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Original Research

Agricultural tractor driving cycle extraction using artificial intelligence

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ABSTRACT

Driving cycle assessment is one of the common methods to evaluate a vehicle's real-world condition also monitor fuel consumption and emissions. The basic challenge in the extraction of the driving cycle is data analysis to develop and define the suitable behavior of the device. Clustering, classification, and recognition of driving patterns are important steps in the extraction of a suitable driving cycle. Generally, the accuracy of modeling and recognition of AI-based methods is indicated by more than 90% and other outputs comply with big data. Thus, in this research, we endeavored to evaluate the effect of using artificial intelligence on the driving cycle of off-road vehicles. The major part of off-road vehicles are agricultural vehicles such as tractors which are divided into three categories based on agriculture operations; light, heavy, and extra heavy. In addition, the procedure of agricultural operation is effective on fuel consumption, loading, and exhaust emissions. The results of this research showed that the use of conventional machine learning methods for clustering and classification can be used for any volume of features. However, with an increase in features, the complexity of region segmentation and the effect of farm management factors cause overtraining conditions in the learning algorithm and reduce the accuracy of the extracted driving cycle and prediction of driving behavior. Therefore, it is necessary to use advanced algorithms with deep learning capabilities. Therefore, extracting the intelligent driving cycle for agricultural tractors based on the type of agricultural operation with the help of artificial intelligence methods can reduce fuel consumption, pollution, and optimal farm management.

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1- Introduction

The driving cycle is used as one of the methods for evaluating performance and emission in an internal combustion engine that is dedicated to both transient and steady-state modes. According to basic explanations for the driving cycle, monitoring of performance parameters, fuel consumption, and pollution of each type of vehicle-based on location within a specified time range is called a driving cycle. Also, speed and acceleration changes can have a significant impact on estimating the driving model of the operator. With these details, three models of normal, aggressive, and gear shift mode driving are used to categorize driving cycle behavior [1].

In according with there are many various categories for vehicles, extraction of their driving cycles will be different. regular driving cycles for urban cars include the new European driving cycle (NEDC), extra-urban driving cycle (EUDC), and ADAC Eco test. What is more, some of the modern driving cycle standards that have universal applications, are called worldwide harmonized light vehicles test cycle (WLTC) and worldwide harmonized light vehicles test procedure (WLTP) [2].

Despite all this information which have been said, countries have extracted specific driving cycles based on their geographical climate, road substruction, and volume of urban and non-urban traffic [3, 4]. As a consequence of this pathway, it is necessary to measure a suitable driving cycle for non-road vehicles [5]. Determine driving cycle for non-road vehicles emanated from driving tests such as Chassis dynamometer and Engine-dynamometer and Permanent and transitory conditions could be different. Agricultural vehicles are placed in the C1 class of non-road vehicles based on ISO 8178 standard [6].

Agricultural vehicle's Driving cycles can be studied in the non-road transient cycle and Non-Road steady-state cycle conditions. Maximum time of NRTC for evaluating fuel consumption and emissions measurement is 1238 seconds [7]. As a result, it is required to check the NRTC driving cycle in line with loads that enter into each part of the tractor. in addition, the slip percentage of driving wheels and soil features can affect the results of the NRTC driving cycle [8]. Based on this, farm management patterns to optimize tractor travel have always been desired by researchers [9]. Such a way of reducing the traffic of the tractor in the field will improve the indicators related to soil porosity and also the optimal use of tillage tools will increase the ability of the soil to withstand erosion [10, 11].

Online monitoring necessity and big data analysis have led to the use of statistical modeling as one of the main steps of driving cycle extraction. Furthermore, by increasing the influenced factors and soil texture changes and loading agricultural implements, the classification of the driving cycle in agricultural machinery has encountered greater complexity. One of the new methods in modeling, clustering, classification and pattern recognition of driving cycles is using artificial intelligence applications based on learning algorithms. Also, supervised, unsupervised, and reinforcement learning algorithms have made driving cycle computation possible for a variety of categories, loads, and geographical conditions [12].

The advantage of advanced - intelligent learning algorithms is that they can be used in combination with optimization methods to extract driving cycles and optimize fuel consumption and emissions parameters. The usage of electronic control units (ECU) and transmission control units (TCU) in heavy-duty tractors and agricultural vehicles and the significance of proper adaptation to functional conditions of the vehicle, has increased the importance of accurate analysis of the driving cycle. Using the K-means intelligent clustering method and Markov matrix for the extraction of loader driving cycle improved continuously variable transmission gearbox performance and reduced fuel consumption [13, 14].

