learning algorithms used in the experiment. (a) Tree (b) KNN (c) SVM (d) ANN

Table 5. Values of the total cost (validation) of the algorithms used

Algorithms	Tree	KNN	SVM	ANN
Total cost (valıdatıon)	2	3	64	64

CONCLUSIONS

When evaluating the results in general, it was concluded that the 540E P.T.O shaft application was the best for use in operating a disc maize silage harvester. The amount of engine power consumption decreased by 8.23% when applying 540E, and by 11.72% when reducing forward speed. Increasing the forward speed also increased the average power consumption of the P.T.O shaft by 21.23%. The results also showed that the correlation coefficient between the energy consumed in the engine and the P.T.O. shaft was 87%. The Tree machine learning algorithm gave the highest prediction accuracy of 98.8%, whereas the algorithms with the lowest prediction accuracy were the SVM and ANN algorithms with an accuracy of 60%. In comparison, the KNN algorithm gave a prediction accuracy of 98.1%. It can be concluded that there is a linear relationship between the energy consumed in the engine and on the P.T.O. shaft, and therefore machine learning techniques can be relied on to predict the energy consumed on the P.T.O. shaft. The results obtained are considered the most important results of machine learning algorithms that focus on statistical analysis. Obtaining accurate forecasts can help in selecting the most suitable tractor for specific tasks and operations, ensuring that the chosen tractor is well suited to the user's needs and requirements, as well as modification, improvement, and selection of appropriate operating parameters that ensure high working efficiency. Future research can be conducted to predict the energy consumed by various other operating parameters, such as other P.T.O. shaft speeds, other forward speeds, the clearance between the fixed and mobile knife of the disc maize silage harvester, and the speed of the rotating cutting disc.

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REFERENCES

1. Nieuwenhof, P. Modeling of the energy requirements of a non-row sensitive corn header for a pull-type forage harvester (Doctoral dissertation) 2003.
2. FAO. Available online: faostat/en/#data/QCL (accessed on 12 January 2024).
3. Savoie, P., Tremblay, D., Theriault, R., Wauthy, J.M., Vigneault, C. Forage chopping energy vs. length of cut. Transactions of the ASAE 1989, 32(2): 437–0442. https://doi.org/10.13031/2013.31022
4. Roberge, M., Savoie, P., Norris, E.R. Evaluation of a crop processor in a pull-type forage harvester. Transactions of the ASAE 1998, 41(4): 967–972. https://doi.org/10.13031/2013.17254
5. Evrenosoğlu, M., Yalçın, H. A study on the operational characteristics of harvesting mechanization systems of corn silage. Journal of Agricultural Machinery Science 2006, 2(1): 65–70.
6. Özbek, O., Al-Sammarraie, M.A.J. Determination of operating characteristics of 540 and 540e P.T.O applications in disc type silage machines. Turkish Journal of Agriculture-Food Science and Technology 2020, 8(8): 1692–1696. https://doi.org/10.24925/turjaf.v8i8.1692-1696.3462
7. Çiftçi, O., Çalışır, S. The impact of a centrifugal pump in the fuel consumption of agricultural tractors with different nominal capacities driven with 540 and 540e P.T.O options. Selcuk Journal of Agriculture and Food Sciences 2018, 32(2): 197–205.
8. AL-sammarraie, M.A.J., Özbek, O. The effect of knife clearance on the machine performance in disc type silage machines. Selcuk Journal of Agriculture and Food Sciences 2019, 33(2): 74–81. https://doi.org/10.15316/SJAFS.2019.159
9. Sümer, S.K., Kocabiyik, H., Say, S.M., Çiçek, G. Comparing of 540 and 540e P.T.O operational characteristics of tractors in field conditions. Journal of Agricultural Sciences 2010, 16.
10. Lin, T., Buckmaster, D.R. Evaluation of an optimized engine-fluid power drive system to replace mechanical tractor power take-offs. Transactions of the ASAE 1996, 39(5): 1605–1610. https://doi.org/10.13031/2013.27675
11. Emaish, H., Abualnaja, K.M., Kandil, E.E., Abdelsalam, N.R. Evaluation of the performance and gas emissions of a tractor diesel engine using blended fuel diesel and biodiesel to determine the best loading stages. Scientific Reports 2021, 11(1): 9811. https://doi.org/10.1038/s41598-021-89287-0
12. Bahnasy, A.F., El-Gwadi, A.A., Morsi, M.E.M. Prediction of tractor fuel consumption and drawbar power using laboratory and field tests. Misr Journal of Agricultural Engineering 2011, 28(1): 19–31. https://dx.doi.org/10.21608/mjae.2011.105368
13. Karwasra, N., Kumar, A., Kalra, A., Mukesh, S., Rani, V. Prediction of tractor power take-off performance using artificial neural network. Journal of Krishi Vigyan 2022, 10(2): 251–258. http://dx.doi.org/10.5958/2349-4433.2022.00046.0