Combining clustering methods with artificial neural networks, intelligent machine learning classification, deep learning, and advanced AI algorithms can be used for the extraction of smart driving cycle [15, 16].

Overall, substantial development of electronic load and traction control systems in agricultural tractors and adaptation between electronic processors and actuators has made the high requirement of smart driving cycle extraction. Besides, the importance of reducing fuel consumption and emissions based on NRTC has led to extraction and classification of driving cycle based on farm spatial patterns, decreasing traffic, farming operations loading conditions, and geographical climate [17].

Nevertheless, the wide range of parameters affecting the precise performance of agricultural tractors highlights the necessity of using artificial intelligence methods. Hence, this study aims to investigate the capabilities of artificial intelligence in improving the driving cycle of agricultural machinery based on the main factors of farm management.

main novelty of this research is to survey studies affiliated with the driving cycle recognition pattern of agricultural tractors to combine with farm management and environmental factors. Due to the difference between the size and limitation of the farm and weather factors, it is necessary to examine AI's abilities to provide a various pattern.

to analyze AI capabilities to extract driving patterns, the subjects of this research are divided into 4 major parts

1) Evaluation equations, factors, and essential parameters to devise the NRTC driving cycle model.
2) Predict the reliability, accuracy, and abilities of a Learning-based AI algorithm that can combine non-correlated factors.
3) Explanation and evaluation of vehicle functions on the farm.
4) Accuracy assessment and adaptation of AI algorithms with driving paradigms and big data.

2- Materials and Methods

To describe the relationship and procedure of smart Driving cycle Extraction, it is needed to introduce equations that explain the relation between the NRTC and the AI algorithm. So, three basic statements have been expressed in this section that show Driving cycle governing equations, a matter of machine learning algorithms based on artificial intelligence, and farm management equations.

2-1- Driving cycle formula

Two important relationships in driving cycle extraction are the estimation of the following integral speed curve over time and vehicle-specific power. Most of the time, for driving cycles, these curves are drawn and determined by time factor then speed changes are achieved. The integral relative positive acceleration equation illustrates the results of instantaneous positive speed. Further, this equation indicates a positive instantaneous acceleration in a given part of the test cycle. According to the vehicle-specific power equation, the amount of fuel consumption and pollutants can be estimated. Eq.1 and Eq.2 represent RPA, VSP, and F_{tr} [5].

$$RPA = \frac{1}{S}\int_0^t V(t) \times a(t)dt \tag{1}$$

$$VSP = \frac{F_{tr} \times V}{m_v} \quad , F_{tr} c_{fr} m_v g + m_v g \sin\theta + \frac{1}{2}\rho_a c_d A_f V^2 + m_v \frac{dV}{dt} \tag{2}$$

S is distance (m), V(t) is positive speed (m/s), a(t) positive acceleration (m/s^2), F_{tr} vehicle traction force (N), mass vehicle (kg), C_{fr} friction coefficient, $\rho_a$volumetric density of air (kg/m^3), C_d drag coefficient is the front surface of the vehicle (m^2). Based on the division made, if RPA less than 0.1(m/s^2) indicates a "soft" driving mode, and higher than 0.2 (m/s^2) indicates a "variable" driving mode. For micro-trip driving cycles, this is about 0.34 (m/s^2).

One of the main parameters to correct the estimation of the driving cycle is the calculation of traveled distance; Because the vehicle spatial changes may be uniform. As a result, the Eulerian equation is used to calculate distance. Eq.3 shows the Eulerian distance formula.

$$S_{ij}^2 = \sum_{k=1}^{p} (x_{ik} - x_{jk})^2 \tag{3}$$

where S_{ij} traveled distance (km), p number of rounds, x_{ik} and x_{jk} the location is at Cartesian coordinates.

Standardization of speed and torque is required for the extraction driving cycle in a transient and steady-state condition. To standardize the speed and torque in dynamometer engine mode of non-road vehicles, Eq.4 and Eq.5 are represented:

$$V = \frac{V_{norm} \times (V_{ref} - V_{norm})}{100} + V_{idle}\, , V_{ref} = V_{low} + 0.95(V_{high} - V_{low}) \tag{4}$$

$$T = \frac{T_{Norm} \times T_{Max}}{100} \tag{5}$$

where V is the actual speed, V_{ref} is 100% speed at the dynamometer, V_{norm} Normalized speed, V_{idle} idle speed of the engine, and V_{high} 70% of the maximum virtual speed that the manufacturer has stated will generate the maximum power and V_{low} 50% of the maximum virtual speed that the manufacturer has announced will generate maximum power. Accordingly, T is the actual torque (N.m) and T_{max} is the maximum torque of the engine.

To assess pollutants emission for NRTC Eq.6 will be used [4]. Moreover, mileage fuel consumption amount is calculated by CO_2 pollutant emission. Eq.7 represents to approximation of fuel consumption based on CO_2 pollutant emission in non-road vehicles.

$$E_{wi} = \frac{wf_{cold} \cdot M_{i,cold} + wf_{hot} \cdot M_{i,hot}}{wf_{cold} \cdot W_{act,cold} + wf_{hot} \cdot W_{act,hot}} \tag{6}$$

$$Q = \frac{M_{CO_2}}{31.5 \times \rho_{fuel}} \tag{7}$$

where wf_{cold} and wf_{hot} weight factor in cold and hot start mode, $M_{i,cold}$ and $M_{i,hot}$ the mass fraction of the pollutant i (gr/test), ,$W_{act,cold}$ and, $W_{act,hot}$ the actual work produced by the engine is hot and cold start mode. M_{CO_2} CO_2 mass fraction and ρ_{fuel} fuel density.

2-2- Driving cycle mechanism

A combination of several mathematical operations and data acquisition is effective in extracting driving cycles. Additionally, essential factors explanation on the driving cycle can help estimate parameters. Figure 1 describes the extraction mechanism of driving cycles and effective parameters.

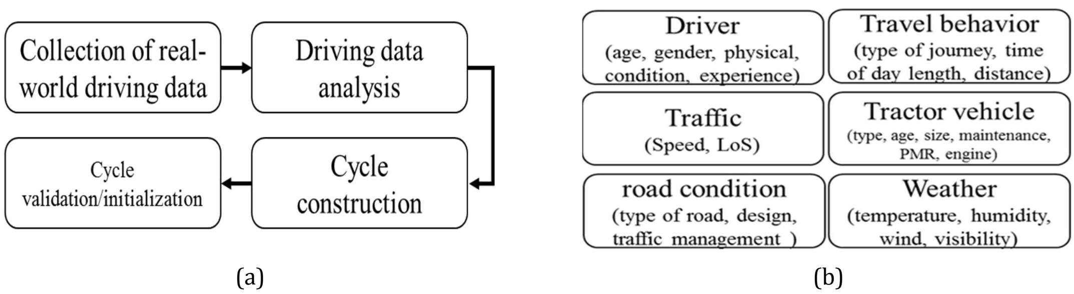

Figure 1 Extraction mechanism of driving cycles and effective parameters. a) the general procedure of the driving cycle, b) essential factors in the Driving cycle

NRTC's general strategy uses for non-road vehicles also contains its specific test procedure. In this method, tractors are classified in speed and acceleration columns. Table 1 describes the conditions of NRTC for non-road vehicles in two classes, C1 and C2.

Table 1 Speed/torque points and weighting factors (%) of the ISO 8178 cycles for non-road engines

Mode	Torque (%)	Speed	Class-1	Class-2
1	100	Rated speed	15	-
2	75		15	-
3	50		15	-
4	25		-	6
5	10		10	-
6	100	Intermediate speed	10	2
7	75		10	5
8	50		10	32
9	25		-	30
10	10		-	10
11	0	Idle/Low	15	15

As specified by time iteration for NRTC, the transient cycle diagram is shown in Figure 2.