14. Rahimi-Ajdadi, F., Abbaspour-Gilandeh, Y. Artificial neural network and stepwise multiple range regression methods for prediction of tractor fuel consumption. Measurement 2011, 44(10): 2104–2111. https://doi.org/10.1016/j.measurement.2011.08.006
15. Jalilnezhad, H., Abbaspour-Gilandeh, Y., Rasooli-Sharabiani, V., Mardani, A., Hernández-Hernández, J.L., Montero-Valverde, J.A., Hernández-Hernández, M. Use of a convolutional neural network for predicting fuel consumption of an agricultural tractor. Resources 2023, 12(4): 46. https://doi.org/10.3390/resources12040046
16. Mohamed, A.A.I., Bahnasy, A.F., Morsi, M.E., El-Gwadi, A.A. Determining tractor performance using tractor mobility number and engine power. Journal of Soil Sciences and Agricultural Engineering 2008, 33(5): 3443–3455. https://dx.doi.org/10.21608/jssae.2008.203077
17. Tucki, K., Orynycz, O., Świć, A., Wasiak, A., Mruk, R., Gola, A. Analysis of the possibility of using neural networks to monitor the technical efficiency of diesel engines during operation. Advances in Science & Technology Research Journal 2023, 17(6). https://doi.org/10.12913/22998624/172003
18. Issa, I.I.M., Zhang, Z., El-Kolaly, W., Yang, X., Wang, H. Design, ansys analysis and performance evaluation of potato digger harvester. International Agricultural Engineering Journal 2020, 29(1): 60–73.
19. Al-Sammarraie, M.A.J., Kırılmaz, H. Technological advances in soil penetration resistance measurement and prediction algorithms. Reviews in Agricultural Science 2023, 11: 93–105. https://doi.org/10.7831/ras.11.0_93
20. Che, D., Liu, Q., Rasheed, K., Tao, X. Decision tree and ensemble learning algorithms with their applications in bioinformatics. Software tools and algorithms for biological systems 2011: 191–199. https://doi.org/10.1007/978-1-4419-7046-6_19
21. Abdulrezzak, S., and Sabir, F. An empirical investigation on snort NIDS versus supervised machine learning classifiers. Journal of Engineering 2023, 29(2): 164–178. https://doi.org/10.31026/j.eng.2023.02.11
22. Kuang, Q., Zhao, L. A practical GPU based kNN algorithm. Proceedings. The 2009 International Symposium on Computer Science and Computational Technology (ISCSCI 2009) 2009.
23. Hussein, M.A. Performance analysis of different machine learning models for intrusion detection systems. Journal of Engineering 2022, 28(5): 61–91. https://doi.org/10.31026/j.eng.2022.05.05
24. Al-Sammarraie, M.A.J., Gierz, Ł., Przybył, K., Koszela, K., Szychta, M., Brzykcy, J., Baranowska, H.M. Predicting fruit's sweetness using artificial intelligence – case study: orange. Applied Sciences 2022, 12(16): 8233. https://doi.org/10.3390/app12168233
25. Muter, Z.K., Molood, A.T. Design the modified multi practical swarm optimization to enhance fraud detection. Ibn AL-Haitham Journal for Pure and Applied Sciences 2020, 33(2): 156–166.
26. Bondar, O. Predictive neural network in multipurpose self-tuning controller. Acta Mechanica Et Automatica 2020, 14(2): 114–120. https://doi.org/10.2478/ama-2020-0017
27. Rezouki, S.E. Artificial neural network model for wastewater projects maintenance management plan. Journal of Engineering 2022, 28(11): 14–31. https://doi.org/10.31026/j.eng.2022.11.02
28. Kumar, M.N., Koushik, K.V.S., Deepak, K. Prediction of heart diseases using data mining and machine learning algorithms and tools. International Journal of Scientific Research in Computer Science, Engineering and Information Technology 2018, 3: 887–898.
29. Dahab, M., Al-Hashem, H.A.E. Study on the effect of tractor power and speed on some field performance parameters working on a clay loam soil. Journal of Soil Sciences and Agricultural Engineering 2002, 27(1): 573–582. https://dx.doi.org/10.21608/jssae.2002.253307
30. Rahim, R., Mamat, R., Taib, M.Y., Abdullah, A.A. Influence of fuel temperature on a diesel engine performance operating with biodiesel blended. Journal of Mechanical Engineering and Sciences 2012, 2: 226–236. https://doi.org/10.15282/jmes.2.2012.10.0021
31. Tu, J.V. Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes. Journal of clinical epidemiology 1996, 49(11): 1225–1231. https://doi.org/10.1016/S0895-4356(96)00002-9
32. Imandoust, S.B., Bolandraftar, M. Application of k-nearest neighbor (knn) approach for predicting economic events: Theoretical background. International journal of engineering research and applications 2013, 3(5): 605–610.
33. Karamizadeh, S., Abdullah, S.M., Halimi, M., Shayan, J., Javad Rajabi, M. Advantage and drawback of support vector machine functionality. In 2014 international conference on computer, communications, and control technology (I4CT) 2014, 63–65. https://doi.org/10.1109/I4CT.2014.6914146