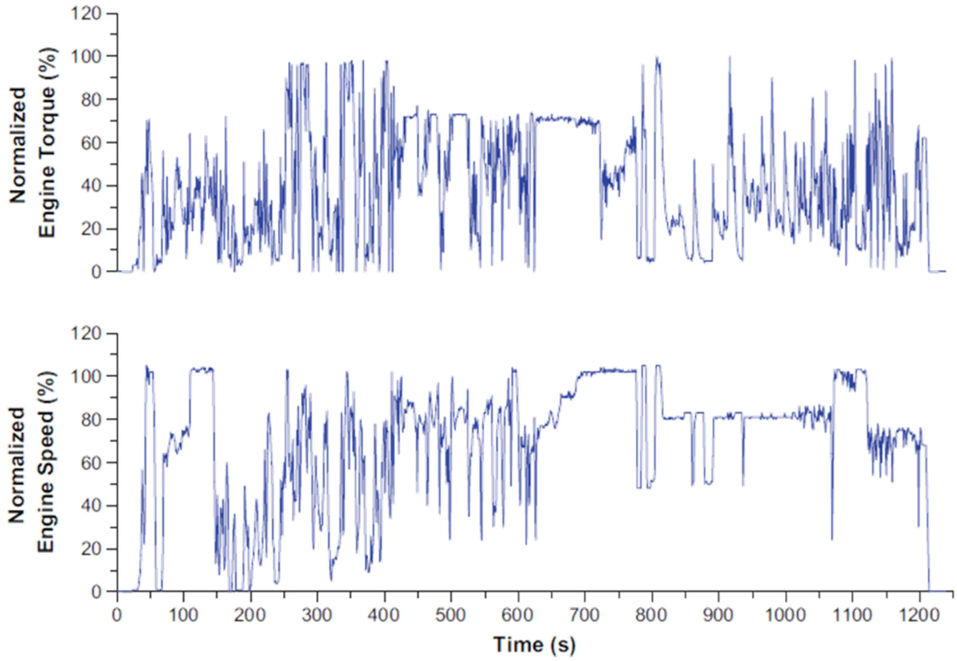

Figure 2 Engine speed and torque profile of the non-road NRTC composite transient cycle

2-3- Artificial intelligence based on learning algorithms

Learning algorithms usage is one of the common methods to develop intelligence for machines. These algorithms can be supervised, unsupervised and reinforced. The validity and accuracy of clustering or classification depends on the data sizing and ability to learn algorithms. Figure 3 clarifies the classification of learning algorithms.

Typical, learning algorithms consist of three steps which are defined by training, testing, and validation concepts. Noise-canceling, Feature reduction, and normalization should be conducted in the preprocessing stage. The aim of using the learning algorithm can be clustering, predicting, or classifying. segmenting, labeling, and determining weighting factors are implemented in the training step. Targeting outputs should be divided into train and test steps. The accuracy of modeling and classification is determined at the test step. Consequently, the accuracy of clustering, prediction, and classification in the test step are indicators of the ability of used algorithms to identify the behavior model for outputs. Increasing data volume and multi-layering outputs requires using deep learning algorithms. Figure 4 shows the flowchart of the machine learning process.

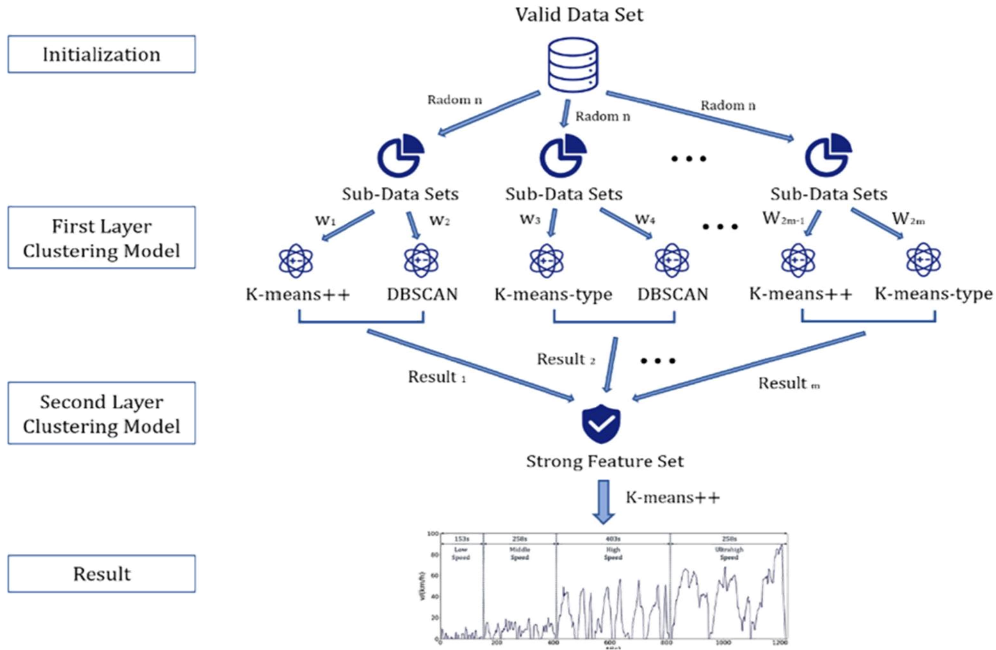

Figure 3 Classify learning methods in AI [18]

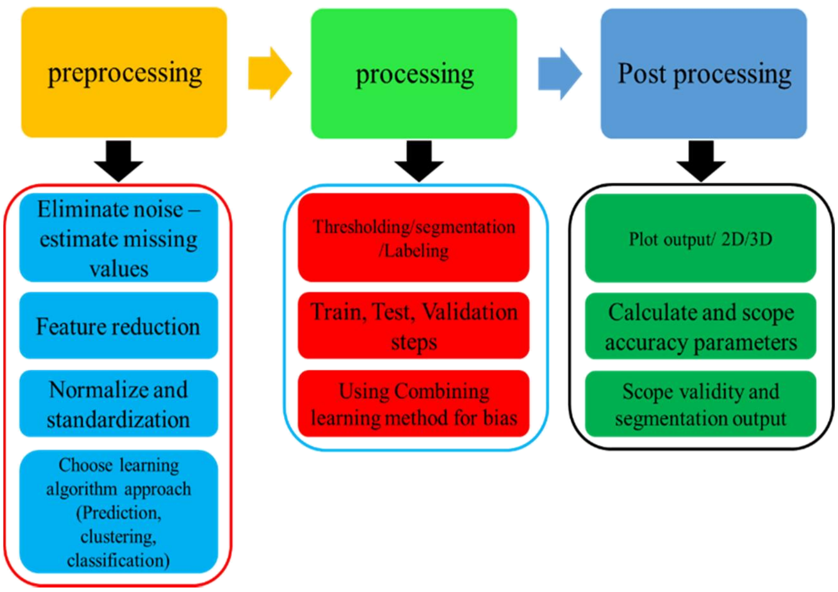

Figure 4 Machine learning algorithm procedure

Different statistical parameters can be used to evaluate the performance of the algorithm. R^2 and MAE are modeling accuracy indices, and P, Recall, and F1 scores are classification validation parameters for evaluating machine learning and deep learning algorithms. The chi-square factor is also used in segmentation algorithms. Eq. 8, Eq. 9, and Eq.10 describe the evaluation parameters for the AI learning algorithm.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}\ , MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \tag{8}$$

$$P = \frac{TP}{TP + FP}\ , R = \frac{TP}{TP + FN}, F1\ Score = \frac{2P \times R}{P + R} \tag{9}$$

$$\gamma^2 \cong \sum_{i=1}^{m} = \sum_{j=1}^{n} \frac{(O_{ij} - E_{ij})^2}{E_{ij}} \tag{10}$$

where y_i target output, $\hat{y}_i$ modeled output, $\bar{y}_i$ averaged output, TP true positive output, FP false positive output, FN false negative output, O_{ij} observed value and E_{ij} excepted value.

Fuel consumption monitoring, driving wheel slipping rate and machine efficiency are substantial parameters in machinery farm management.

2-4- Machinery farm management parameters

Fuel consumption rate is a common parameter in driving cycle and machinery farm management. Other parameters directly and indirectly have effects on fuel consumption. What is more, artificial intelligence algorithms are capable of ability to estimate the interaction between driving cycle variables and farm management factors. Eq.11 and Eq.12 describe the driving wheel slipping rate and the machine's efficiency.

$$SR = \frac{V_{act} - V_{ref}}{V_{ref}} \times 100 \tag{11}$$

$$\eta_M = \frac{E_{FC}}{T_{FC}} \times 100 \tag{12}$$

That's E_{FC} actual power farm harvesting and T_{FC} theoretical power farm harvesting. These two parameters can also be used for other ground preparation stages.

3- Results and Discussion

3-1- Artificial intelligence capability for extracting Driving cycle

According to the volume of data collection and several features that are required to extract the driving cycle by using different artificial intelligence algorithms. The main capability of AI is appropriate adaptability to data collection volume. However, it must be mentioned that the conventional feed-forward learning algorithm's accuracy will reduce when faced with large data, consequently, the performance of classification and clustering results also decreases. Results of the research have shown that using enhanced artificial neural network learning algorithms for big data can apply to online feature reorganizing and analyzing different parameters conditions of the driving cycle. changing speed and loading, according to ECU's command to operators may bring down the ability of intelligence prediction. Therefore, using an intelligent learning algorithm based on time series can partially solve this problem [19]. Figure 5 shows the structure of the artificial neural network for extraction of the diesel engine driving cycle.

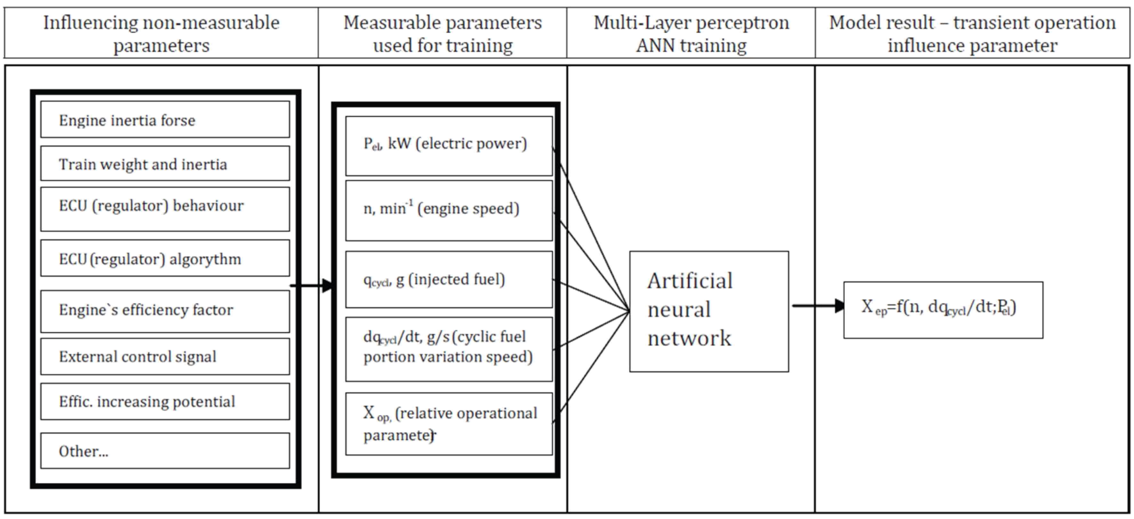

Figure 5 ANN structure for extract driving cycle [20]

Major results of smart driving cycle extraction in agriculture tractors are optimized gear shifting and improved traction and drivability. One of the important requirements for utilizing more efficient power units such as EV and HEV and reducing fuel consumption by considering engine downsizing strategy in tractors is the use of intelligent power transmission systems. The optimal operation of the CVT and automatic power transmission subsystems (hydro-electronic clutches, Torque convertor, and traction control device) depends on extracting the accurate driving cycle of the tractor. Dynamic loading of implements, variable soil texture, and weather conditions cause unsteady forces to be applied to the power transmission system of agricultural tractors. The capability of a smart driving cycle in predicting sudden loads is based on designed scenarios. Table 2, shows an implementation of various driving cycles on gear shifting performance and fuel consumption of heavy-duty and HEV diesel engines that can be used as new power units for agriculture tractors.

Another essential characteristic of the AI learning algorithm is an effective classification of main parameters in driving cycle extraction. In this method, each important output for the extraction of the driving cycle is classified as a single independent layer and will be combined in the output layer. this state caused to extraction universal intelligent driving cycle for agricultural tractors or any other vehicle [16]. Figure 6 shows the intelligent classification of parameters associated with the driving cycle. The SVM, Random Forest, and Decision Tree are ordinary classifiers in this method.

Table 2 Effect of various driving cycles on gear shifting performance and fuel consumption of heavy-duty and HEV diesel engine

Engine type	Gear transmission	Driving cycle	Main fuel consumption (1/100km)	improved fuel consumption (%)	ref
HEV Diesel engine (5Lit)	I-Shift, automatic gear shifting Gearbox (12 range)	SORT 1	24.11	0	[21]
		ECE	21.01	0.7	
		Manhattan	27.34	4.7	
		UDDS	19.21	7.3	
Heavy-duty Diesel engine (7Lit,4 Cylinder)	Automatic gear shifting	NRTC	-	3	[22]
HEV Diesel engine (6 Cylinder,8.6)	12 speed AMT	CHTC-TT	40.42	-9.39	[23]
		CLTC	45.21	0.8	
		C-WTVC	47.13	8.04	

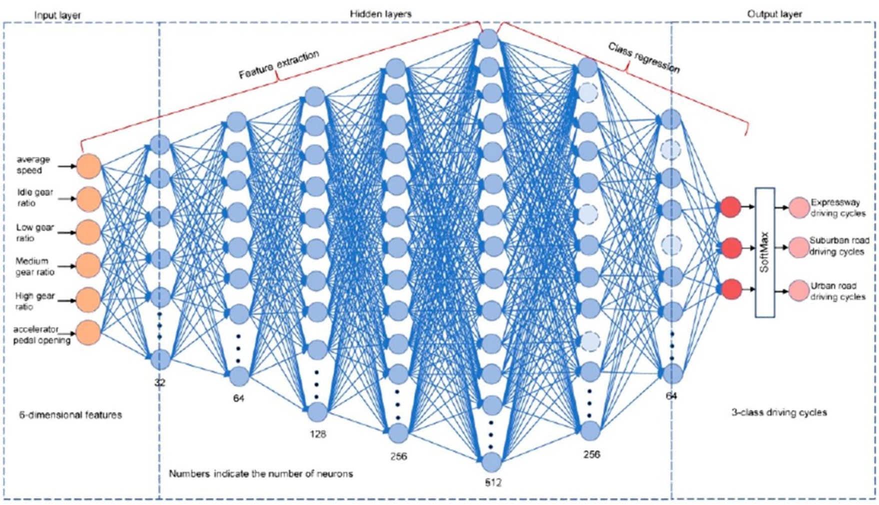

Figure 6 Two-stage NN structure [24]

3-2- Data collection volume and modeling accuracy

One of the main problems in intelligent driving cycle extraction is lake of the accuracy of algorithms in modeling and clustering procedures. two main reasons such as unequal distribution and high volumes of data are making problems for conventional and upgraded machine learning methods to extract intelligent driving cycles in non-road vehicles. In this case, using deep learning methods can resolve the stated problems. Figure 7 shows subgroups of the algorithms of intelligent learning.

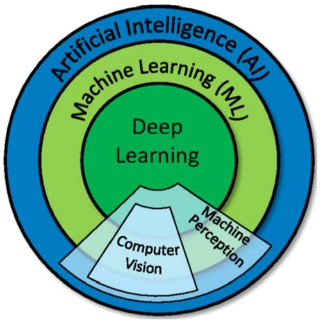

Figure 7 Different subgroups of artificial intelligence methods [25]

The major advantages of deep learning algorithms are using advanced mathematical equations, convolution filtering, multi-layered dimensional-reduction structures, and series-parallel processing that can analyze a large amount of data in an extremely short time. On the other hand, deep learning methods do not have a clear order as previous methods and they have to be used based on user experience. using deep learning methods also requires advanced and high-speed hardware. To better understand of capabilities of intelligent learning algorithms analyzing depend on the volume of inputs and number of features, a comparative has been done. Table 3 shows, evaluation indicators of the modeling are expressed by extracting the intelligent driving cycle based on the used learning algorithm.

Table 3 Evaluation parameters and capabilities of a learning algorithm for smart driving cycle

Learning algorithm	R^2_{Pre} (%)	Data volume	Reference
Clustering (k-means)	86.12	80000	[14]
NN-Histogram 2D (H2D)	97.2	120000	[15]
Deep learning-MLP	99	Big data ($> 10^5$)	[24]
Deep learning (ELM-BP-GRNN)	95	Big data ($> 10^5$)	[20]

According to the ability of AI to extract intelligent driving cycles with high adaptivity and reliability, the idea of using AI algorithms has suitable potential to incorporate machinery farm management and other factors into the driving cycle will be reinforced. Thereupon, it is necessary to research to introduce an appropriate artificial intelligence algorithm which based on the indigenous driving cycle of agricultural tractors.

4- Conclusions

To conclude, in this study, we tried to evaluate the capability of learning-based artificial intelligence algorithms to extract agricultural tractors' driving cycles. Due to the complexity and wide variety of factors affecting the performance and pollutants of agricultural vehicles during field operations, it demands more specific research to extract the driving cycle of commercial tractors. Owing to, the high potential of artificial intelligence methods in clustering and classification of features, it is possible to extract smart driving cycle results of agricultural vehicles by using them. Eventually, the results of this study are:

- The first indicator of separation of driving cycles for farm tractors can be defined as the ratio of weight to braking power.
- Smart gear shifting based on traction, weight of devices, and drivability is possible by employing an intelligent driving cycle. Furthermore, Changing the number of wheels in a tractor can be done automatically.
- Fuel consumption reduction, emissions and driving wheel slipping rate (%) are among the advantages of smart driving cycles in agricultural tractors.
- important capability of artificial intelligence indicates that approved that the highest segmented pattern (accuracy above 95%) is related to deep learning algorithms. Even so, the requirement of using these algorithms will be to utilize big data (Data collection of more than 105).
- Combining farm management methods and online decision-making capabilities would be effective in improving driving cycle visibility and adaptability in agricultural vehicles.

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List of Abbreviations

Artificial Intelligence	*AI*
China heavy-duty commercial test cycle for tractor-trailer	*CHTC-TT*
China light-duty vehicle test cycle	*CLTC*
China World Transient Vehicle Cycle	*C-WTVC*
European Urban Driving Cycle	*EUDC*
False-negative	*FN*
False positive	*FP*
New European Driving Cycle	*NEDC*
Non-Road Transient Cycle	*NRTC*
Non-Road Steady-state Cycle	*NRSC*
Relative Positive Acceleration, m/s^2	*RPA*
True positive	*TP*
Urban Dynamometer Driving Schedule	*UDDS*
Variable Specific Power	*VSP*
World-Wide harmonized Light vehicle Test Cycle	*WLTC*
World-Wide harmonized Light vehicle Test Procedure	*WLTP*

List of Symbols

Acceleration, m/s^2	a
The front area of the vehicle, m^2	A_f
friction coefficient	C_{fr}
Drag Coefficient	C_d
actual power farm harvesting	E_{FC}
Excepted Value	E_{ij}
Weighted value of Emission	E_{wi}
Vehicle Traction Force	F_{tr}
Mass Fraction, gr/gr	M
observed value	O_{ij}
Fuel consumption, gr/kW.h	Q
accuracy	R^2
Distance, m	S
Slipping ratio, %	SR
speed	V
time	t
actual Torque farm harvesting	T_{FC}

weight factor	w_i
location	x
Target output	y_i
Modelled output	$\hat{y}_i$
Density	ρ
Chi-square factor	γ^2
Machinery efficiency	η_M

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کاربرد هوش مصنوعی برای استخراج چرخه رانندگی تراکتور کشاورزی

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کلیدواژه‌ها:
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چکیده

یکی از روش‌های رایج در پایش مقدار مصرف سوخت و آلایندگی وسائل نقلیه استفاده از چرخه رانندگی اختصاصی آن خودرو است. به دلیل اهمیت استخراج چرخه رانندگی در خودروهای سواری، اغلب تحقیقات به سمت بررسی چرخه رانندگی خودروهای سبک بوده است. یکی از چالش‌های مهم در استخراج چرخه رانندگی هر وسیله نقلیه‌ای تحلیل داده‌ها، طبقه‌بندی و تشخیص الگوی رانندگی است. از جمله وسائط نقلیه غیرجاده‌ای، تراکتورهای کشاورزی است که به اندازه آن‌ها بستگی به عملیات کشاورزی دارد. همچنین عملیات کشاورزی انجام شده در مصرف سوخت، بارگذاری و آلایندگی تراکتورهای کشاورزی اثرگذار است. روش‌های جدید تحلیل و تشخیص الگوی رانندگی عموماً بر اساس روش‌های مبتنی بر هوش مصنوعی است. معمولاً دقت تشخیص و الگوی روش‌های مبتنی بر هوش مصنوعی بزرگتر از ٪۹۰ است و دیگر ویژگی آن‌ها در تطبیق با کلان داده‌هاست. نتایج این تحقیق نشان داد که استفاده از روش‌های متداول یادگیری ماشین برای خوشه‌بندی و طبقه‌بندی برای هر حجمی از ویژگی‌ها قابل استفاده است. با این حال، افزایش ویژگی‌ها، پیچیدگی تقسیم‌بندی نواحی و تأثیر عوامل مدیریت مزرعه باعث اختلال در روند آموزش الگو و کاهش دقت چرخه رانندگی استخراج‌شده و پیش‌بینی رفتار رانندگی می‌شود. بنابراین استفاده از الگوهای پیشرفته با قابلیت یادگیری عمیق برای بهبود دقت استخراج چرخه رانندگی در تراکتورهای کشاورزی ضروری است. لذا استخراج چرخه رانندگی هوشمند برای تراکتورهای کشاورزی بر اساس نوع عملیات کشاورزی به کمک روش‌های هوش مصنوعی می‌تواند موجب طراحی بهینه این دست از وسائط نقلیه غیر جاده‌ای شود و بطور همزمان خروجی‌های آلایندگی و متغیرهای اثرگذار عملیات کشاورزی را در الگوی رانندگی دخیل کند.

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